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Asset Pricing Models and the Performance of European Energy Indices

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Abstract

In this paper, we analyze the abnormal returns of European Energy indices and the factor loadings based on the well-known Fama and French three-factor (FF3) and five-factor (FF5) models. We extend this methodology by introducing one more factor, a European volatility index ($VSTOXX_t$) to the FF3 and FF5 methodologies and we use data from Refinitiv Eikonovera period lasting from 2010 to 2023. The econometric findings indicate that Energy indices do not produce significant alphas, verifying literature studies on negative excess returns. Observations also show medium betas, indicating a medium level of systematic risk. Furthermore, we notice sufficient evidence that the European Energy Indices tilt to large cap, value stocks, robust operating profitability, and low-risk investment strategies. Lastly, the performance and the validity of adding an extra determinant factor on both the FF3 and FF5 models resulted in a novelty finding of volatility tilting and dispersion of returns bias on European Energy portfolios. Robustness tests of a complementary index, (MSCI), obtain the same results. This paper contributes to the growing empirical literature on Fama and French three-factor and five-factor models and provides additional insight for academics, policymakers, and investors.

Keywords

Energy Indices, Volatility, $VSTOXX_t$, Fama-French, Crisis, Asset Pricing Models

1. Introduction

Economic and geopolitical crises have been a recurring phenomenon in the past decades. In most cases, the effects of these crises harmed the markets in which they occurred, not only in the purely economic field but at the societal or political level as well. Some of the events affected the global economy, such as the Global Economic Crisis (2007-2010). Additionally, some of these events only affected individual countries. A glaring example is the isolated financial and debt crisis in Europe, which had mostly affected Iceland, Portugal, Italy, Greece, and Spain, resulting in a loss of confidence in the European economic environment. However, some of these events proved so grave and devastating that markets on a global scale were affected. Examples of such catastrophic events are the Global Financial Crisis in line with the Global Recession (2007-2010) and the COVID-19 pandemic crisis economic fallout (Ozili & Arum, 2023; Cheema et al., 2022; Borio, 2020; Zhang & Droadstock, 2020).

All financial crises, mostly the recent pandemic Covid19 one, in addition to global climate change, triggered increasing attention to climate policy, energy transition, economic resilience, sustainable administration, and sustainable economy. Investment decisions made by individuals or institutional investors nowadays start to accommodate their risk and decision problems like climate change, rising economic inequality, unequal human rights, high geopolitical tension that injects risk into a business, and high volatility in energy markets (Zehir & Aybars, 2020).

According to the International Energy Agency, (IEA, 2020) natural gas prices have seen the biggest increase, the recent years hitting around ten times their level in 2019. The strong increases in natural gas prices have prompted substantial switching to the use of coal rather than natural gas to generate electricity in key markets especially in Europe driving up CO_2 emissions from electricity generation globally. The global changes which are affecting countries at the moment, act as a censor of modern energy relations, and energy market development strategies in general. It is denoted by academics that the development of the energy market is no longer considered in terms of its efficiency but more in terms of its survivability under the influence of external environmental factors (Kostin et al., 2022).

Recent economic crises led the energy market to instability and uncertainty and the COVID-19 pandemic slowed down, and temporarily froze, the global economy and the functioning of the financial sector (Kozak, 2021). During the last decade, a lot of changes have taken place in the worldwide energy market. Globalization of the economy, as well as increased volatility of energy prices, lead market participants to be more aware of the world financial crisis and try to capture the most significant risks in the market by using risk management models in order to reduce their risk exposure (Galyfianakis et al., 2016a). Although renewable energy has become increasingly important in recent years and investors and managers are incorporating them into their portfolios, fossil fuels still leading the energy market, which appears to be very uncertain and erratic (Garcia-Olivares, 2015).

In our survey, we take under consideration the importance of the energy market to the global economy and the aspect claiming that globalization of the economy and financialization of commodity markets, particularly of Energy commodities, brought market participants to believe that much of the commodity price turbulences are because primary commodities had become new asset class (Chatziantoniou et al., 2021; Fattouh et al., 2013; Kaufmann & Ulman, 2009). Although a strand of the literature deals with portfolio evaluations and asset pricing, especially in northern America, surprisingly, few empirical studies on this subject have been performed in the European context using European Energy Indices and applying the Fama and French approach. Therefore, further analysis of Energy benchmarks in Europe throughout the period, which will encompass all the recent crises that happened from 2010 to 2023, is essential to further investigate.

The main aim of this paper is to demonstrate the applicability of asset pricing Fama and French 3-factor and Fama and French 5-factor models to the European Energy market. We also extend this methodology by introducing the European volatility index ($VSTOXX_t$) in the FF3 and FF5 methodologies, which enable us to acquire further awareness concerning Energy excess returns or alphas and risk. Our study contributes to the extent of the relatively empirical literature by studying European energy benchmarks and measuring Jensen's alpha against European energy benchmarks and the factor loadings based on the Fama-French three-factor (FF3) and the Fama-French five-factor (FF5) models. We also extend this methodology by introducing the volatility index ($VSTOXX_t$) in the above methodologies (FF3 and FF5), whichenables us to extend our knowledge concerning Energy excess returns or alphas and risk. Nevertheless, this paper addresses an up-to-date topic that is of concern to academic researchers, investors, and policymakers.

This article is organized as follows: The Literature Review section provides a review of the relevant literature on the examined topic. The data and Methodology section discusses the data gathered and describes the elaborate deconometric methodology. The empirical Results section shows the main econometric findings of this study. Finally, the last section provides conclusive remarks and policy implications.

2. Literature Review

The growth in the volume of commodity assets and portfolio asset pricing attracted academic interest. Methodologically, portfolio analyses of asset-pricing models have evolved from CAPM, a single-factor model to several multifactor models. Numerous tests indicate that the market beta coefficient alone, measuring an overall market factor (Rm-Rf), is not sufficient to explain the cross-sectional variation of expected returns. Extensions of the model have been developed with the aim of more completely describing the returns of risky assets.

The research for a better asset pricing model during 1990s gave, by Fama and French (1992, 1993), the *three-factor pricing model* (FF3) that extend the one-factor CAPM model. In addition to the beta of CAPM, two other factors were introduced to explain variations in stock returns: firm size (SMB)[1] and book-to-market equity (HML)[2]. The three-factor model has been improved with the addition of new variables. It has become widely used alike for estimating cross-sectional equity returns, and aims to capture these two well-known premiums by augmenting CAPM with additional factors to proxy size and value (Foye, 2018).

Additionally, Fama and French (2015) further developed the asset pricing model to five factors, (i.e., the market factor, the size factor, the value factor, the profitability factor, and the investing factor), which include common risk factors for profitability and investment. They conclude that the five-factor model describes better the average return performance than the traditional three-factor model. In the same line Chen and Gao (2020), report that the five-factor model performs better than the three-factor model.

In recent years, a variety of empirical work has addressed the relationship between volatility indices and stock market returns. In many studies, the role of fear in the stock markets is measured by market volatility. More particularly, the VIX index is known as the investor fear gauge. It captures investors' expectations of market volatility. With this in mind, Durand et al. (2011) investigate how changes in market volatility, taking the VIX index as its proxy, affect the expected returns on the US stock market. They used a Fama-French three-factor model to denote that the expectations of market volatility captured by the VIX affect equities by acting on the risk premia in the augmented Fama-French three-factor model. Along the same line, Economou et al. (2018) examine the impact of investors' fear on herding estimations as it is captured by the implied volatility indexes. In the same vein, Cai et al. (2009) argue that the VIX index is considered a barometer to gauge investors' fear.

Horvath and Wang (2021) evaluate the performance of Fama and French models on the U.S. stock market. They report that R^2 of growth portfolios decreases during the global financial crisis. Yamani and Swanson (2014) imply a composite of GARCH and FF two-factor model to investigate the behavior of the value premium within a crisis period. They document that equity markets are more integrated after the financial crisis.

Several academics have investigated the performance of implied volatility indices and stock market returns. Many studies have proved a negative correlation between changes in volatility and stock market returns. According to Giot (2005), there is a strong negative relationship between changes in implied volatility indices and stock indices. Rubbaniy et al. (2014) investigate the forecasting power of implied volatility indices on stock returns. They conclude that volatility indices can be used to predict the 20-day and 60-day forward-looking returns.

[1]A portfolio of low market capitalization stocks is financed by selling a portfolio of stocks with high market capitalization.

[2]A portfolio of "value" stocks is financed by shorting "growth" stocks.

Smales (2022) utilizes measures of implied volatility based on major stock market indexes. They conclude that U.S. market uncertainty plays an important role in global stock market uncertainty. Sarwar (2012) analyzed the relationship between the CBOE market volatility index and stock market returns in the U.S., and BRIC to uncover if VIX serves as an investor fear gauge. The results suggest that there is a strong negative contemporaneous relation between VIX and stock markets and VIX is an investor fear gauge not only for the stock market but also for equity markets. Marrero et al. (2015) investigated two different energy portfolios, an electric-generating technology mix, and a road transport fuel mix. They imply the Mean-Variance Portfolio Theory (MVPT) to evaluate the average cost and the associated volatility of alternative energy combinations, and the Capital Asset Pricing Model to identify the risk associated with energy. They conclude that both, electricity generation and fuel use imply idiosyncratic risks. Furthermore, Emna and Myriam (2017), report that there is a strong negative and asymmetrical relationship between implied volatility indices and stock market returns. Chen and Gao (2020) employed a Fama and French three–factor model to examine how three defined volatility risk factors derived from VIX may affect the pricing of assets. In a recent paper Gavrilakis and Floros (2024) by implying the CAPM, FF3, FF5 methodologies reported that European and Global indexes based ESG leaders' portfolios produce negative abnormal returns during 2012-2022, verifying the reports of previous studies and deduced that European ESG portfolios are tilt towards large cap, robust operating profitability and against aggressive investment.

As Energy is one of the primary drivers of the economy considering the impact of negative externalities of energy, energy sustainability is increasingly gaining importance (Galyfianakis et al., 2016b). In recent years have been published many studies related to sustainable investments (SI) beyond the traditional practice of shareholders wealth maximization. The role of a sustainable (low-environmental impact) organization has become crucial in financial markets and investors ask companies that focus on sustainability, green bonds, and social impact assets (Ciciretti et al., 2021; Evans & Peiris, 2010). The relationship between a company's sustainable activity and its financial performance has attracted the attention of researchers (Aboud & Diab, 2019; Cunha et al., 2020).

3. Data and Methodology

3.1. Data

The data of the analysis are collected from Eikon, which is a set of software products and financial tools provided by Refinitiv. The sample includes two energy market indices namely STOXX Europe 600 Energy, and the MSCI Europe Energy Index. The sample period is from 2010 to 2023. This period includes the financial crisis in Europe of the COVID-19 pandemic spread. Toimprove our econometric methodology on the Fama-French three-factor (FF3) and the Fama-French five-factor (FF5) models with the addition of a new factor, we extract, as well from Eikon, the VSTOXX volatility Index for the above-mentioned period. Among all the European volatility indexes is the most watched. It was created in 1999 and measures the volatility of the Euro Stoxx 50, the Eurozone blue chip stock index.

3.2. Regression Analysis

In this paper, we analyze the **abnormal returns** of European Energy indices and explore the factor loadings based on the Fama-French three-factor (FF3) and the Fama-French five-factor (FF5) models. We also extend this methodology by augmenting the volatility index ($VSTOXX_t$) in the above methodologies (FF3 and FF5), which enable us to gain further awareness concerning the Energy excess returns or alphas and risk. There are two prime reasons for considering volatility as an added factor. Firstly, volatility behavior is a dominant factor in portfolio analysis and secondly, a volatility index can capture short-term mood sentiments (Whaley, 2009).

A model that is widely used is the Capital Asset Pricing Model (CAPM) by Treynor (1961):

$$ENERGY_{it} - R_{ft} = a_{it} + \beta_1 (MKT_t) + \varepsilon_{it} \tag{1}$$

where $ENERGY_{it} - R_{ft}$ is the excess return of the European energy index; R_{ft} is the one-year Treasury Bill rate; a_{it} is the Jensen's alpha; MKT_t is the market risk premium $(R_{mt} - R_{ft})$ on day *t;* β_1 is the beta or the sensitivity of the $ENERGY_{it}$ to the market, and ε_{it} is the error term. Some authors have criticized its capacity to appreciate the firm performance (Andrei et al., 2023; Shi & Li, 2023; Fama & French, 1992). With this in mind, in our investigation, we use the models employed by the Fama and French, specifically the Fama and French three-factor model (FF3) and Fama and French five-factor model (FF3).

In short, the three-factor model is as follows:

$$ENERGY_{it} - R_{ft} = a_{it} + \beta_1 (MKT_t) + \beta_2 (SMB_t) + \beta_3 (HLM_t) + \varepsilon_{it} \tag{2}$$

(SMB_t) and (HLM_t) are the size and value firm characteristics respectively.

SMB_t (Small minus Big) represents the size premium, meaning large-cap assets are expected to earn lower returns than small-cap assets (Zehir & Aybars, 2020).

HLM_t (High minus Low) stands for the value premium; stocks with low book-to-market ratios are expected to underperform those with high book-to-market ratios.

In our study, we extend the FF3 and FF5 models by augmenting the $VSTOXX_t$ indicator.

Thus, the Fama and French three-factor model becomes as following:

$$\begin{aligned} ENERGY_{it} - R_{ft} = a_{it} &+ \beta_1 (MKT_t) + \beta_2 (SMB_t) + \beta_3 (HLM_t) \\ &+ \beta_4 (VSTOXX_t) + \varepsilon_{it} \end{aligned} \tag{3}$$

The regression coefficients β_1, β_2, and β_3 explain the Energy sensitivities to the pre-specified indicators.

Equation (4) is the Fama and French (2015) five-factor model (FF5):

$$ENERGY_{it} - R_{ft} = a_{it} + \beta_1(MKT_t) + \beta_2(SMB_t) + \beta_3(HLM_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \varepsilon_{it} \quad (4)$$

where (SMB_t) and (HLM_t) denote, respectively, the size and value firm characteristics, (RMW_t) and (CMA_t) are, returns for profitability and investment factors and RMW_t (Robust minus Weak) relates to the profitability premium, meaning stocks with weak operating profitability are foreseen to underperform stocks with robust operating profitability. Lastly, CMA_t (Conservative minus Aggressive) is the return difference between stocks that invest conservatively minus those that invest aggressively.

Equation (5) represents the Fama and French (2015) five-factor model extended by augmenting the volatility index, $VSTOXX_t$. The regression coefficients β_4 and β_5 are the Energy sensitivities to profitability and investment factors.

$$ENERGY_{it} - R_{ft} = a_{it} + \beta_1(MKT_t) + \beta_2(SMB_t) + \beta_3(HLM_t) + \beta_4(RMW_t) + \beta_5(CMA_t) + \beta_6(VSTOXX_t) + \varepsilon_{it} \quad (5)$$

We applied the traditional OLS with Newey and West's (1987) standard errors to evaluate the coefficients.

The value MKT_t is the market risk premium $(R_{mt} - R_{ft})$ or the excess return on the market and is calculated as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate (R_{ft}). The values of MKT_t, SMB_t, HLM_t, RMW_t and CMA_t for the regression models were derived from Kenneth R. French Library (2023).

4. Results and Discussion

Table 1 depicts the descriptive statistics of Energy and volatility indicators. The results show, on average, a significant dispersion for all Energy indices, while the annual mean standard deviation (volatility) suggests that Energy investing indicates low risk. It should be noted that the mean values for all of the variables are positive. The summary statistics show the daily returns' negative asymmetry (negative skewness values for energy indexes while the VSTOXX displays positive). Thus, an investor may expect frequent small gains and more losses. We indicate positive skewness for the volatility index. The positive skewness of the volatility index is due to the fact that its mean is higher than the median.

Furthermore, the distributions of the Energy indexes are leptokurtic as kurtosis values are above 12, indicating the presence of fat tails in the series, and for volatility index is mesokurtic. The Kurtosis of all factors is higher than the normal distribution kurtosis, which is commonly considered to be 3. Kurtosis is only valid when used in connection with standard deviation. The distributions are non-normal for all series as Jarque-Bera statistics show significant p-values, indicating the departure from normality and the arrival of volatility clustering.

The following Table 2 illustrates the OLS regression results (with HAC standard errors) of STOXXEnergy Index. The resultssuggest that all the Energy indices underperformed (with negative risk-adjusted abnormal returns) against the market. Irrespective of our sample, the Energy index presents medium to high betas (β), indicating a medium to high level of systematic risk. The Energy indicator depicts a negative loading on SMB_t, implying a tilt toward large-cap firms. The negative correlation with SMB_t suggests that during the period under examination, which includes the financial crisis, investors preferred to invest in big companies when the stock market rises.

The factor loadings for the determinant HLM_t are broadly significantly positive in all series, which means a bias towards value stocks. The portfolios report a favorable loading on RMW_t, indicating a tilt toward robust operating profitability.

The Energy indicators depict a positive loading on CMA_t (0,139) implying a tilt toward conservative firms. Our results support the existing "fly to quality" theory, which is related to the actions investors take when risk changes. This theory postulatesthat an increase in the expected risk of equities increases the demand for conservative assets that serve as a haven from risk. This finding supports the literature results that FF3 and FF5 effectively explain Energy performance concerning market returns (Zaremba & Czapkiewicz, 2017; Guo et al., 2017). Furthermore, the results confirm that our augmented FF3 and FF5 model explains significantly all the factor loadings.

Table 3 shows similare to Table 2 results and also reports that the fear or volatility index $(STOXX_t)$ is significant and negative in both models thus all indices indicatea volatility bias. The results confirm the existing theory and volatility index $(STOXX_t)$ is negatively correlated with the STOXX Energy Index.

Table 1. Descriptive statistics.

Statistic	STOXX EUROPE 600 ENERGY INDEX	MSCI EUROPE ENERGY INDEX	EURO STOXX 50 VOLATILITY INDEX (VSTOXX)
Min	−16.630	−18.080	−35.260
Max	15.850	19.377	62.560
Mean	0.012	0.029	0.23096
SD	0.01467	0.01582	0.07212
Skewness	−0.381	−0.12839	1.2970
Kurtosis	13.903	17.336	6.4668
JB test	28002.2***	43401.5***	6847.42***

Normality test based on skewness, kurtosis values and Jarque-Bera test ***$p < 0.01$.

Table 2. Regression equation table for european energy STOXX europe index.

FAMA FRENCH 3 FACTORS							
	a	b	SMB_t	HML_t	R^2		
STOXX EUROPE	**−0.0037****	0.689***	−0.453***	0.771***	0.54		
FAMA FRENCH 5 FACTORS							
	a	b	SMB_t	HML_t	RMW_t	CMA_t	R^2
STOXX EUROPE	**−0.0183***	0.709***	−0.419***	1.212***	1.103***	0.139*	0.56

Note: ***, * denote statistical significance at the 1%, and 10% levels, respectively. The risk-free rate (R_{ft}) and the values MKT_t, SMB_t, HML_t, RMW_t and CMA_t for the regression models were derived from the Kenneth R. French data Library. The R^2 is adjusted and describes the goodness of fit of the model.
The regression results of STOXX EUROPE 600 Energy index against FF3, FF5.
Daily price data are obtained from the Refinitive Eikon database (2024) from 17/09/2010 to 29/12/2023).

Table 3. Regression equation table for european energy STOXX index and volatility.

FAMA FRENCH 3 FACTORS AND VSTOXX								
	a	b	SMB_t	HML_t	VSTOXX	R^2		
STOXX EUROPE	0.0102*	0.5360***	−0.3645***	0.7866***	−0.03999***	0.56		
FAMA FRENCH 5 FACTORS AND VSTOXX								
	a	b	SMB_t	HML_t	RMW_t	CMA_t	VSTOXX	R^2
STOXX EUROPE	−0.0048*	0.5402***	−0.3193***	1.2676***	1.1905***	0.1205***	−0.0438***	0.59

Note: ***, * denote statistical significance at the 1%, and 10% levels, respectively. The risk-free rate (R_{ft}) and the values MKT_t, SMB_t, HML_t, RMW_t and CMA_t for the regression models were derived from the Kenneth R. French data Library.
The R^2 is adjusted and describes the goodness of fit of the model.
The regression results of STOXX EUROPE 600 Energy index against, FF3, FF5, (including VSTOXX in the models).
Daily price data are obtained from the Refinitive Eikon database (2024) from 17/09/2010 to 29/12/2023).

Table 4 illustrates the OLS regression results (with HAC standard errors) of MSCI Energy index. The results of all factor models suggest that all the Energy index underperformed (with negative risk-adjusted abnormal returns) against the market. Irrespective of our sample, the MSCI Energy index presents medium betas (β), indicating a medium level of systematic risk. The Energy indicator depicts a negative loading on SMB_t (−0.541) implying a tilt toward large-cap firms. Thus, the negative correlation with SMB_t might suggest that during the period under examination, which includes the financial crisis, investors preffered to invest in big companies, when the stock market rises.

The factor loadings for the determinant HLM_t are broadly significantly positive (0.937) in all series, which means a bias towards value stocks. The portfolios report a favorable loading on RMW_t, (1.386) indicating a tilt toward robust operating profitability. The Energy indicators depict a positive loading on CMA_t (0.366) implying a tilt toward conservative firms. Overall, our results support the existing "fly to quality" theory, which is related to the actions investors take when risk changes. This theory postulatesthat an increase in the expected risk of equities increases the demand forconservative assetsthat serve as a haven from risk (Papadamou et al., 2021; Beber et al., 2009).

Table 5 also reports that the fear or volatility index $(STOXX_t)$ is significant

Table 4. Regression equation table for MSCI energy index.

FAMA FRENCH 3 FACTORS							
	a	b	SMB_t	HML_t	R^2		
STOXX EUROPE	−0.0005**	0.650***	−0.541***	0.937***	0.50		
FAMA FRENCH 5 FACTORS							
	a	b	SMB_t	HML_t	RMW_t	CMA_t	R^2
STOXX EUROPE	−0.018*	0.697***	−0.472***	1.367***	1.302***	0.394***	0.53

Note: ***, * denote statistical significance at the 1%, and 10% levels, respectively. The risk-free rate (R_{ft}) and the values MKT_t, SMB_t, HML_t, RMW_t and CMA_t for the regression models were derived from the Kenneth R. French data Library.
The R^2 is adjusted and describes the goodness of fit of the model.
The regression results of MSCI Energy index against FF3, FF5.
Daily price data are obtained from the Refinitive Eikon database (2024) from 17/09/2010 to 29/12/2023)

Table 5. Regression equation table for MSCI energy index and volatility.

FAMA FRENCH 3 FACTORS AND VSTOXX								
	a	b	SMB_t	HML_t	VSTOXX	R^2		
STOXX EUROPE	−0.0151*	0.4989***	−0.4600***	0.9510***	−0.0389***	0.52		
FAMA FRENCH 5 FACTORS AND VSTOXX								
	a	b	SMB_t	HML_t	RMW_t	CMA_t	VSTOXX	R^2
STOXX EUROPE	−0.00290*	0.5278***	−0.3794***	1.4238***	1.3867***	0.3668***	−0.0432***	0.55

Note: ***, * denote statistical significance at the 1%, and 10% levels, respectively. The risk-free rate (R_{ft}) and the values MKT_t, SMB_t, HML_t, RMW_t and CMA_t for the regression models were derived from the Kenneth R. French data Library.
The R^2 is adjusted and describes the goodness of fit of the model.
The regression results of **MSCI Europe energy index** against FF3, FF5, (including VSTOXX in the models).
Daily price data are obtained from the Refinitive Eikon database (2024) from 17/09/2010 to 29/12/2023.

and negative in both models indicating a volatility bias. As we have seen previously in the literature review, there is a negative relationship between market volatility and market excess return. The reference paper of Durand et al. (2011) also reportsa negative correlation between VIX and US stock markets. We can conclude that an increase in volatility leads to a decrease in stock markets. Therefore, declining markets are characterized by higher volatility and negative market returns.

5. Concluding Remarks

In this paper, we investigate the risk-adjusted performance of European energy portfolios in European Energy markets from 2010 to 2023. The Energy portfolios did not produce significant alphas, verifying literature studies on negative excess returns. The regression models FF3 and FF5 were used to test the loading factors' validity and interpret the returns' cross-section. We noticed sufficient evidence that the European Energy Indices tilt to large cap, value stocks, robust operating profitability, and low-risk investment strategies. In contrast, we reported no significant evidence for European Energy Indexes regarding size, operation profitability, and investment strategy. Furthermore, we examine the performance and the validity of adding another determinant factor (volatility-STOXX) to both the FF3 and FF5 factor models, resulting in a novelty finding of volatility tilting and dispersion of returns bias on European Energy portfolios. Robustness tests applied with the complementary index (MSCI), with overall obtaining the same results.

This finding has practical implications for investors and fund managers exposed to Energy assets in managing Energy funds and constructing sustainable portfolios. The current study contributes to the literature by providing valuable updates on factor loadings of different regression models on European Energy portfolios. Furthermore, by using well-known regression equation methodologies, this study investigates how those portfolios are affected by a European volatility index, by providing helpful insights to investors and policymakers to better understand pricing anomalies and behavioral finance. A limitation to be acknowledged is the lack of data for European Energy indices. It is considered crucial to run further research by including in our estimation methodology global data and augmenting more determinant factors to both FF3 and FF5 asset pricing models.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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