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Volatility Dynamics and Hedging Effectiveness Between Cleaner Transport Sector ETFs and Traditional ETFs

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ABSTRACT:
This thesis examines the volatility dynamics and hedging effectiveness between cleaner transport sector ETFs and traditional ETFs. The aim of this study is to gain knowledge of the individual dynamics of cleaner transport sector ETFs, as well as their relationship to traditional ETFs, to provide valuable insights to investors.

Earlier research on the volatility dynamics and hedging properties of traditional and sustainable financial assets has usually been directed to broader ESG or sustainable energy-related ETFs. This thesis contributes to the literature by narrowing the segment and focusing on the cleaner transport sector. For this analysis, both univariate EGARCH(1,1) and multivariate DCC-GARCH models are deployed.

The findings indicate that both cleaner transport sector ETFs – CLNR and FDRV – exhibit considerable volatility, mostly driven by global market events and risks, along with possible regulatory and sector-specific risks. Both ETFs exhibit relatively strong dynamic condition correlation with SPY, emphasizing the similarity in asset allocation on equities. Moreover, CLNR and FDRV both indicate a very high volatility persistence, whereas only CLNR as the only ETF displays a relatively strong asymmetric response to negative shocks. Out of all the ETFs, USO displays the most significant and highest individual volatility, but this is most likely due to large-scale geopolitical factors, and the time frame the study falls under. As for hedging, both cleaner transport ETFs indicate significant hedging effectiveness with SPY, but this result is invalid. Due to the strong conditional correlations, as well as the fact that the hedge would require over-leveraging and going from 90% asset allocation to 100% on SPY, the hedge is neither effective nor practical in real-world scenarios.

KEYWORDS: cleaner transport sector ETF, volatility dynamics, hedging, portfolio management, diversification, risk management

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TIIVISTELMÄ:
Tämä opinnäytetyö tutkii puhtaamman liikenteen alaan liittyvien ETF:ien ja perinteisten ETF:ien välistä volatiliteettidynamiikkaa sekä niiden suojaavuuden tehokkuutta. Työn tavoitteena on ymmärtää puhtaamman liikenteen ETF:ien yksilöllisiä dynamiikkoja ja niiden suhdetta perinteisiin ETF:iin, tarjoten näin arvokkaita näkemyksiä sijoittajille.

Aiemmat tutkimukset volatiliteettidynamiikasta ja kestävien sekä perinteisten rahoitusvarojen suojaavuudesta on yleensä keskittynyt laajempiin ESG- tai uusiutuvaan energiaan liittyviin ETF:iin. Tämä työ täydentää kirjallisuutta rajaamalla tarkastelun puhtaamman liikenteen alaan. Analyysia varten hyödynnetään sekä yhden muuttujan EGARCH(1,1)-mallia että monimuuttujan DCC-GARCH-mallia.

Tulokset osoittavat, että sekä CLNR että FDRV, puhtaamman liikenteen ETF:t, osoittavat huomattavaa volatiliteettia, joka johtuu pääasiassa globaaleista markkinatapahtumista ja -riskeistä, sekä mahdollisista sääntely- ja sektorikohtaisista riskeistä. Molemmat ETF:t osoittavat suhteellisen vahvaa dynaamista ehdollista korrelaatiota SPY:n kanssa, mikä korostaa niiden samankaltaisuutta osakerahastoihin allokaation suhteen. Lisäksi CLNR ja FDRV osoittavat erittäin korkeaa volatiliteetin pysyvyyttä, kun taas ainoastaan CLNR reagoi suhteellisen voimakkaasti negatiivisiin markkinashokkeihin. Kaikista ETF:istä USO osoittaa merkittävimmän ja korkeimman yksilöllisen volatiliteetin, mikä johtuu todennäköisesti laajamittaisista geopoliittisista tekijöistä ja tutkimuksen aikavälistä. Suojauksen osalta molemmat puhtaamman liikenteen ETF:t osoittavat merkittävää suojaavuuden tehokkuutta SPY:n kanssa, mutta tämä tulos on epävalidi. Vahvojen ehdollisten korrelaatioiden sekä sen vuoksi, että suojaus vaatisi ylivivuttamista ja omaisuusallokaation muuttamista 90 prosentista 100 prosenttiin SPY:ssä, suojaus ei ole tehokas eikä käytännöllinen todellisissa sijoitustilanteissa.

AVAINSANAT: puhtaamman liikenteen sektori ETF, volatiliteetti dynamiikka, suojautuminen, salkun hallinta, hajauttaminen, riskienhallinta

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1 Introduction

There has been a significant growth in the concept of Environmental, Social, and Governance (ESG) investing over the past few decades, ever since ESG factors started influencing investment decisions. Within recent years, there has been a notable increase in public awareness and concern regarding environmental sustainability among individuals, corporations, and industries. The United Nations Principles for Responsible Investment, launched in 2006, has been one of the major factors in promoting ESG principles, with different relevant parties committing to responsible investment practices (UN PRI, 2021). Today, ESG investing is a globally known, studied, and slowly adopted concept among retail investors and corporations, embracing not only its potential to deliver long-term financial performance but also its positive non-financial impact (Friede, et al., 2015).

Within the ESG framework, the cleaner transport sector has become and has been one of the key areas of focus due to its high potential to reduce global greenhouse gas emissions significantly. An example of major steps in the field is the development of electric vehicles and new emerging technology related to matter (Hawkins et al., 2012). In addition, Nykvist and Nilsson (2015) illustrate the continuous decrease in battery costs for electric vehicles. This again enables growth in the electric car market, as the costs can be reduced, thus becoming increasingly more attractive for consumers and companies. As an example, electric car market sales increased around 18% in 2023, compared to a 4% increase in 2020 (International Energy Agency, 2024). Taking these numbers into account, one can assume that the markets, both for vehicles and new technology, will only increase in the future due to nonstop ongoing research and development.

The cleaner transport sector is now filled with momentum for innovation and growth. Electric vehicles have changed the automotive industry forever, with companies like

Tesla proving to other automakers that electric vehicles could work for both consumers and corporations. Even the public transportation systems are also transitioning to cleaner modes, e.g., electric buses (Sperling & Gordon 2009). Across the world, various governments are implementing tougher emission policies and environmental laws while offering subsidies to promote and practice more sustainable modes of transportation and technology. These kinds of measures are required to combat climate change and reduce the dependence on fossil fuels (International Energy Agency, 2020).

Furthermore, advancements in ride-sharing platforms – and micromobility options such as e-scooters – are also contributing to building and improving the cleaner transport sector. As these concepts have become increasingly popular, large companies such as Uber are investing in electric vehicles to reduce their carbon footprint (Uber Technologies Inc., 2024). Other electrical ways of transportation rather than automotive, such as electric scooters, electric bikes, and electric mopeds, have also grown significantly (International Energy Agency, 2020). Overall, the cleaner transport infrastructure, whether being vehicles or technology related to the matter, is accelerating and growing day by day.

1.1 Purpose of the Study

Due to the rapid growth and innovation within the cleaner transport sector, a comprehensive understanding of the related investment opportunity, especially within Exchange-Traded Funds (ETFs), is needed. ETFs are a popular financial product due to their ability to offer diversified exposure to asset classes, sectors, and themes (Hill & Mueller, 2001). Cleaner transport sector ETFs, which specifically focus on companies developing and deploying sustainable transportation technologies, as well as on companies that support the transition to more environmentally efficient transportation technologies, have emerged just around the late 2010s and early 2020s. These relatively new ETFs have the potential to offer investors the possibility to maximize their returns while considering environmental impact.

For investors seeking to manage risk and optimize their portfolios, understanding the volatility dynamics of these ETFs is crucial. Due to their nature, cleaner transport sector ETFs may exhibit different volatility patterns compared to traditional ETFs. This can be solely due to differences in the ETFs' securities, for example including established companies with more predictable performance compared to newer emerging ones. Thus, there can be considerable variation regarding how different market variables could impact these ETFs. This research aims to provide insights and clarification into these volatility patterns, which may help investors make more informed investment decisions in the future.

Moreover, the study concentrates on hedging effectiveness. With this, the study takes into account the practical implication of incorporating cleaner transport sector ETFs into investment portfolios. Given the differences in their nature, cleaner transport sector ETFs may provide distinctive hedging opportunities. By analyzing and evaluating the effectiveness of hedging involving cleaner transport ETFs, the study aims to provide insights to investors and help with optimal protection on investments against market movements.

The study is relevant due to the ongoing and increasing amount of ESG factors affecting investment decisions and the overall growing attention on sustainable development. With increasing attention to ESG factors, beyond mere financial returns, cleaner transport sector ETFs could prove to play a significant role in diversified portfolios in the future. Moreover, cleaner transport sector ETFs are relatively new concepts with very little research on them. This study helps investors understand their behavior in relation to other traditional ETFs, giving new important information regarding future investment decisions.

1.2 Hypothesis Development

This thesis studies the volatility dynamics and hedging effectiveness between cleaner transport sector ETFs and traditional ETFs. The aim is to understand the individual dynamics, as well as the relationship between these assets. To the author's knowledge, no similar study on cleaner transport sector ETFs has been made, thus reflecting the hypotheses of past studies is challenging. However, due to the emerging and policy-sensitive nature of the cleaner transport sector, the following hypothesis is formed:

H1: Cleaner transport ETFs exhibit higher volatility and volatility persistence compared to traditional ETFs.

Moreover, due to the methodology of this study, the asymmetric volatility responses are captured. Given the previous research (see, for example, Çelik et al., 2022; Chen & Chen, 2023; Rizvi et al. 2021), and the assumption that the cleaner transport sector may have a stronger response asymmetrically to negative market shocks, the second hypothesis is formed:

H2: Cleaner transport sector ETFs display stronger asymmetric volatility responses to negative market shocks, than traditional ETFs.

Lastly, given the past research on traditional ETFs and the hedging possibilities (see, for example, Kang et al., 2021; Çelik et al., 2022; Cheng et al. 2018), the last hypothesis is formed:

H3: Traditional ETFs, particularly gold and oil, provide an effective hedge for cleaner transport sector ETFs, with dynamic correlation showing an inverse relationship during periods of market stress.

1.3 Structure of the Study

The thesis is structured as follows:

Chapter one provides an introduction to the growing importance of environmental sustainability, the evolution of cleaner transportation, and the relevance of Cleaner Transport ETFs. It describes the purpose of the study, introduces hypotheses, and presents the structure of the thesis. Chapter two reviews the theoretical background of volatility and hedging. Moreover, it introduces theories and models associated with these concepts, taking also an analytical approach. Chapter three reviews existing literature related to ESG investing, cleaner transportation, and the financial instruments related to these two. The focus will be on previous studies on volatility dynamics and hedging effectiveness. Chapter four presents the research methodology used in the study, including data and the models used to measure volatility dynamics and hedging effectiveness.

Chapter five presents the empirical findings of the study, describing the results and the volatility patterns of selected ETFs and the hedging possibilities. It examines and discusses the factors influencing these dynamics and the possible impact of market conditions. The purpose is to reflect the findings with possible similarities presented in chapter three. Chapter six, the last chapter, summarizes the key findings of the study and suggests possible areas for future research. It also highlights the importance of cleaner transport in the world of sustainable finance.

2 Theoretical Background

The theoretical part of the study first presents volatility, which is the degree of variation in the price of a financial instrument. Volatility is a globally recognized and accepted concept, and it plays a significant part in risk management and derivative pricing. The theoretical part also includes hedging, which is a risk management technique used to offset potential future losses by taking a contrary position in a related asset. This section of the study will explore the theoretical background of both concepts, including statistical models used for measuring volatility and examples of hedging techniques.

2.1 Volatility

Volatility in finance is a statistical measure that represents the degree of variation in a financial instrument's price over time. Thus, it works as a measure of risk and uncertainty that come with price fluctuations. Simplified, there are three kinds of volatility, implied volatility, historical volatility, and expected volatility (Dicle & Levendis, 2019). According to Dicle and Levendis (2019), referring to Hull and White (1987) as well as Merton (1973), the first one represents how the volatility of the instrument will or could be in the future, considering traded option prices. So, it takes account of the expected future volatility inevitably. Historical volatility on the other hand is solely based on historical market data, taking only into account the price changes regarding past periods which have already happened. Understanding volatility plays a crucial role in, for example, derivatives pricing, financial risk management, trading strategy implementation, and portfolio optimization. Due to its significance in asset pricing and overall market behavior, the subject has received a lot of attention and has been researched a lot, for example (Andersen, et al., 2006; Andersen, et al., 2003). Andersen et al. (2006), emphasize that volatility modeling is essential for applications in risk management and overall empirical finance.

The ARCH model, developed by R. F. Engle (1982), is one of the key models estimating volatility. By representing and modeling the variance as a function of prior errors, which are generally common in financial time series, the model aims to capture the characteristics of time-varying volatility (Engle, 1982). As for the simple ARCH(q) process, it can be presented as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-1}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 \quad (1)$$

where σ_t^2 is the conditional variance at the time t, $\alpha_0$is a constant representing the baseline level of variance, α_i(for $i = 1,2, \ldots, q$) are the coefficients for ε_{t-i}^2, and ε_{t-i}^2 are the prior errors (shocks). Moreover $\alpha_0 > 0, i > 0$. After the development of the ARCH model, due to limitations such as every other model, multiple extensions and variants of the model have been developed and presented. One of these extensions is called the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model, which was developed by Bollerslev (1986).

2.1.1 Univariate GARCH Models

The GARCH model extends the ARCH model by allowing past variance in addition to prior error terms to influence current variance estimates. The model can be roughly divided into two categories: univariate and multivariate models. The main difference between univariate and multivariate models is that the univariate GARCH models are limited to one asset at a time. Similar to the ARCH model, multiple extensions of the GARCH model have been developed and presented ever since (Teräsvirta, 2006). The most common univariate GARCH model GARCH (q, p) process can be presented as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_j \sigma_{t-j}^2 \quad (2)$$

where σ_t^2 is the conditional variance at the time t, $\alpha_0$is a constant representing the baseline level of variance, α_i(for $i = 1,2, \dots, q$) are the coefficients for ε_{t-i}^2, ε_{t-i}^2 are the prior errors (shocks), β_j are the coefficients for σ_{t-j}^2, and σ_{t-j}^2 are the conditional variances from previous periods. So, the model resembles ARCH(q) model (1), with addition of β_j capturing the past variances.

While the univariate GARCH model is powerful, it operates on the assumption that the variance of a single time series depends on its own prior squared returns and prior variances (Bollerslev, 1986). As the model is simple, it lacks the capability of capturing the complexities of financial markets where assets usually are correspondent (Teräsvirta, 2006). To address this issue, models such as the Exponential GARCH (EGARCH) and the Threshold GARCH (TGARCH) have been developed. For instance, the EGARCH model, introduced by Nelson (1991), modifies the simple GARCH model by allowing for asymmetric effects of positive and negative shocks on volatility, while it also ensures the positivity of conditional variance at every point in time without parameter restrictions (Teräsvirta, 2006). The common EGARCH (p, q) process can be presented as follows:

$$\log(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left[\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}} \sigma_{\{t-i\}} \right) \right] + \sum_{i=1}^{q} \gamma_i \left[\left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| E \left(\left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| \right) \right) \right] + \sum_{i=1}^{q} \beta_j \log\left(\sigma_{t-j}^2\right), \tag{3}$$

where $\log(\sigma_t^2)$ is the natural logarithm of the conditional variance at time t, $\alpha_0$is a constant, α_i are the coefficients for the standardized residuals that capture the asymmetric effect of shocks, γ_i are the coefficients for the magnitude of standardized residuals that capture the leverage effect, $E\left(\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|\right)$ is the expected value of the magnitude of the standardized residuals which are assumed to be constant, β_j are the coefficients for σ_{t-j}^2, and $\frac{\varepsilon_{t-i}}{\sigma_{t-i}}$ are the standardized residuals. As we can see, the basic ARCH model allows different extensions by adding specific differing variables, thus also changing the intention of the model.

2.1.2 Multivariate GARCH Models

Unlike univariate GARCH models, multivariate GARCH models allow the modeling of the volatilities and covariances of multiple time series simultaneously (Engle & Kroner, 1995). This is critical in, for example, portfolio management, i.e., understanding the interdependencies between asset returns is essential for risk assessment and optimization (Bollerslev et al., 1988). One of the most common multivariate GARHC models is called the VECH model, introduced by Engle, Wooldridge, and Bollerslev (1988). This model allows for straightforward modeling of the variance-covariance matrix, by stacking the elements of this matrix into a vector (Bollerslev et al., 1988). The common VECH model can pe presented as follows:

$$\mathrm{vech}(\mathbf{H}_t) = \mathbf{c} + \sum_{i=1}^{q} \mathbf{A}_i \mathrm{vech}(\varepsilon_{t-i}\varepsilon'_{t-i}) + \sum_{j=1}^{p} \mathbf{B}_j \mathrm{vech}(\mathbf{H}_{t-j}) \tag{4}$$

where $\mathbf{H}_t$ is the conditional covariance matrix, $\mathbf{c}$ is a constant vector, and $\mathbf{A}_i$ as well as $\mathbf{B}_j$ are matrices of parameters, that are to be estimated. Yet, this model still suffers from some limitations. It suffers from a high number of parameters when dealing with large datasets, making it computationally demanding (Bollerslev et al., 1988). Moreover, to make $\mathbf{H}_t$ positive definite, conditions must be made.

To tackle this problem, another popular model called the BEKK model was introduced, which was developed by Engle and Kroner (1995). This alternative model ensures positive definiteness. The BEKK model can be presented as follows:

$$\mathbf{H}_t = \mathbf{CC}' + \sum_{i=1}^{q}\sum_{k=1}^{K}\mathbf{A}'_{ki}\,\varepsilon_{t-i}\varepsilon'_{t-i}\mathbf{A}_{ki} + \sum_{i=1}^{p}\sum_{k=1}^{K}\mathbf{B}'_{ki}\mathbf{H}_{t-i}\mathbf{B}_{ki} \tag{5}$$

where $\mathbf{C}$ is a constant triangular matrix that ensures the positive definiteness of $\mathbf{H}_t$, and $\mathbf{A}_{ki}$ as well as $\mathbf{B}_{ki}$ are the parameter matrices that capture the effects of past shocks and past conditional covariances.

2.1.3 CCC-GARCH Model and DCC-GARCH Model

When focusing on conditional variances and correlations, the most basic multivariate correlation model is called the Constant Conditional Correlation (CCC) GARCH model, which was developed by Bollerslev (1990). This model simplifies the modeling of time-varying covariances by assuming that the correlations between assets remain constant over time. The model can be presented as follows:

$$\mathbf{H}_t = \mathbf{D}_t\mathbf{R}\mathbf{D}_t \tag{6}$$

where $\mathbf{R}$ is the constant correlation matrix, i.e., $\mathbf{R} = p_{\mathrm{ij}}$, $p_{\mathrm{ii}} = 1$, $\mathrm{i} = 1, \dots, \mathrm{n}$, $\mathrm{n} =$ number of assets, and $\mathbf{D}_t$ is the diagonal matrix, i.e., $\mathbf{D}_t = \mathrm{diag}(h_{it}^{\frac{1}{2}}, \dots, h_{\mathrm{nt}}^{\frac{1}{2}})$. With this, the off-diagonal elements of $\mathbf{H}_t$ are then given by:

$$[\mathbf{H}_t]_{ij} = h_{it}^{\frac{1}{2}}h_{jt}^{\frac{1}{2}}p_{\boldsymbol{ij}}\,,\ i \neq j \tag{7}$$

where $i \geq 1, j \geq n$. Now, the processes are modeled using the univariate GARCH(p, q) framework. Given this, the conditional variances can be expressed in the following vector form (Silvennoinen & Teräsvirta, 2007):

$$\mathbf{h}_t = \omega_t + \sum_{j=1}^{q} \mathbf{A}_j \mathbf{r}_{t-j}^{(2)} + \sum_{j=1}^{p} \mathbf{B}_j \mathbf{h}_{t-j} \,, \tag{8}$$

where ω is a $N \times 1$ vector, both $\mathbf{A}_j$ and $\mathbf{B}_j$ are $N \times N$ diagonal matrices, and $\mathbf{r}_t^{(2)} = \boldsymbol{r_t} \odot \boldsymbol{r_t}$, which represents the Hadamard product. For the conditional covariance matrix $\mathbf{h}_t$ to be positive definite, the conditional correlation matrix $\mathbf{R}$ must be positive-definite, and the elements of ω, as well as the diagonal elements of $\mathbf{A}_j$ and $\mathbf{B}_j$, need to be positive (Silvennoinen & Teräsvirta, 2007). However, the positivity of $\mathbf{A}_j$ and $\mathbf{B}_j$ is only required when $p = q = 1$.

As mentioned, by assuming that the conditional correlations between asset returns are constant over time, the model significantly reduces the complexity involved in estimating the covariance matrix. This is, especially in high-dimensional settings (Bollerslev, 1990). However, with simplicity, the model also showcases limitations. For example, this constant conditional correlation is very unrealistic in financial markets where correlations often fluctuate in response to economic events and investor behavior. For this, the Dynamic Conditional Correlation (DCC) GARCH model was developed by Engle (2002). It is an extension of the CCC GARCH model, in which the model allows for time-varying correlations between multiple assets, rather than $\mathbf{R}$ staying constant, i.e., $\mathbf{R}$ becomes $\mathbf{R_t}$ dynamically depending on the time t. Thus, the model becomes:

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R_t} \mathbf{D}_t \tag{9}$$

whereas the equation (8) becomes:

$$[\mathbf{H}_t]_{ij} = h_{it}^{\frac{1}{2}} h_{jt}^{\frac{1}{2}} p_{\boldsymbol{ij,t}} \,.\; i \neq j \tag{10}$$

The matrix process can be presented as follows:

$$\mathbf{Q}_t = (1 - \alpha\ - \beta)\mathbf{S} + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta\mathbf{Q}_{t-1}\ ; \tag{11}$$

$$\mathbf{R}_t = \left(\mathbf{I} \odot \mathbf{Q}_t^{-1/2}\right)\mathbf{Q}_t\left(\mathbf{I} \odot \mathbf{Q}_t^{-1/2}\right) \tag{12}$$

where in equation (11), $\mathbf{Q}_t$ is the time-varying covariance matrix, $\mathbf{S}$ represents the unconditional covariance matrix of the standardized residuals, and both α as well as β are scalar parameters, subject to, $\alpha > 0$, $\beta > 0$, $\alpha + \beta < 1$. With this, positive definiteness is guaranteed. In equation (12), which is the rescaled equation, $\mathbf{I}$ is the identity matrix of appropriate dimension, which ensures that the operations within the equation maintain the correct dimensions for matrix multiplication, and $\mathbf{Q}_t^{-1/2}$ is the inverse square root of the diagonal elements of $\mathbf{Q}_t$. Moreover, to ensure $\mathbf{R}_t$ is a positive-definite, $\mathbf{Q}_t$ has to be positive-definite.

The DCC GARCH model overall enables large correlation matrix estimations, thus making it particularly useful for portfolio management and risk assessment. Furthermore, it is particularly useful for this research, as the study analyzes the relationships between different ETFs. For more detailed information on the models related, multiple studies have been conducted, for example, see Engle and Sheppard (2001), Engle (2002; 2004), Teräsvirta (2006), and Silvennoinen and Teräsvirta (2007).

2.2 Hedging

Hedging is a strategy used in financial risk management in which an investor protects investments from potential market movements by taking offsetting positions in related assets (Hull, 2018). It serves as a vital tool for minimizing potential losses without necessarily sacrificing potential gains, which is especially valuable in volatile markets. Understanding related concepts such as hedging ratios and general weighting strategies is essential, as these determine the optimal allocation of hedging instruments within a portfolio. Furthermore, abstract models and frameworks, such as the Capital Asset Pricing Model (CAPM), help in understanding how different financial instruments interact with each other, and what their combined impact on a portfolio's performance is (Bollerslev et al., 1988). These concepts not only offer practical guidelines but also provide a robust foundation for advanced hedging strategies that aim to maximize returns while keeping risk within acceptable level.

2.2.1 Modern Portfolio Theory and Hedging

Hedging is associated with Modern Portfolio Theory as it emphasizes diversification among assets that are not perfectly positively correlated, in order to attain the best possible balance between risk and return. The theory, developed by Harry Markowitz (1952), revolutionized investment strategies. The Moden Portfolio Theory suggests that by spreading investments across various asset types that do not move in sync, i.e., have low or negative correlations, investors can maintain and gain potential returns while reducing overall volatility (Elton et al., 2014; Covel, 2023). In other words, the core idea is to construct a diversified portfolio of assets that maximize returns while minimizing risk through the reduction of unsystematic risk (Markowitz, 1952).

Hedging plays a role in Modern Portfolio Theory by making portfolio diversification stronger and minimizing risk. This enables investors to achieve positions along the efficient frontier – a curve that represents the plotting of the highest expected return for a given level of risk. Using different hedging strategies, such as using derivatives like options and futures, allows investors to manage exposure to market risks such as interest rate changes or commodity price fluctuations, that cannot be eliminated with basic diversification (Hull, 2018). With this, investors can stabilize returns and thereby get more aligned with the principles of Modern Portfolio Theory and move their portfolios closer or even along with the efficient frontier (Markowitz, 1952).

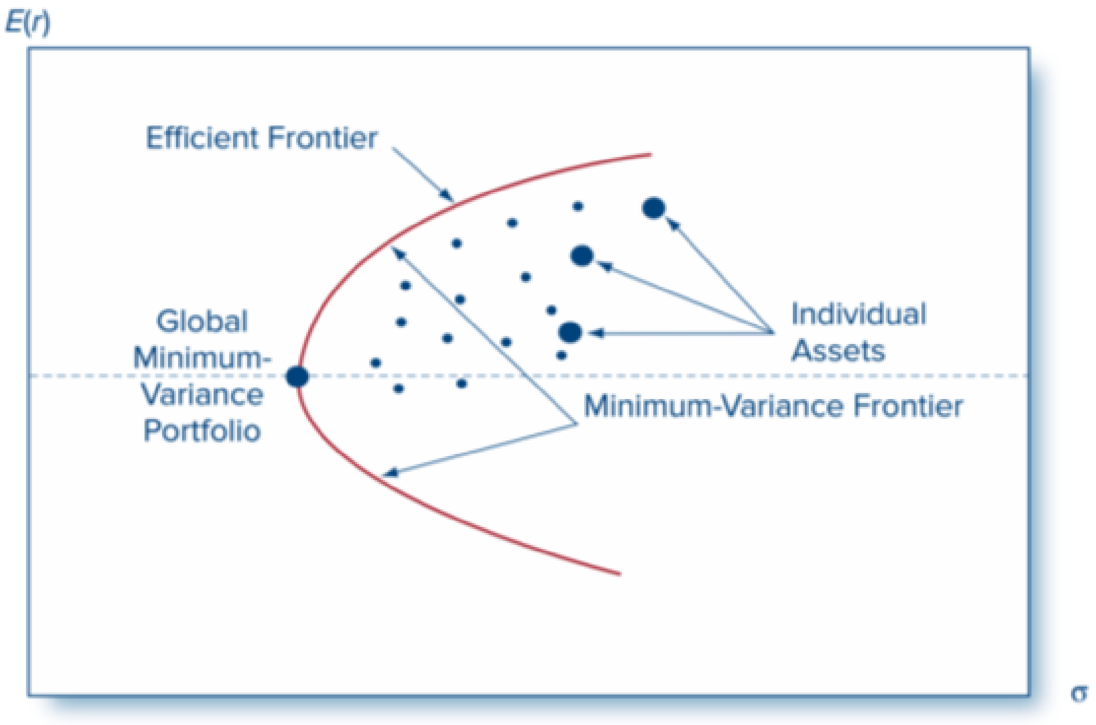


Figure 1: Efficient Frontier (Bodie et al., 2023).

2.2.2 Capital Asset Pricing Model and Hedging

Following Modern Portfolio Theory, the CAPM is heavily associated with hedging. The CAPM, developed by Sharpe (1964), Lintner (1965), and Mossin (1966), is a foundational financial model that describes the relationship between systematic (market) risk and expected return. In theory, the CAPM allows investors to calculate the expected return on a hedged portfolio with respect to market risk using the beta β. The investors can reduce the systematic exposure in their portfolio by using hedging strategies within the CAPM framework while targeting a desired potential expected return (Bodie et al., 2018). The formula can be presented as follows:

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \tag{13}$$

where $E(R_i)$ is the expected return on an asset or portfolio, R_f is the risk-free rate, β_i is the assets or portfolios market beta, and $E(R_m)$ is the expected market return. The beta β_i can be presented as follows:

$$\beta_i = \frac{COV(R_i, R_m)}{\sigma^2(R_m)} \tag{14}$$

where R_i is the expected return on an asset or portfolio, R_m is the market return, $COV(R_i, R_m)$ is the covariance between the asset's or portfolio's returns and the market return, and σ^2 is the variance of the market return.

So, the CAPM helps in understanding that hedging is not just about minimizing losses but also about achieving a balanced risk-adjusted return, and it guides investors on how to calibrate their portfolios for both stability and performance. Though similar to other models, CAPM itself has limitations. For example, the CAPM uses a single factor, market beta, to explain the returns. In reality, other factors, such as interest rates and liquidity impact these returns (Bodie et al., 2018). Moreover, CAPM does not take account of dynamic changes in market conditions or volatility. Due to these limitations, in addition to others, the CAPM in association with hedging can be considered only a good supportive framework.

2.2.3 Hedging Ratios, Weighting Strategies, and Hedging Effectiveness

Effective hedging in portfolio management is dependent upon the appropriate asset weighting and the active rebalancing of these weights to maintain the desired risk level

(Bodie et al., 2018). Consequently, optimizing weighting strategies, such as strategic and tactical asset allocation, is essential so that an investor can match the risk profile of a portfolio with the investor's goals and desired risk levels. Rasmussen (2003) describes strategic asset allocation as setting long-term weights for each asset class based on expected returns, risk, and correlations between asset class returns, whereas tactical asset allocation encourages systematically adjusting the portfolio to capitalize on short-term market conditions. Even though this type of short-term market exploitation is relatively hard, adjustment of portfolio weights is critical for maintaining optimal exposure and minimizing risk, thus ensuring the portfolio remains balanced even as market conditions shift.

By taking the rebalancing concept further by actively adjusting the hedging ratios to respond to the changing market conditions, investors can reduce exposure when risk increases and increase exposure when market conditions are more favorable. This type of active rebalancing is called dynamic hedging. While static hedging is simple, dynamic hedging usually tends to outperform, especially in volatile market conditions. For example, Tong (1996) found out that dynamic hedging offers greater hedging performance, though only slightly. Moreover, Ford et al., (2005) researched the emerging market of Malaysian, in which they studied the stock index futures. Similar to previous research on the developed stock index futures markets, their findings point out that the dynamic model provides a better hedging performance. However, this is not always the case, as Tompkins (2002) found that in some scenarios and specific exotic options, static hedging would perform even better than dynamic hedging. However, a common phenomenon is that dynamic hedging outperforms static approaches in terms of minimizing risk and optimizing returns, as adjustments to market conditions and volatility are set frequently.

This dynamic approach takes us back to the DCC-GARCH model, discussed earlier. Due to the DCC-GARCH model’s ability to estimate time-varying correlations between assets, the model is highly relevant for dynamic hedging strategies. The model captures the volatility clustering and changing relationships between assets, making it optimal for dynamic hedging compared to static approaches. As the correlations between assets and volatility change, investors can use the DCC-GARCH model to adjust hedge ratios and respond to shifts in market conditions, resulting in more precise risk management (Engle, 2002). This flexibility again enhances the effectiveness of hedging, particularly in volatile markets.

As for modeling and calculating the optimal portfolio weight and hedging ratio, Kroner and Ng (1998) along with Kroner and Sultan (1993) present solid illustrations. Kroner and Ng (1998) define the optimal risk-minimizing portfolio weight as follows:

$$\omega_t^{AB} = \frac{h_t^B - h_t^{AB}}{h_t^A - 2h_t^{AB} + h_t^B} \tag{15}$$

and

$$\omega_t^{AB} = \begin{cases} 0, if\ \omega_t^{AB} < 0 \\ \omega_t^{AB}, if\ 0 \leq \omega_t^{AB} \leq 1 \\ 1, if\ \omega_t^{AB} > 1 \end{cases} \tag{16}$$

where ω_t^{AB} is the weight of asset B in a hedged portfolio consisting of asset A and asset B at the time t. h_t^A and h_t^B are the variances of return of assets A and B at the time t, respectively, whereas h_t^{AB} is the conditional covariance of returns between asset A and asset B at the time t. The conditions presented in equation (16) ensure that the weight is non-negative and does not exceed the total capital allocated. Given all this, the optimal weight would be $1 - \omega_t^{AB}$.

As for the optimal hedging ratio β_t^{AB}, Kroner & Ng (1998) present it as follows:

$$\beta_t^{AB} = \frac{h_t^{AB}}{h_t^{A}} \tag{17}$$

The authors, along with Kroner and Sultan (1993), state that for one to minimize the portfolio risk, an investor should go short $\$\beta$ of asset A in relation to \$ long position of asset B. As for hedging effectiveness (HE), which is a measure used to evaluate the performance of the hedging in hand, i.e., risk reduction, Ku et al. (2007) present it as follows:

$$HE = \frac{Var_{unhedged} - Var_{hedged}}{Var_{unhedged}} \tag{18}$$

where $Var_{unhedged}$ is the variance of returns for an unhedged portfolio, and Var_{hedged} is the variance of returns for a hedged portfolio. The authors state the greater the HE values, the greater the risk reduction. Using these metrics along with related theory, investors can construct a risk-minimized portfolio and continuously evaluate the success of the strategies at hand as well as the concrete portfolio performance.

3 Literature Review

The literature review section of the study presents and discusses research regarding ETFs. The aim is to define the concepts and examine previous research regarding them. It will take part in both traditional ETFs and research regarding them, as well as sustainable ETFs and research regarding them. For the traditional ETFs', the focus will be on research related to volatility dynamics and hedging of gold, oil, and stock ETFs. Similarly, this focus applies to sustainable ETFs. Moreover, this section will also review some specific sector ETF studies, as the study at hand relates to a similar concept.

3.1 Exchange Traded Funds

Exchange-traded funds (ETFs) represent one of the most popular investment vehicles available to investors in the modern financial landscape. This is due to multiple reasons, such as flexibility, cost-effectiveness, ease of access, and as Gastineau (2010) emphasizes, shareholder protection and tax efficiency. Generally speaking, ETFs track a specific index, commodity, or basket of assets. The first ever ETF in the United States, SPDR S&P 500 ETF (SPY), was launched in 1993 and was designed to replicate the performance of the S&P 500 Index, providing a transparent, liquid, and easy way to track large-cap U.S. equities (Gastineau, 2010). Ever since ETFs have rapidly evolved as well as increased in number and are being traded on major stock exchanges throughout the day during trading hours. To illustrate the increase, according to Statista (2024), there were 10 319 ETFs globally in 2023 in comparison to only 276 ETFs in 2003.

ETFs provide several advantages compared to mutual funds. Similarly, as stated by Gastineau (2010), Poterba and Shoven (2022) discuss the ETF structure, which allows for more tax-efficient treatment. This is due to the "in-kind" creation and redemption, which allows for minimizing the taxable events for investors. Additionally, ETFs generally have a cost advantage over mutual funds, as they are passively managed rather than taking an active approach to research and maintain, followed by trading costs, thus also resulting in higher expense ratios (Carhart, 1997; Sivanmalaiappan, 2013). Moreover, as mentioned above, ETFs are traded throughout the day responding to fast market changes, whereas mutual funds trade once per day based on the net asset value, which is calculated after the market closes. Although ETFs offer numerous advantages such as mentioned, just like any other financial instrument or vehicle, they also have downsides. For example, Bae and Kim (2020) conducted a study on ETF returns and pointed out that there tends to be a connection between illiquid ETFs and tracking errors. So, liquidity risk is an important risk factor affecting the returns of ETFs.

As ETFs have evolved as well as increased in number, nowadays, ETFs can be classified into various categories depending on the methodology and the asset type they hold (Joshi & Dash, 2024). BlackRock, Inc., the world's largest asset manager, categorizes the following common types of ETFs available today for investors: equity ETFs, bond/fixed income ETFs, commodity ETFs, currency ETFs, specialty ETFs, factor ETFs, and sustainable ETFs (BlackRock, Inc., 2024). Equity ETFs track stock indices and offer exposure to multiple sectors or market caps, whereas bond/fixed-income ETFs focus on government or corporate bonds, offering a safer investment choice with lower risk. Commodity ETFs provide exposure to raw materials such as gold or oil, whereas currency ETFs focus on a single currency or a combination of currencies. Specialty ETFs on the other hand consist of two fund types; inverse funds and leveraged funds, that are designed to achieve greater returns with greater risk. Factor ETFs, also known as Smart Beta ETFs, employ a rules-based approach to determine the investments included in the fund portfolio. Lastly, sustainable ETFs focus on traditional investment approaches that consider ESG factors. BlackRock, Inc. (2024) along with others mentioned earlier in this study, emphasize these ETFs for their continuous rapid growth.

3.2 Equity ETFs

As ETFs have rapidly evolved as well as increased in number, plainly following this, multiple studies regarding equity ETFs' have been also conducted ever since. Caginalp et al. (2014) conducted a study that examines the price dynamics of U.S. equity ETFs, specifically selecting a sample of 78 large-cap ETFs, each with a market capitalization of at least \$500 million. The daily data is from February 2008 to the first two weeks of June 2011. The authors aim to explore and provide insights into how these ETFs react to factors such as market volatility, liquidity shocks, and investor sentiment. For this, the study uses the SAS procedure PANEL with the Two-Way Fixed-Effects Model (FIXTWO option), which allows for the isolation of the price dynamics. Caginalp et al. (2014) find that the selected U.S. equity ETFs exhibit nonlinear price dynamics, especially during periods of market volatility. The analysis suggests investor sentiment significantly drives these nonlinear behaviors. Thus, in theory, these liquid ETFs provide investors with efficient means to reactively hedge significant equity positions.

Aber et al. (2009) on the other hand conducted a study in which they examined the price volatility and tracking ability of four U.S.-based iShares ETFs, IVV, IWF, IWM, and EFA, in comparison to conventional Vanguard open-end funds, that track the same benchmarks as the corresponding ETFs. The authors use high-frequency trading data, including daily returns and NAVs, ranging from the inception date of each fund to the 14th of December 2006. As for performance measures, the authors use the daily returns, tracking errors, and the premium and discount positions, in relation to the conventional mutual fund of the ETFs. After conducting the analyses, Aber et al. (2009) find that in comparison between ETFs and mutual funds, ETFs are potentially overvalued by the market in comparison to their NAVs. Moreover, ETFs exhibit significant price fluctuations, which allows investors to gain potential additional returns if actively traded. As for co-movement, both fund types were similar, though the Vanguard mutual funds tracked their benchmark slightly better.

Further, Ben-David et al. (2018) investigate whether ETFs increase the volatility of the stocks they hold, by examining 454 U.S. equity ETFs from January 2000 to December 2015. The authors provide a solid empirical analysis of the statistically significant liquidity of ETFs in comparison to the basket of underlying securities, after which they use OLS and instrumental variable regressions for their analysis. The analysis also takes advantage of the Russell Index reconstitution. As for results, the authors find that ETF ownership significantly increases stock volatility and that stocks with higher ETF ownership experience a greater negative autocorrelation in returns, indicating increased noise and non-fundamental volatility. Moreover, as the authors observe that the volatility introduced by ETFs is not entirely diversifiable, it may be suggested that ETFs could be a “new form of systematic risk”.

In addition to the mentioned studies in this paper, numerous literatures exist on the volatility linkage between ETFs and stocks. For one, Yavas and Rezayat (2016) conducted a study on returns and these volatility spillovers, but they examined them in the U.S., Europe, BRIC, and MIST countries, as well as South Africa, rather than choosing one segment. For this, they used the daily returns of 11 country-specific ETFs, ranging from February 2012 to February 2014. Using the multivariate auto-regressive moving averages (MARMA) model and GARCH model, the authors focus on the returns, spillovers, and volatility persistence as well as transmissions. The findings reveal significant co-movement among all the country ETFs, and volatility spillovers from the U.S. market to India, Turkey, Russia, and Mexico. As for the European market, the volatility spill is towards Mexico and South Korea. Though the study revealed significant co-movements, investors can still exploit these global ETF volatility spillover linkages, and possibly use them for risk management measures such as hedging, i.e., to absorb the shocks.

As for additional research on hedging, a study conducted by Alexander and Barbosa (2008) explores the hedging effectiveness of four major U.S. ETFs: the SPDR S&P 500 ETF

Trust (SPY), the Invesco QQQ ETF (QQQ), the SPDR Dow Jones Industrial Average ETF Trust (DIA), and the iShares Russell 2000 ETF (IWM). The authors use daily data from May 2000 to September 2006, covering periods both related to positive and negative market events. The primary goal of the study is to assess the performance between "naive hedge" (a simple 1:1 hedging ratio) and minimum variance hedging ratios. As measures, the authors use three performance criteria, i.e., negative skewness, excess kurtosis, and effective reduction in variance. Alexander and Barbosa (2008) use three different models for achieving the minimum variance hedge ratios. These are Ordinary Least Squares (OLS), Exponentially Weighted Moving Average (EWMA), and a VAR-GARCH model. The authors find that using OLS, EWMA, or GARCH models, the naïve hedge would not improve the minimum variance hedging, though when peak moments of negative skewness and positive kurtosis are taken into account, there is a clear preference. Generally, among the minimum variance hedging methods, the EWMA model provides the best performance, though the performance difference is small. Moreover, the minimum variance cross-hedging outperformed the naïve strategy of matching long and short positions.

3.3 Gold ETFs

As mentioned, due to the evolution of ETFs, classification into various categories was more or less inevitable. One of the ETF categories, commodity ETFs, provides exposure to raw materials such as gold, which has been used and has been a popular investment throughout history. Similar to equity ETFs, Gold ETFs have been and remain a common subject of research. Pullen et al. (2014) conducted a study on the investment characteristics of various gold assets, including gold ETFs. The authors aim to analyze the safe haven, hedging, and diversification factors of the assets, using daily data ranging from 1987 to 2010. The results reveal that gold ETFs, along with gold stocks and gold mutual funds, are likely to work as diversifiers, though unlike stocks and mutual funds, the ETFs also show support for safe haven properties.

Similarly, Cheng et al. (2018) conducted a study regarding the role of gold in the financial markets; specifically, whether it has changed after the introduction of gold ETFs. With daily data from 7 different countries, the authors examine whether gold still serves as a hedge or safe haven and whether gold ETFs have the possibility to substitute physical gold in these terms. The findings of the study indicate that the role of gold ETFs is significant and that it affects the role of gold. Further, the safe haven and hedge functions of gold weaken after the ETFs, excluding currency markets, and gold ETFs perform as a stronger safe haven during extreme stock market declines. With these results, it is worth considering the future of physical gold as an investment regarding risk management and overall portfolio management.

Due to the nature of gold and other gold assets, Gold ETFs are also usually compared with other ETFs. Naveen (2016) conducted a study in which the author examines the performance and volatility characteristics between gold ETFs and equity ETFs in the Indian financial markets, the National Stock Exchange (NSE), with data ranging from 2013 to 2015. The study uses several performance evaluation metrics including standard deviation and beta for volatility, and Sharpe ratio and Treynor ratio for performance. The author finds, given the time period of the study, that gold ETFs generally performed poorly, delivering negative returns with relatively high volatility. Equity ETFs on the other hand displayed greater returns, though having also higher volatility, as reflected in the beta values. For all ETFs, the risk-adjusted returns measured by the Sharpe ratio were negative, reflecting overall poor performance. Though, it is worth mentioning that the data used in the study is relatively slim, which automatically introduces limitations, and does not necessarily give reliable results from a broader perspective.

For more studies in the Indian financial markets, Eswara (2015) provides an empirical analysis of the performance of gold ETFs during the post-crash period. The study utilizes five ETFs listed on the NSE, over a period of five years from 2010 to 2014, and aims to evaluate the relationship of spot price of gold in relation to these ETFs. Moreover, the study explores the possible relationship and impact of gold price movements on NIFTY 50, which is the most known stock market index in India. After conducting regression and correlation techniques, Eswara (2015) finds that gold ETFs generally effectively mirror spot gold prices. Thus, it can be assumed that gold ETFs can be used as a safe haven instrument, as mentioned before. Moreover, the findings reveal that the relationship between gold ETFs and NIFTY is inverse, which indicates that the hedging possibilities could be very efficient.

Another study, conducted by Kaur and Singh (2020), focuses on the relationship between gold ETFs and spot gold as well as gold futures in the NSE. The authors analyze 13 gold ETFs listed in the NSE, in comparison to the Ahmedabad market gold spot price and near-month future data from MCX. Using Gregory-Hansen statistics, the Toda-Yamamoto test of causality, and the Vector Error Correction Model (VECM), the results reveal and suggest that there is a long-term cointegrating relationship between gold ETFs and both gold spot prices and futures prices. Once again, this suggests that gold ETFs work as an excellent alternative to physical gold. Moreover, the study reveals that there is a linkage between gold spot and future price changes to gold ETFs, which may provide trading opportunities for excessive returns for active traders.

3.4 Oil ETFs

Like gold ETFs, oil ETFs have been heavily studied ever since their introduction. A similar study as conducted by Cheng et al. (2018), Ivanov (2011) studies the influence of ETFs in relation to their respective futures and underlying commodities, taking into account oil and silver in addition to gold. The author uses ultra-high frequency data collected from March 1, 2009, to August 31, 2009, and uses VECM for the analysis. Similar to the studies reviewed before, the results indicate that the gold ETFs and both spot and futures markets have a price discovery linkage and that the ETF closely tracks its underlying asset. As for oil ETF, the tracking is similar, i.e., it follows the underlying asset. Though, for oil ETF's pricing deviations, the study suggests that even though the role of oil ETFs is increasing, the pricing discovery process is still heavily led by futures markets. Regardless, the study showcases the importance of oil ETFs in the markets.

In a similar study conducted by Xu et al. (2020), the authors explore the intraday return predictability for crude oil, gold, and silver ETFs in relation to their volatility indices, using high-frequency data from 2007 to 2020. For this, the authors use in-sample (IS) and out-of-sample (OOS) analyses. The study reveals evidence of predictability in all markets, but the patterns differ across commodities. In the case of crude oil ETF (USO), the results show statistically significant predictability at the 1% level, particularly from the first half-hour interval to the last half-hour return, whereas the volatility index OVX shows statistically significant predictability at the 5% level for different last-hour intervals to the last half-hour return, and no predictability from the first half-hour. So, there is divergence. Moreover, Xu et al. (2020) find that the intraday momentum is stronger in cases of high volatility and larger jumps, suggesting that market conditions heavily influence the patterns.

Further, a doctoral dissertation conducted by Yu (2015) explores the relationship between oil ETFs and the underlying crude oil prices, specifically focusing on USO and PowerShares DB Oil Fund (DBO), which both track The West Texas Intermediate (WTI) crude oil benchmark. The study covers daily data from the launch of each ETF up to March 31, 2012, taking account of periods before and after the 2008 financial crisis, as well as the whole time period. The author employs several econometric techniques, including the Engle-Granger two-step method, Granger Causality Test, dynamic models, and nonlinear cointegration tests, to investigate the short- and long-term relationships. As for results, Yu (2015) finds that the prices of USO, DBO, and WTI are co-integrated in a nonlinear fashion, confirming the long-term balance relationship. Moreover, the findings suggest a two-way direction causal relationship between the ETFs and WTI, implying that the contribution to the price discovery process goes both ways. The linear and nonlinear Error Correction Model reveals that generally in the long-term, oil ETFs take the lead in the adjustments in price changes, whereas crude oil takes the lead in the short-term. Overall, considering the structural nature of oil ETFs and various statistical tests and models employed, the results are relatively multiplex, yet conclusions can be drawn.

As for hedging, Murdoc and Richie (2008) conducted research on the hedging effectiveness of USO, by investigating the price relationship between USO and spot prices as well as futures prices of crude oil. Moreover, the study also examines the impact of USO on the market quality in the underlying oil futures market, when it was introduced. For the analyses, the authors use daily data from July 2005 to July 2008 and complete several statistical techniques, such as correlation analysis and multivariate regression models. The results indicate that the correlation between USO and futures prices is higher, compared to the correlation between USO and spot prices, though, during contango, which is when futures prices are higher than spot prices, the USO prices deviate more significantly from futures. Moreover, the study shows that USO is a more effective hedge during backwardation due to the correlation changes and the deviation between USO and futures narrows. Additionally, the tightening in bid-ask spreads and volatility decrease indicates that the introduction of USO enhanced liquidity in the futures market. Overall, while the USO provides a hedging mechanism, it also introduces additional risks due to the deviations from the futures prices during specific market conditions.

3.5 Sustainable ETFs

As mentioned by BlackRock, Inc. (2024) and others, the interest and increase in sustainable investing has been increasing and is growing continuously. Thus, this interest of investors also aims towards sustainable ETFs, side by side with the growth ETFs have gained. Various studies have been conducted regarding sustainable ETFs, specifically aimed towards return variations, volatility dynamics, and hedging possibilities. Sustainable ETFs vary a lot regarding the goals of the ETFs, though arguably the most common factor is environmental, i.e., ultimately advancements reducing carbon emissions and green energy. Given the increased attention of individual investors as well as institutional funds, these ETFs have the potential to be effective hedging instruments or possibly a way for investors to earn additional gains.

A relatively early study on the subject conducted by Sabbaghi (2011), the author investigates the behavior of sustainable green ETFs, focusing on the return characteristics, volatility dynamics, and market efficiency. The study uses the daily returns ranging from January 2005 to October 2009, from a dataset of 15 ETFs that track indices emphasizing ESG factors. Using GARCH methodology, the author finds that across the green ETFs, there is strong evidence of volatility persistence, which also indicates volatility clustering. The study reveals that the market-wide cumulative green returns tend to be slightly positive until the end of 2008, after which returns decline due to the global financial crisis. Similar to many other investment instruments, these ETFs show a trend upward after the crisis, which again suggests potential gains in the future.

A more recent study, conducted by Rizvi et al. (2021), examines the relationship and connectedness between green and grey energy ETFs, i.e., renewable energy compared to fossil fuels and conventional energy, respectively, focusing on return and volatility spillovers. The overall data consists of daily prices of these ETFs, along with bond and equity ETFs, from October 2015 to October 2020. For the returns and volatility spillover analysis, the study uses Vector Autoregression (VAR) and BEKK multivariate GARCH models. The authors find that green energy ETFs increasingly play a central role in the financial markets. The green energy ETFs have a notable role in transmitting return shocks whereas in contrast, grey energy ETFs, while still impacting the bond market, show a declining influence on equity markets. Even though these green energy ETFs have gained themselves an influential position in the financial markets, it is still important to mention that, for example, at the time of conducting this study, grey energy still heavily dominates the energy market with a total share of over 80%. Thus, even though green energy is gaining a more influential position, the total share distribution of energy markets is still heavily leaning on grey energy.

As for hedging regarding sustainable energy ETFs, Çelik et al. (2022) investigate the dynamic connectedness and hedging possibilities between clean energy ETFs and implied volatility indices CBOE Energy Sector ETF Volatility Index (VXXLE) and CBOE Crude Oil ETF Volatility Index (OVX). The authors analyze daily data ranging from October 2011 to January 2021, using TVP-VAR and Asymmetric Dynamic Conditional Correlation (ADCC) GARCH models. The results reveal that the total connectedness index is relatively high, indicating a strong interdependence between the ETFs and volatility indices. Moreover, this value is significantly higher during periods of market turbulence, such as COVID-19. As for the hedging possibilities, the authors find that both VXXLE and OVX provide hedging benefits for clean energy ETFs, though VXXLE works as a more effective option during turbulent market periods. Though, it is worth mentioning that it is also the more expensive option.

As mentioned by Sabbaghi (2011), similar to other assets, green ETFs suffered from the global financial crisis in 2008. Pisani and Russo (2021) conducted a study on the financial performance of European ESG funds during the COVID-19 pandemic, which also had a significant effect on the financial markets. The authors examine the returns, volatility, and contagion risk of 30 ESG ETFs benchmarked against the MSCI Europe index, over the period from January 2015 to September 2020. For the ESG criteria regarding the data, the authors use the Morningstar Sustainability ESG rating. Using univariate and multivariate GARCH models along with event study-based methodology, the authors find that ETFs with higher ESG ratings demonstrate better performance during the pandemic, exhibiting lower volatility and risk contagion compared to those with lower ratings. These findings are major, as they indicate that sustainable funds offer investors not only the option for more ethical investment but also the benefits of minimizing risks during crises. Thus, investors should consider these ETFs when constructing a portfolio.

Another very recent study conducted by Xu et al. (2024) examines the dynamics of return connectedness among global sustainable ETFs as well as explores strategies for optimizing portfolio performance. The authors analyze data from six major global ESG ETFs, BMO MSCI US ESG Leaders Index ETF, BMO MSCI China ESG Leaders Index ETF, BMO MSCI India ESG Leaders Index ETF, BMO MSCI Canada ESG Leaders Index ETF, BMO MSCI EAFE ESG Leaders Index ETF, and BMO MSCI Global ESG Leaders Index ETF, covering the period from 2020 to 2023, using a time-varying parameter vector autoregressive (TVP-VAR) model and various portfolio strategies. The findings reveal that out of these ETFs, the European ETF plays a significant role in the global ESG investment system. This is most likely because the European ESG market is remarkably larger compared to others, and due to strict regulatory frameworks, the market also reflects stability. Thus, this influence also indicates and translates to reduced portfolio volatility when the European ETF is included. As for the strategies, Xu et al. (2024) find that during times of crisis, portfolios with a higher allocation to developed markets tend to showcase better performance. However, during early COVID-19, all the 6 ETFs suffered major declines and none of them showcased superior resilience.

For ESG equity ETFs, a study conducted by Chen & Chen (2023) focuses on the dynamics between returns and volatilities of ESG and non-ESG ETFs with respect to their tracking stock indices. The research aims to explore the spillover effects, as well as leverage effects, using 4 ESG and 4 non-ESG ETFs from the U.S., Germany, the U.K., and Japan, data ranging from January 2014 to June 2022, according to the inception days. For the analysis, the authors use GARCH-M-ARMA and EGARCH-M-ARMA models. The authors find that the ESG ETFs have a significant positive bilateral relationship with their stock indices, similar to non-ESG ETFs. With this, one can conclude that both ESG and non-ESG ETFs considerably affect the markets. Moreover, the study finds that the leverage effect is present across all the ETFs and indices, indicating that negative shocks tend to increase volatility more than positive ones. Overall, the results highlight the interconnectedness between these investment vehicles. The study underscores the growing importance of ESG investments, indicating that the findings have potential implications for investors who are keen on constructing portfolios that balance ESG considerations with market performance.

3.6 Sector ETFs

As far as the author knows, similar studies on Cleaner Transport ETFs have not been conducted. Thus, a few studies within differing sectors are presented in addition to previous research, as the study in hand follows a similar analysis. In the first study, Kang et al. (2021) explore the frequency spillovers and connectedness between 9 US sector equity ETFs, oil, gold, S&P 500, and uncertainty indicators OVX, VIX, as well as Economic Policy Uncertainty (USEPU). For this, the authors use a time-frequency approach along with a wavelet-based spectral decomposition method (VAR-FEVD). The findings reveal that both oil and the VIX are the primary transmitters of spillovers in both the short- and long-term horizon, whereas USEPU has the smallest impact, in regard to sector ETFs. As for hedging, both gold and oil work as optimal hedges, oil being the most effective for each sector ETF. The strongest hedging effectiveness can be found for Consumer Staples ETF, which may be due to the tendency of inelastic demand for consumer staples. Overall, once again, the study highlights the importance of hedging costs when optimizing a hedge, as well as the importance of incorporating uncertainty factors into portfolio strategies.

Another very recent study, conducted by Yousaf et al. (2024), focuses on the extreme connectedness between artificial intelligence (AI) tokens, AI ETFs, and various other asset classes, such as gold, USDI, Equity-MSCI world, and more. Even though the study examines both AI tokens and AI ETFs, it is an adjacent study regarding AI sector ETFs. The authors use the QVAR approach and aim to understand the dynamics across varying market conditions, i.e., bearish market, normal market, and bullish market, as well as the portfolio implications, by using DCC-GARCH. The findings indicate that AI ETFs act as net emitters of return spillovers under normal market conditions. During extreme market conditions, these ETFs are sensitive to market shocks, due to a rise in connectedness levels. Overall, the AI ETFs have a strong role in spillovers to other assets. This same phenomenon has been observed multiple times during the other studies reviewed.

4 Data & Methodology

The study aims to investigate the volatility dynamics and hedging effectiveness between cleaner transport sector ETFs and traditional ETFs. This section of the study describes the data, as well as the methodologies used in the study. For the analyses and plotting, RStudio is deployed, i.e., all results are computed in RStudio, along with the descriptive statistics, are created in RStudio.

4.1 Data

The data consists of 5 ETFs, including cleaner transport sector ETFs and traditional ETFs. To make the analysis more robust, the study uses two cleaner transport sector ETFs. The first ETF, IQ Cleaner Transport ETF (CLNR), tracks NYLI Candriam Cleaner Transport Index. CLNR focuses on companies that support the transition to more environmentally efficient transportation technologies, i.e., engaging in renewable energy production, sustainable battery mining, vehicle production, and sustainable infrastructure for transportation. The second ETF, Fidelity Electric Vehicles and Future Transportation ETF (FDRV), tracks Fidelity Electric Vehicles and Future Transportation Index - Benchmark TR Net. FDRV focuses on companies that are engaged in the production of electric and/or autonomous vehicles and their components, technology, or energy systems. Moreover, companies engaged in other ways that still aim to advance the future of transportation are also focused on. As for the traditional ETFs', the study uses the United States Oil Fund, LP (USO), SPDR Gold Shares (GLD), and SPDR S&P 500 ETF Trust (SPY). The study utilizes the daily data of each ETF, ranging from October 21st, 2021, to June 11th, 2024. It is worth mentioning, that both CLNR and FDRV ETFs were launched in October 2021, and the starting date for the data is selected from Yahoo Finance, so the launching date is not included. Given the data range, the number of observations is 663 for each set.

To better understand the characteristics of each ETF in the analysis, the study presents the main descriptive statistics of returns, including mean, standard deviation, skewness, kurtosis, and Jarque-Bera test, as well as stationarity tests ADF- and PP test. The daily logarithmic returns of the ETFs are calculated in RStudio using the “na.omit()” function, which removes any incomplete cases in vector, matrix, or dataset. As for logarithm, RStudio uses the following formula:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) = ln(P_t) - ln(P_{t-1}) \tag{19}$$

where $ln(P_t)$ indicates the log of adjusted closing price of the ETF on day t.

Table 1: Descriptive Statistics of Log Returns & Standard Stationary Tests.

Funds	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	ADF Test	PP Test
GLD	0.0003741731	0.00894162	-0.01788358	1.0446101	30.08898 ***	-8.492238 ***	-698.6102 ***
USO	0.0004135918	0.02256223	-0.71989479	2.8281965	277.39111 ***	-10.124522 ***	-559.7124 ***
SPY	0.0003087636	0.01135086	-0.17171276	1.6127658	74.88454 ***	-8.498451 ***	-611.2214 ***
CLNR	0.00001923386	0.01379794	0.14464192	1.2472739	45.15119 ***	-8.018621 ***	-627.0517 ***
FDRV	-0.0009941165	0.02158950	0.14861100	0.5973455	12.26052 ***	-8.203070 ***	-607.5638 ***

All descriptive statistics are computed using Rstudio. Specifically, tseries and PerofrmanceAnalytics libraries are deployed. *p < 0.01* ***

The descriptive statistics in Table 1 provide insights into the return characteristics of each ETF. The mean daily returns suggest that on average, all funds – except for FDRV – have positive returns over the time period. USO along with GLD has the highest mean returns, which may directly reflect market uncertainty, i.e., geopolitical risks, high inflation, and more. As for SPY and CLNR, both have positive mean returns, though CLNR clearly falls behind the traditional ETFs. Conversely, FDRV exhibits a negative mean return, which may be due to broader problems in the sector, such as increased competition and market dynamics. Although CLNR and FDRV both aim for similar causes, they differ in their holdings, which also explains the clear difference in mean returns. For example, FDRV has a regional allocation of 64,2% in North America and only 10,49% in Europe, whereas CLNS has a regional allocation of 37,07% in North America and 35,31%

in Europe. Thus, the difference may also be due to the positive regulatory frameworks and the market stability in Europe, regarding ESG. Moreover, FDRV has a sector allocation of 35,07% in Electronic Technology, 23,82% in Producer Manufacturing, and 21,3% in Consumer Durables, whereas CLNR has a higher position of 30,84% in Producer Manufacturing, a smaller position of 28,34% in Electronic Technology, and smaller position of 19,44% in Consumer Durables.

As for standard deviation, USO, along with the highest mean return, has the highest standard deviation of 0.02256223. This indicates the USO is the most volatile asset among the ETFs, which also aligns with the typical price behavior of oil. SPY and CLRN exhibit nothing abnormal. FDRV on the other hand surprisingly exhibits the second-highest standard deviations, which again, may be due to broader problems in the sector. And, as expected, GLD has the lowest standard deviation of 0.0003741731, aligning with its reputation as a stable asset. Skewness and kurtosis values are computed to provide a deeper insight into the distributional characteristics of the ETFs, i.e., asymmetry and "peakedness" of the distributions. GLD, USO, and SPY have a negative skewness, indicating that the distributions are skewed to the left, whereas the positive skewness of FDRV and CLNR indicate that the distributions are skewed to the right. The negative skewness in USO is higher, which leads to a more clear difference in the tail, whereas GLD and SPY have only a slight tilt. Moreover, the relatively high kurtosis value of USO also reflects a more peaked distribution with heavier tails. Conversely, the low kurtosis value of FDRV reflects a more spread-out distribution with lighter tails.

Finally, the Jarque-Bera test, with all p-values being extremely low, i.e., statistically significant, rejects the null hypothesis of normality, which is expected. Moreover, the results of the ADF and PP tests reject the null hypothesis of non-stationarity. Thus, it is suggested that the returns series are stationary. For visual interpretation, the histograms of log returns for ETFs are plotted in RStudio. The data has been inspected and despite the visual gaps seen in SPY and CLNR ETFs in Figure 1, the overall trend behavior and density are consistent with expectations and do not indicate errors in data. Moreover, the data has been calculated in Excel for additional certainty.

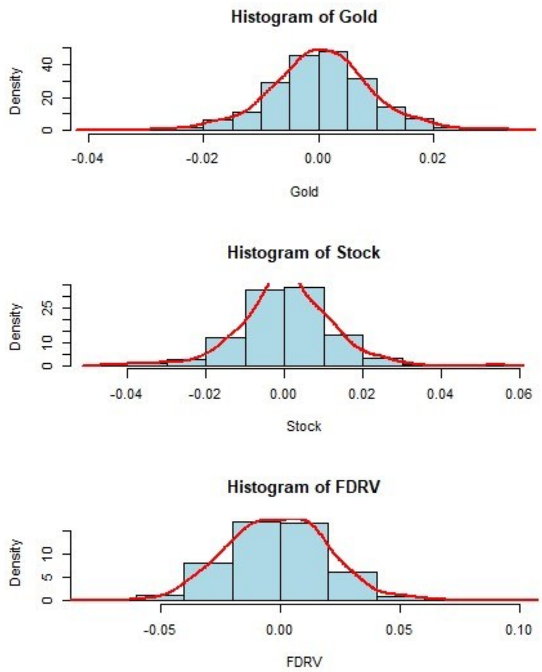


Figure 2: Histograms of Log Returns for ETFs.

The unconditional correlation matrix between each asset is also computed, as presented in Table 2. As expected, the unconditional correlation between CLNR and FDRV is notably high, which indicates a strong positive relationship between their returns. This also indicates that these ETFs may not offer much diversification benefit from each other. As for the unconditional correlation between cleaner transport sector ETFs and traditional ETFs, the values are relatively low, except for SPY. The relatively low unconditional correlation with CLNR and FDRV in regard to gold and oil indicates hedging possibilities, which is also in alignment with the third hypothesis. However, for each correlation coefficient, the p-value is calculated, and each value indicates high statistical significance.

Table 2: Unconditional Correlation Matrix.

Funds	GLD	USO	SPY	CLNR	FDRV
GLD	1.000000	0.2462208 ***	0.1388243 ***	0.2092870 ***	0.1512981 ***
USO	0.2462208 ***	1.000000	0.1525100 ***	0.1242530 ***	0.1164675 ***
SPY	0.1388243 ***	0.1525100 ***	1.000000	0.8868420 ***	0.8057951 ***
CLNR	0.2092870 ***	0.1242530 ***	0.8868420 ***	1.000000	0.9186982 ***
FDRV	0.1512981 ***	0.1164675 ***	0.8057951 ***	0.9186982 ***	1.000000

The unconditional correlation matrix is computed using Rstudio. *p* < *0.01* ***

Furthermore, the daily logarithmic returns for each ETF are squared to obtain a time series of volatility, i.e., approximate realized volatility, capturing the return fluctuations over time. The graphs in Figure 3, Figure 4, Figure 5, Figure 6, and Figure 7 display each ETF's returns and volatility over time, with the returns represented as blue lines and the volatility as red lines, showcasing the differing patterns of each ETF.

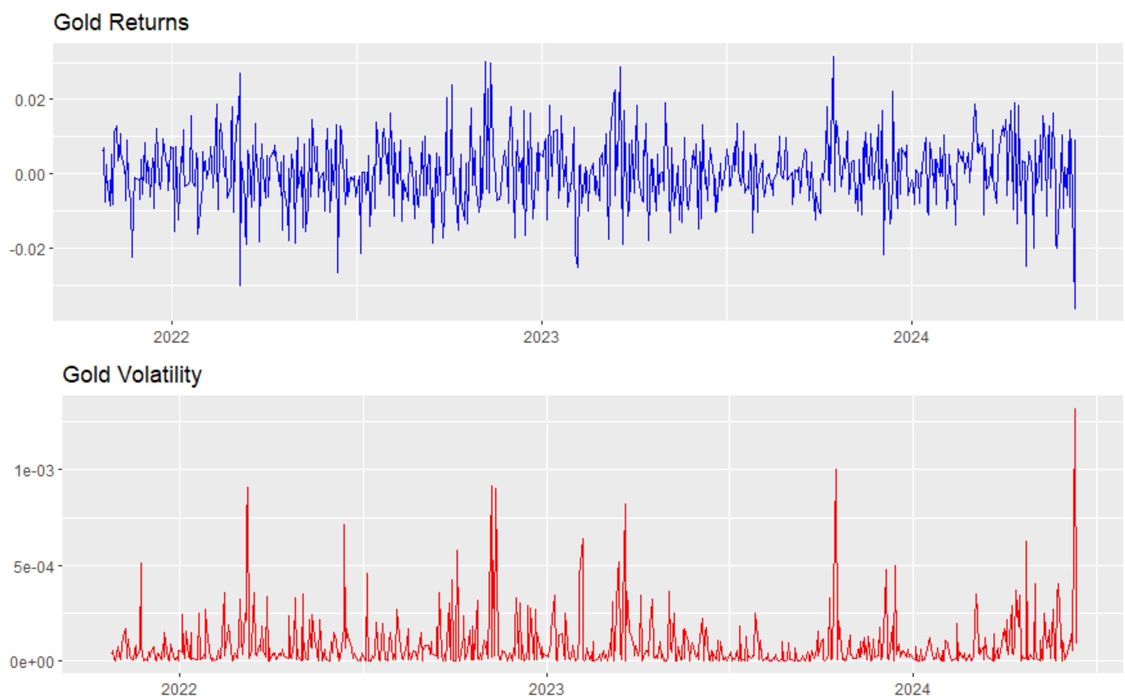


Figure 3: Gold ETF Log Returns and Volatility.

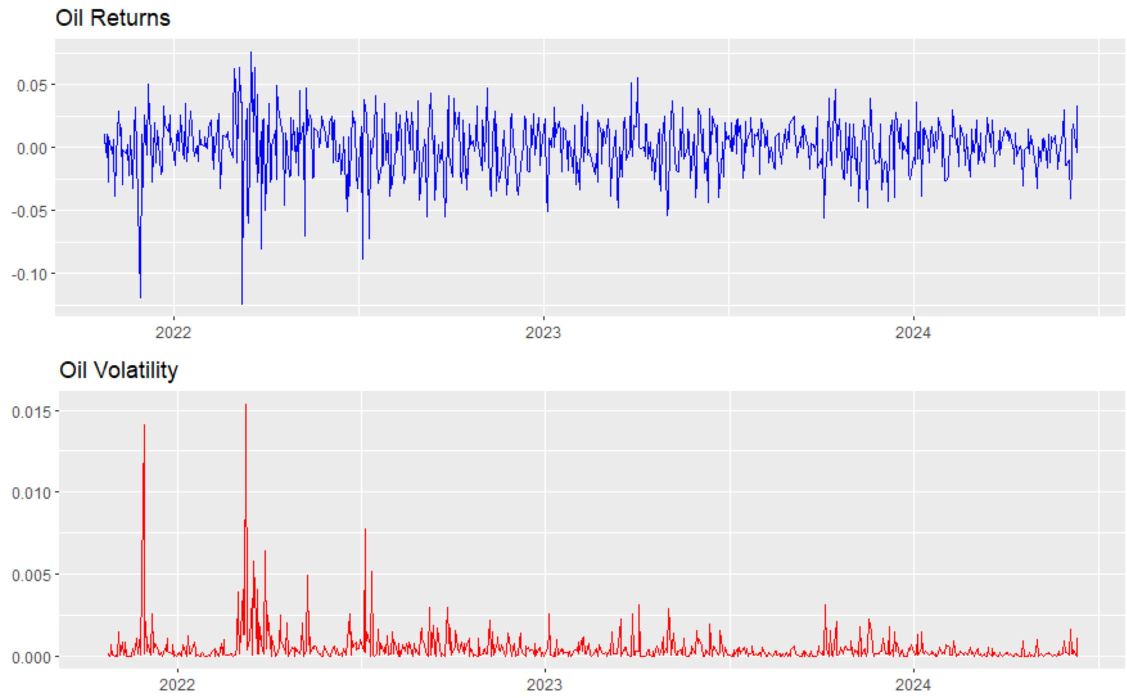


Figure 4: Oil ETF Log Returns and Volatility.

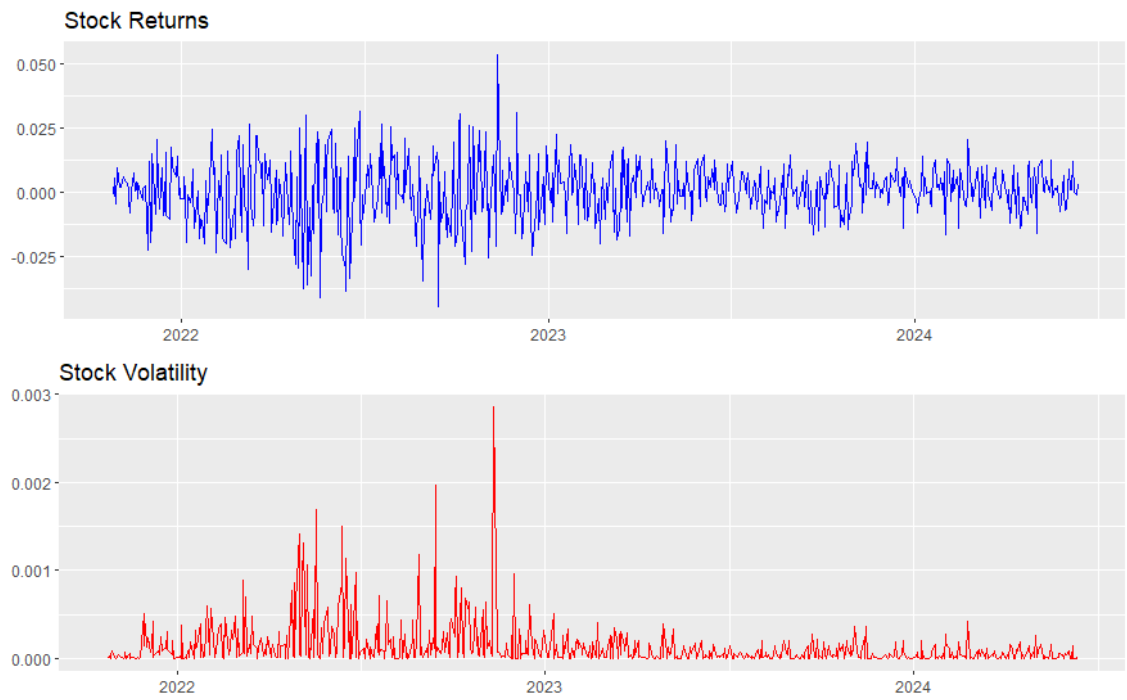


Figure 5: Stock ETF Log Returns and Volatility.

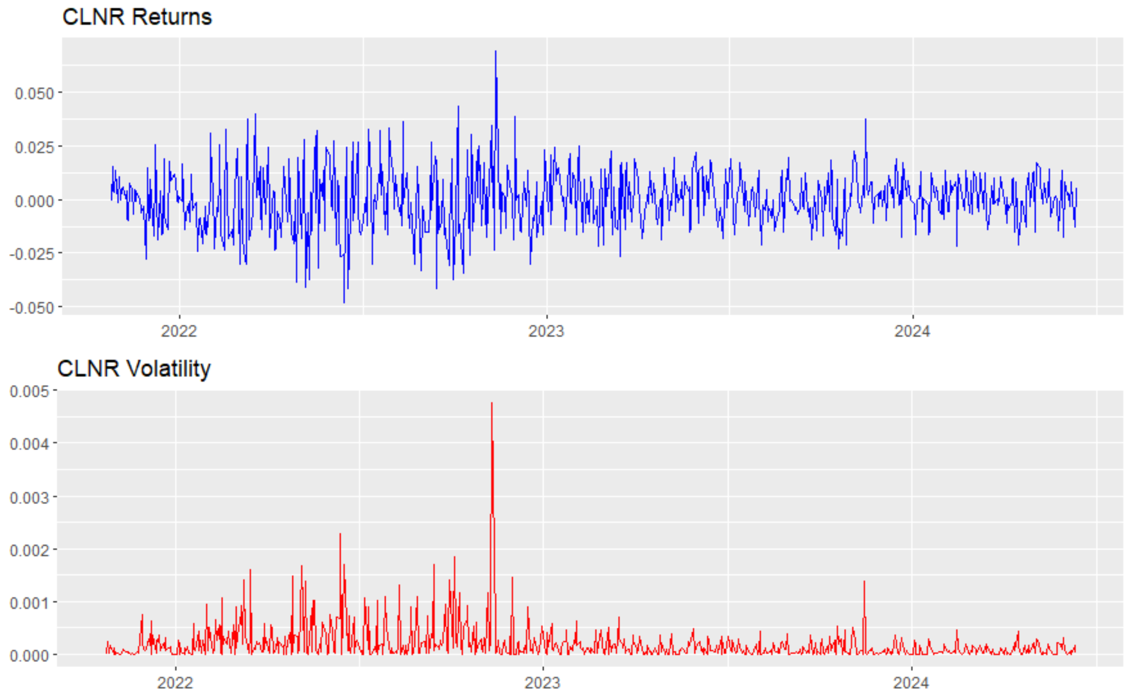


Figure 6: CLNR ETF Log Returns and Volatility.

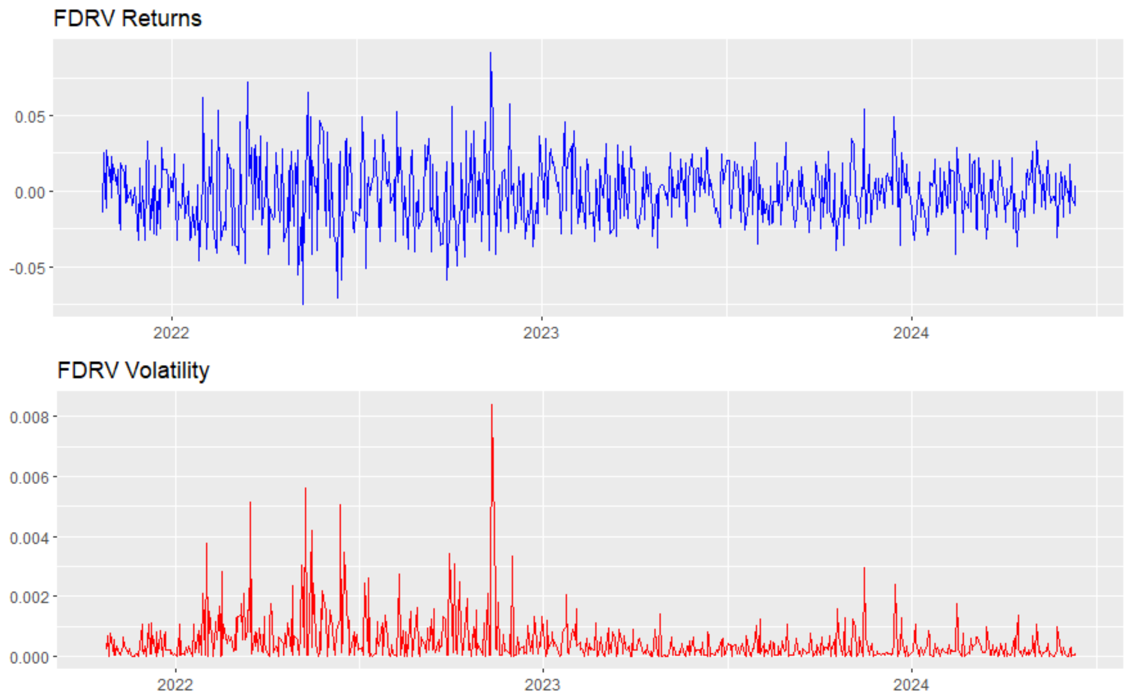


Figure 7: FDRV ETF Log Returns and Volatility.

4.2 Methodology

Given the descriptive statistics, stationarity tests, and simple volatility plotting, advanced volatility modeling techniques are needed. In this study, both univariate EGARCH(1,1) model as well as multivariate DCC-GARCH model are deployed, to model and capture the complex relationship and time-varying nature of the ETFs. The univariate EGARCH(1,1) model is deployed to understand the individual volatility characteristics of each ETF, whereas the multivariate DCC-GARCH model is deployed to evaluate the dynamic correlations between them. After this, the optimal hedge ratios, portfolio weights, and hedging effectiveness are computed, to assess the practical implications of hedging strategies. Similar to the descriptive statistics, the analyses are conducted in RStudio. Before choosing the univariate GARCH model, a fitting scenario was conducted, which resulted in the EGARCH(1,1) model as the best fit for the given data. Based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, the EGARCH model provided the best fit for the majority of assets compared to other GARCH variants, i.e., the standard GARCH model and GJR-GARCH model. This model was thus selected for further analysis to ensure compatibility with the multivariate DCC-GARCH model to be deployed later on for dynamic correlation estimation.

4.2.1 Univariate EGARCH(1,1) Model

Following the work of Nelson (1991), this study deploys the EGARCH(1,1) model that modifies the simple GARCH model by allowing for asymmetric effects of positive and negative shocks on volatility, while also ensuring the positivity of conditional variance at every point in time without parameter restrictions. The model is deployed to understand and assess the unique volatility behavior of each ETF, before examining their dynamic relationship with each other. The EGARCH(1,1) model can be specified as follows:

$$\log(\sigma_t^2) = \omega + \alpha_1 \left[\frac{\varepsilon_{t-1}}{\sigma_{t-1}} - E\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)\right] + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \log(\sigma_{t-1}^2) \tag{20}$$

where $\log(\sigma_t^2)$ is the logarithm of the conditional variance at the time t, ω is a constant, α_1 is the ARCH effect, i.e., the coefficient for the standardized residuals that capture the past shocks, γ_1 is the coefficient for the magnitude of standardized residuals that capture the leverage effect, $E\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)$ is the expected value of the magnitude of the standardized residuals which are assumed to be constant, β_1 is the GARCH parameter, i.e., the coefficient for σ_{t-j}^2, and $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is the standardized residuals. In RStudio, the “rugarch” package is used, as it provides functions specifically designed for univariate GARCH models, including the EGARCH(1,1) model.

4.2.2 Multivariate DCC-GARCH Model

Following the work of Engle (2002), this study deploys a multivariate DCC-GARCH model to examine the time-varying dynamic correlation between the ETFs. In Section 4.2.1, the individual volatilities for each ETF’s return series are computed. Now, the conditional correlation at the time t for each pair of ETFs is estimated as follows:

$$\mathbf{Q}_t = (1 - \alpha \ - \beta)\mathbf{S} + \alpha\varepsilon_{t-1}\varepsilon_{t-1}' + \beta\mathbf{Q}_{t-1} \tag{21}$$

where $\mathbf{Q}_t$ is the time-varying covariance matrix, $\mathbf{S}$ represents the unconditional covariance matrix of the standardized residuals, and both α as well as β are scalar parameters determining the rate of decay of past shocks and correlations, subject to, $\alpha > 0$, $\beta > 0$, $\alpha + \beta < 1$. With this, positive definiteness is guaranteed. In RStudio, the “rmgarch” package is used, as it provides functions specifically designed for multivariate GARCH models, including the DCC-GARCH model.

4.2.3 Hedge Ratios, Optimal Weights, and Hedging Effectiveness

As for practical implications, the study calculates hedge ratios, optimal portfolio weights, and hedging effectiveness. The hedge ratio β_{AB} is determined using the conditional co-variance and variance that are obtained from the DCC-GARCH model. The hedge ratio is estimated as follows:

$$\beta_{AB} = \frac{Cov_{AB,t}}{Var_{B,t}} \tag{22}$$

where $Cov_{AB,t}$ represents the conditional covariance between assets A and B at the time t, and $Var_{B,t}$ represents the conditional variance of asset B.

For optimal portfolio weights on the other hand, for a portfolio consisting of two assets A and B, the optimal weight ω_t^{AB} for asset A, is estimated as follows:

$$\omega_{AB,t} = \frac{Var_{B,t} - Cov_{AB,t}}{Var_{A,t} - 2Cov_{AB,t} + Var_{B,t}} \tag{23}$$

and

$$\omega_t^{AB} = \begin{cases} 0, if\ \omega_t^{AB} < 0 \\ \omega_t^{AB}, if\ 0 \leq \omega_t^{AB} \leq 1 \\ 1, if\ \omega_t^{AB} > 1 \end{cases} \tag{24}$$

where $Var_{A,t}$ and $Var_{B,t}$ represent the conditional variances of assets A and B at the time t, respectively.

Finally, the hedging effectiveness is estimated as follows:

$$HE = 1 - \frac{Var_{hedged}}{Var_{unhedged}} \tag{25}$$

where Var_{hedged} and $Var_{unhedged}$ are the variances of the hedged and unhedged portfolios, respectively. In RStudio, the “rmgarch” package is used. All the equations used in the analysis, i.e., (20), (21), (22), (23), and (24), are in line with the theory discussed in section 2.2.3.

5 Empirical Results

The purpose of this section is to try and interpret the results obtained from the analyses of volatility dynamics and hedging effectiveness between cleaner transport sector ETFs and traditional ETFs. The aim is to examine the individual volatility behaviors as well as the relationship between the ETFs and discuss the possible factors and market conditions influencing these dynamics. Furthermore, the practical implication, hedging effectiveness, is evaluated. Accordingly, this section aims to address and provide answers to the hypotheses presented in Section 1.2.

5.1 Individual Volatility Dynamics

Table 3: Results of the EGARCH(1,1) Model.

Funds	α_1	β_1	ω	γ_1
GLD	0.0823411259 ***	0.9229369170 ***	-0.7286030488 ***	0.1078077780 ***
USO	-0.0227836877	0.9567652695 ***	-0.3352393650 ***	0.2009822897 ***
SPY	-0.1155347981 ***	0.9853953127 ***	-0.1372182426 ***	0.0430859720 ***
CLNR	-0.0695837404 ***	0.9952823043 ***	-0.0419884290 ***	-0.0253276439 ***
FDRV	-0.0511031273 ***	0.9972137964 ***	-0.0227708270 ***	0.0280999447 ***

All descriptive statistics are computed using Rstudio. Estimates are run with a EGARCH(1,1) model with a Student's t-distribution. α_1 represents ARCH effect, β_1 GARCH effect, ω_1 constant, and γ_1 leverage effect. *$p < 0.01$ ***, $p < 0.05$ **, $p < 0.1$ **.

Table 3 presents the results of the EGARCH(1,1) Model computed in RStudio. As mentioned, the ARCH effect, α_1, represents the sensitivity of each ETF's volatility to previous shocks, whereas the GARCH effect, β_1, represents the volatility persistence. Constant term ω represents the baseline level of volatility, and γ_1 parameter captures the leverage effect, which represents the asymmetric response of volatility, i.e., does negative shocks have a larger impact on increasing volatility, rather than positive shocks.

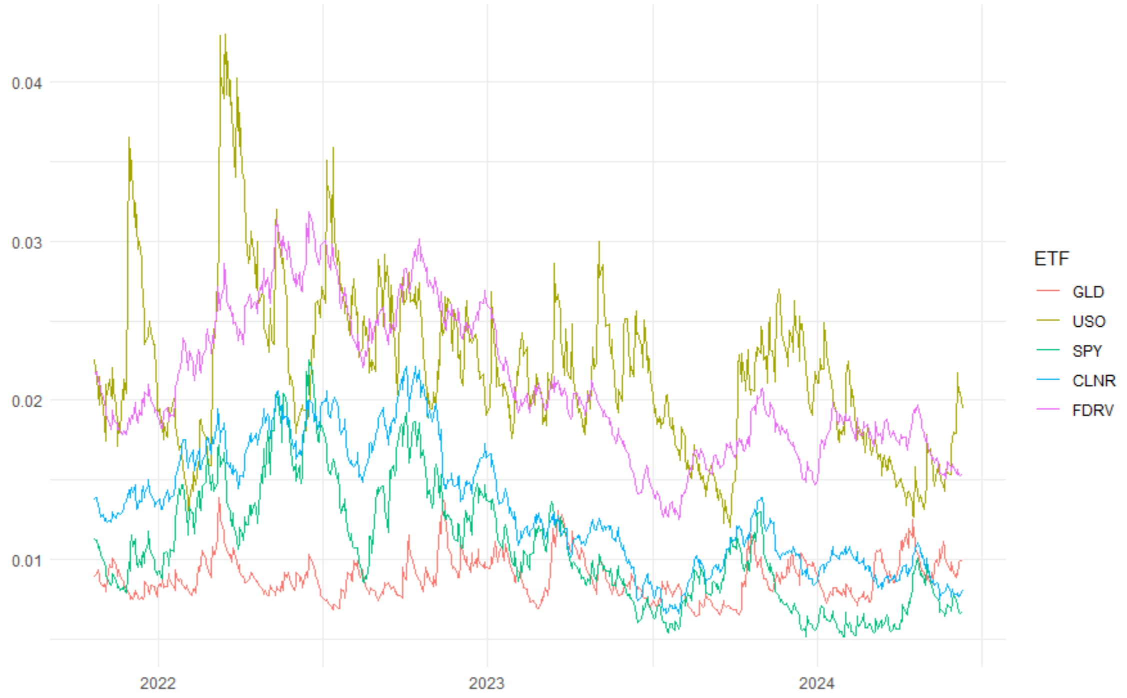
As seen in Table 3, all ETFs have a negative ARCH effect α_1 value, except for gold. This suggests that gold's volatility increases in response to recent shocks, which is aligned with previous studies and the usual investor behavior, i.e., transferring capital to safe havens during market turbulence. For the other ETFs, USO, SPY, CLNR, and FDRV, the results suggest that the volatility would decrease in response to recent shocks. For SPY, this result is quite surprising. One of the reasons could be an immediate volatility response in the stock markets. Moreover, unlike the other ETFs, USO does not indicate statistical significance, which indicates that oil volatility does not decrease in a similar matter. This may be due to some stabilizing factors in the oil market, such as the overall market dynamics of oil and supply controls by the Organization of the Petroleum Exporting Countries (OPEC). As for FDRV and CLNR, the values are statistically significant, yet they do not indicate a strong reaction, like SPY or GLD.

As for the GARCH effect β_1, all ETFs exhibit relatively high values and statistical significance. Both CLNR and FDRV have the highest values, which indicates a very high volatility persistence. This may suggest that the cleaner transport sector is affected by prolonged volatility, possibly due to the speculative nature of the sector and related technologies, as well as policy-related uncertainty. GLD on the other hand exhibits the lowest persistence of the ETFs. Though, it is high, which is again aligned with its reputation. As for USO and SPY, the persistence is also high yet falling under the values of CLNR and FDRV. Given these results, the high volatility persistence is in accordance with H1.

As seen in Table 3, all leverage effect γ_1 values are statistically significant, which indicates that each ETF demonstrates some asymmetric responses. However, GLD, USO, SPY, and FDRV exhibit positive values, which suggests that volatility increases with both positive and negative shocks and that there is not a strong leverage effect. There is a clear difference in values between gold and oil compared to other ETFs, which is most likely explained by the nature of the assets and the market dynamics regarding them. Conversely, to other ETFs, CLNR exhibits a negative leverage effect, which suggests that it is more sensitive to negative shocks compared to positive ones. These results are partly aligned in H2, but not completely, as FDRV displays a lack of strong asymmetric response to negative shocks.

Lastly, the baseline level of volatility, constant term ω, is statistically significant across the ETFs. Furthermore, interestingly, the value is negative for each ETF. Given the EGARCH(1,1) model, this is not uncommon, but it indicates that the model adjusts to a lower starting point. This then gives room for volatility to increase in response to shocks. Moreover, higher constant values, seen in ETFs such as GLD and USO, may also suggest that the base volatility levels are higher. Given this, it may be that both FDRV and CLNR exhibit low baseline volatility. Now, following the analysis of the EGARCH(1,1) model, the conditional volatility dynamics of each ETF are also plotted in Figure 8. With this visual, the conditional volatility behaviors over time can be compared and reflected to different market shocks. Moreover, the figure enables us to assess whether there are any distinctive differences between cleaner transport sector ETFs and traditional ETFs. The estimates are fitted with an EGARCH(1,1) model using a Student's t-distribution in RStudio.

Figure 8: Conditional Volatility Dynamics of ETFs, EGARCH(1,1) Model.



As seen in Figure 8, each ETF has its own distinct conditional volatility patterns. USO exhibits the highest level of conditional volatility, whereas FDRV exhibits the second highest level of conditional volatility, which is somewhat surprising. These two ETFs together exhibit the highest levels of conditional volatility throughout the time period. The patterns across FDRV, CLNR, and SPY are relatively similar, with the most notable difference in the conditional volatility levels, which indicates that they are affected similarly by underlying market shocks and or events. Given this, the results suggest that both CLNR and FDRV behave very similarly to traditional equity assets. Some sector-specific shocks may cause variation, but the overall trend is similar, which means that these ETFs are exposed to general market movers, such as economic cycles and significant investor sentiment.

Where USO displays the highest level of conditional volatility, GLD on the other hand exhibits the most stable, clearly distinct low conditional volatility. Both gold and oil have their completely unique patterns, differing a lot compared to SPY, CLNR, and FDRV. As for oil, this is most likely due to supply and demand shifts and geopolitical factors, whereas gold is aligned with its reputation as a safe haven. Moreover, global events and factors, such as demand recovery after COVID-19, the start of the Russia-Ukraine war, and inflation as well as interest rate pressures – causing overall economic concerns – affect these commodities. However, the reaction to these shocks and events can also be seen with SPY, CLNR, and FDRV.

5.2 Dynamic Conditional Correlations

Table 4: Time-varying Dynamic Conditional Correlations.

FUND Pair	Mean	Standard Deviation	Max	Min
CLNR-GLD	0.2344231	0.22670602	0.6818908	-0.4165131
CLNR-USO	0.1270770	0.15038603	0.5259175	-0.4223788
CLNR-SPY	0.8629933	0.03403338	0.9224564	0.7204986
FDRV-GLD	0.1652219	0.18428423	0.6131497	-0.3054198
FDRV-USO	0.1216089	0.08618195	0.2946382	-0.2288128
FDRV-SPY	0.7884798	0.04610876	0.8465357	0.6686621

All descriptive statistics are computed using Rstudio. Multivariate DCC-GARCH(1,1) model with t-distribution is deployed.
The columns display the mean, standard deviation, maximum, and minimum of the estimated dynamic conditional correlations.

As seen in Table 4, the mean, standard deviation, maximum, and minimum values for CLNR and FDRV are computed pairwise, regarding the traditional ETFs; GLD, USO, and SPY. For CLNR-GLD, the mean correlation is positive on average, yet relatively weak. On the other hand, the standard deviation is quite strong, which suggests inconstancy in their relationship. The value also goes negative at some points. As for FDRV-GLD, similar values can be seen. The mean correlation is positive on average, though it is relatively weak. Like CLNR-GLD, the standard deviation is quite strong, and one can see the value going negative at some points. For additional interpretation, the time-varying conditional correlations for CLNR-GLD and FDRV-GLD are plotted in Figure 9 and Figure 10, respectively. With these figures, it can be seen that the negative correlation usually appears mainly during global events and market uncertainty followed by them. For example, the early 2022 drop is most likely caused by the start of the Russia-Ukraine war and the early 2023 drop is most likely in relation to Silicon Valley Bank Collapse.

Similar to the relationship between CLNR and gold, CLNR-USO has a positive mean correlation on average, though it is weak. The standard deviation is quite strong, which again suggests inconsistency in their relationship. And like the relationship with gold, the values go negative at some points. As for FDRV-USO, the values exhibit similar results. The main difference is the notably lower standard deviation, which indicates that the relationship is more stable. The difference is most likely caused by the asset allocation of the ETFs. The time-varying conditional correlations for CLNR-USO and FDRV-USO are plotted in Figure 9 and Figure 10, respectively. As seen in the figures, the patterns are relatively similar, with the major difference in the standard deviation.

CLNR-SPY exhibits a strong positive conditional correlation, with an average of 0.8629933. Moreover, the standard deviation is very low, indicating a rather stable relationship. Similar values can be seen from FDRV-SPY, though the conditional correlation is slightly lower, and the standard deviation slightly higher. With these results, it is further suggested that both CLNR and FDRV are heavily influenced by the general market trends and follow the volatility patterns of other equity assets. Given this, the hedging potential is possible when combining cleaner transport sector ETFs with gold and oil. Though, it is worth mentioning, that given the high correlation with SPY, these ETFs might not significantly bring any additional diversification or protection benefits. The conditional correlations of CLNR-SPY and FDRV-SPY are plotted in Figure 9 and Figure 10, respectively. Furthermore, given the differences in the plots, it is suggested that FDRV-SPY might have more minor variations, which causes a higher standard deviation compared to CLNR-SPY. Moreover, it is worth mentioning that the conditional correlation of FDRV-SPY has been declining for a time now, on a broader timescale.

Figure 9: Time-varying Conditional Correlations between CLNR and traditional ETFs.

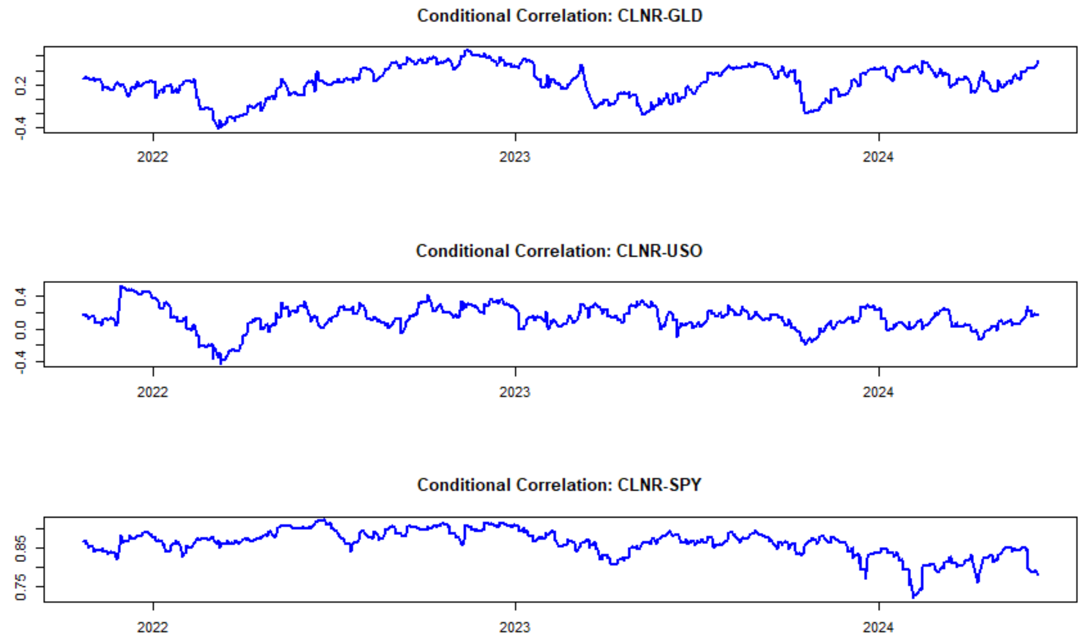
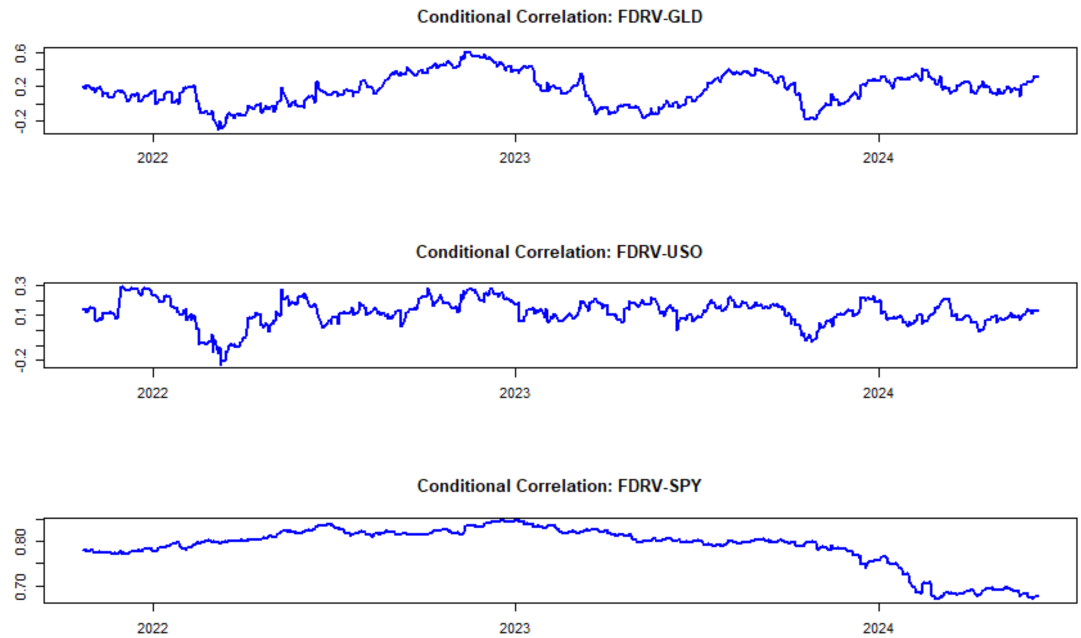


Figure 10: Time-varying Conditional Correlations between FDRV and traditional ETFs.



5.3 Hedging Effectiveness

Table 5: Hedge Ratio, Portfolio Weight, and Hedging Effectiveness.

FUND Pair	β_{AB}	ω_{AB}	HE
CLNR-GLD	0.35652502	0.7103789	10.33%
CLNR-USO	0.07160743	0.2458247	3.41%
CLNR-SPY	1.08617420	0.9204393	73.95%
FDRV-GLD	0.39438773	0.8818015	5.79%
FDRV-USO	0.11180418	0.4792142	2.02%
FDRV-SPY	1.59456912	1.0000000	61.42%

All descriptive statistics are computed with Rstudio. The computing is aligned with the theory presented in Section 4.2.3.

The results seen in Table 5 are computed in RStudio, aligned with the formulas presented in Section 4.2.3. In RStudio, the outputs from the EGARCH(1,1)/DCC-GARCH model are used, i.e., the conditional variance and conditional covariance estimates. Moreover, the computations are looped through each pair. β_{AB} represents the hedge ratio, ω_{AB} represents the portfolio weight, and *HE* represents the hedging effectiveness. Generally speaking, the closer the value is to 1 for *HE*, the better the hedging effectiveness is.

By systematically interpreting the results, pair-by-pair, CLNR-GLD has a hedge ratio β_{AB} of 0.35652502, which suggests that for every dollar of CLNR, approximately 0.36 dollars towards gold are required in order to minimize the portfolio risk. Moreover, the portfolio weight ω_{AB} of 0.7103789 suggests that slightly over 70% of the portfolio should be allocated to gold, which is relatively high given diversification. Furthermore, the hedging effectiveness *HE* of 10.33% is relatively decent, indicating a moderate hedging effectiveness. Given these results, it is suggested that gold provides decent capability for CLNR regarding efficient hedging, though it is not highly efficient. As for FDRV-GLD, the results exhibit similar values. Hedge ratio β_{AB} of 0.39438773 suggests that for every dollar of

FDRV, approximately 0.39 dollars towards gold are required to minimize the portfolio risk, and the portfolio weight ω_{AB} of 0.8818015 suggests that almost 90% of the portfolio should be allocated to gold. As for the hedging effectiveness *HE*, the value is almost twice lower than as of CLNR, 5.79%. So, it is suggested that gold provides relatively low and limited capability for FDRV regarding efficient hedging. Given these results, it is suggested that gold offers better hedging benefits for CLNR than FDRV, being overall decently moderate.

For CLNR-USO, the hedge ratio β_{AB} of 0.07160743 suggests that for every dollar of CLNR, approximately 0.07 dollars towards oil are required to minimize the portfolio risk, which is relatively low. Moreover, the portfolio weight ω_{AB} of 0.2458247 suggests that around 25% of the portfolio should be allocated to oil. The hedging effectiveness is low, 3.41%, which indicates that oil is ultimately an ineffective hedge for CLNR. The hedging effectiveness is so low that it is almost worth neglecting. Once again, FDRV-USO exhibits similar results. Hedge ratio β_{AB} of 0.11180418 suggests that for every dollar of FDRV, approximately 0.11 dollars towards oil are required to minimize the portfolio risk and the portfolio weight ω_{AB} of 0.4792142 suggests that slightly less than 50% of the portfolio should be allocated to oil, which indicates a moderate exposure. Though, the hedging effectiveness *HE* is even worse than that of CLNR, 2.02%. This value indicates that the weak relationship with oil does not provide an effective hedge for FDRV.

As for CLNR-SPY, the hedge ratio β_{AB} of 1.08617420 suggests that for every dollar of CLNR, approximately 1.09 dollars towards stocks are required to minimize the portfolio risk. For FDRV-SPY, on the other hand, the hedge ratio β_{AB} of 1.59456912 suggests that for every dollar of FDRV, approximately 1.59 dollars towards stocks are required to minimize the portfolio risk. With these results, if given the so-called “one-dollar hedge” framework, this means an investor would over-leverage the hedge on both hedges. This means that the investor would need to put more capital into the hedge, rather than the exposure the investor is trying to protect, which again indicates higher costs versus potential risk reduction. Moreover, the portfolio weight ω_{AB} of 0.9204393 on CLNR-SPY suggests that over 90% of the portfolio should be allocated to stocks, whereas FDRV-SPY results indicate full allocation to SPY. The RStudio calculation for portfolio weight is capped at 1. These suggestions are not optimal. The hedging effectiveness for CLNR-SPY and FDRV-SPY are high, 73.95% and 61.42%, respectively, but as mentioned, this hedge is not ideal in the real-world scenario. As displayed in Section 5.2, both these pairs have a highly positive conditional correlation. Given this, instead of being a hedge, SPY basically works as a tracking asset for these cleaner transport sector ETFs.

Ultimately, given the values and conditional correlation for the SPY-pairs, a real-world implication of this hedge is not optimal. While the calculations are accurately computed and they align with the theory presented earlier in the study, the unusually high hedge ratios, weighting, and high positive correlations with SPY suggest the limitations of using highly correlated assets as hedges, at least in this framework. Looking back to oil, the results indicate its inefficiency as a hedge. This leaves gold as only a relatively moderate hedge, though it is not extensively impactful. This insight is partly aligned with H3, acknowledging gold as a potential hedge, whereas oil is somewhat neglected.

5.4 Limitations

While this study provides new insights into cleaner transport sector ETFs, specifically regarding the volatility dynamics and hedging effectiveness of CLNR and FDRV, this study also suffers from certain limitations. These limitations may cause relatively significant variations in the displayed results, which is why they are addressed. Firstly, one of the most significant limitations is the relatively narrow data used in the study. The optimal timeframe would be at least 5 years, whereas the timeframe for this study is less than 3 years. Furthermore, the period is affected by major global events and anomalies within the financial markets, which also may affect the results.

In addition to the data limitations, this study uses specific model assumptions. While both EGARCH and DCC-GARCH models are acceptable tools for financial modeling for capturing volatility dynamics and time-varying correlations, they exhibit assumptions. Moreover, the metrics related to hedging effectiveness may not give real-world practicality, especially with the given dataset. Furthermore, the study does not take transaction costs and liquidity constraints into account, which all have a significant impact on hedging strategies in reality. Nonetheless, given the limitations of the study, it still gives valuable insights to investors and may help them while constructing their portfolios.

6 Conclusion

This study was conducted due to the popular and increasing concept of ESG investing, and the relatively new concept of cleaner transport sector ETFs. More precisely, this study aimed to examine and interpret the volatility dynamics and hedging effectiveness of cleaner transport sector ETFs – CLNR and FDRV – in relation to traditional ETFs, GLD, USO, and SPY. The purpose of the study was to gain knowledge of the individual dynamics, as well as the relationship between these ETFs, to provide valuable insights to investors. With this information, investors could potentially manage risk and optimize their portfolios for additional gains, by including these ETFs in their portfolios. Moreover, cleaner transport sector ETFs are relatively new concepts with very little research on them, thus this study gives insights for future academic research. The study used a univariate EGARCH(1,1) model to examine the individual volatility of each ETF, as well as a multivariate DCC-GARCH(1,1) model to examine the time-varying conditional correlations of the cleaner transport ETFs in relation to traditional ETFs. Moreover, the study examined whether these cleaner transport sector ETFs could work as a hedge, by assessing the hedging effectiveness.

The findings suggest that both CLNR and FDRV exhibit considerable volatility, mostly driven by global market events and risks, along with possible regulatory and sector-specific risks. This conclusion is derived from the individual dynamics as well as the relatively strong dynamic condition correlation with SPY, emphasizing the similarity of asset allocation on equities. Moreover, CLNR and FDRV both indicate a very high volatility persistence, whereas only CLNR as the only ETF displays a relatively strong asymmetric response to negative shocks. For gold and oil, the individual volatility dynamics as well as dynamic conditional correlation exhibit a weaker relationship with CLNR and FDRV. Oil displays the most significant and highest individual volatility, but this is most likely due to large-scale geopolitical factors, and the time-frame the study falls under. Given these results, it is suggested that the first hypothesis is partly accepted, whereas the second hypothesis is completely accepted. As for hedging, both cleaner transport ETFs indicate significant hedging effectiveness with SPY, but this result is invalid. Given the similarity in correlations, as well as that the hedge would require over-leveraging and going from 90% asset allocation to 100% on SPY, the hedge is not effective nor practical in real-world scenarios. As for oil and gold, gold indicates a very moderate hedging effectiveness, whereas oil indicates only a limited hedge. Given this, the third hypothesis is partly accepted.

While the findings provide useful insights, the study also suffered from limitations. The short timeframe of the study along with model assumptions, and the fact that real-world variables such as transaction costs along liquidity factors are not taken into account, the results may be restricted. This said, future studies could expand these findings on cleaner transport sector ETFs by adding multiple more ETFs with a broader timeframe to the data and using differing models for specific results. With this, investors could gain additional insights on the dynamics of these ETFs, and possibly optimize them in their portfolios.

In summary, this study's findings offer valuable insights into the volatility dynamics and hedging effectiveness of cleaner transport sector ETFs and traditional ETFs. The results indicate that there are pros and cons when investing in these ETFs, and investors should carefully consider whether to implement them into their portfolios or not. Given the increasing ESG phenomenon related to investing, these types of sector-specific ETFs may play a significant role in the future. For now, these ETFs should be approached with proper caution, at least until more research is conducted.

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