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Risk-Return Dynamics of Renewable vs Non-Renewable Energy Portfolios: An Analysis of Volatility and Returns

Jeremy Cheung

Reading School, Erleigh Road, Reading, Berkshire, RG1 5LW, UK; jeremycheung2007@gmail.com

ABSTRACT: This paper examines the performance dynamics of renewable and non-renewable energy portfolios by analyzing the relationship between volatility and returns. Using a dataset of daily closing prices from 2021 to 2024, covering eight stocks each in the renewable energy and non-renewable energy sectors, and the NASDAQ Composite Market Index, the study identifies a distinct risk-return trade-off among all benchmark portfolios. The findings show that the non-renewable energy portfolio exhibits higher returns but also increased volatility, highlighting that greater risk is associated with greater returns. In contrast, the renewable energy portfolio demonstrates the highest average volatility while producing relatively low returns, suggesting it may not be an efficient investment choice. However, the diversified composite energy portfolio successfully generated higher returns than the market while offering lower risk in terms of volatility. The paper concludes that investors in the energy sector must navigate different risk preferences: those seeking higher returns may be drawn to non-renewable energy, while those prioritizing stability in an evolving energy market may prefer to diversify their portfolios with some renewable energy stocks. These insights offer valuable information for portfolio construction and risk management strategies.

KEYWORDS: Mathematics, Analysis, Volatility, Cumulative Return, Renewable and Non-renewable Energy.

Introduction

In recent years, the renewable energy sector has grown in popularity and size within the world of investment, driven by increasing awareness of climate change and the transition to sustainable energy production. However, investors must navigate the unique complexities of risk-return relationships when investing in this field. This study aims to analyse the volatility and return of five distinct portfolios, composed of renewable energy, non-renewable energy, the market index, a composite energy portfolio, and a combined portfolio.

A consensus in the existing literature states that risk and return form a direct, positive correlation. An investment with higher risks generally requires higher returns for it to be considered reasonable and efficient.[1] This fundamental relationship underpins modern portfolio theory, as introduced by Markowitz.[2]

Risk in the context of investment is defined as the potential for the actual returns to differ from expected returns.[3] This divergence typically involves the possibility of losing some or all of the original investment, while also referring to the variability of returns around the expected outcome. Although risk is difficult to quantify, it can be assessed using several indicators.

Firstly, the uncertainty of returns is captured by volatility, which measures stock price fluctuations over time. Higher volatility typically indicates greater risk. Standard deviation provides a similar measure of dispersion, indicating the extent to which returns deviate from their mean. This addresses the fundamental characteristics of risk.

Risk can be further categorized into systematic and unsystematic risk. Systematic risk, also known as market risk, arises from broader economic variables such as recessions, inflation, and changes in interest rates. This cannot be mitigated effectively through diversification as its impact radiates throughout the entire market, though in varying degrees. Unsystematic risk, on the other hand, is company or industry-specific and can be reduced through diversification.[4]

This study provides a comprehensive analysis of the volatility and returns of renewable and non-renewable energy companies against a market index. We have also built a composite energy portfolio and a customized combined portfolio to assess the role of diversification. Using statistical techniques such as t-tests, scatter plots, and regression analysis, this research contributes to the growing literature on energy sector integration and portfolio optimization. These insights are particularly relevant for investors seeking energy-focused diversification strategies.[5]

Under the current political climate, renewable energy sources are expected to gradually replace fossil fuels. However, recent geopolitical conflicts have injected uncertainty into global energy markets. The economic sanctions and destruction of infrastructure during the war in Ukraine have disrupted global energy supply chains, especially between Russia and Europe. Consequently, the growing demand for energy independence reinforced short-term reliance on traditional fossil fuels while uncovering renewable energy's costly and unreliable nature, as well as their lack of technological maturity.[6] Integrated oil and gas companies had benefited from increased energy prices, leading to significant revenue growth. Investor sentiments, therefore, shifted towards traditional energy stocks, whose stability is represented by strong cash flows, regular dividend payments, and share buybacks.[7]

This paper reassesses the relationship between renewable and non-renewable energy investments using a recent dataset. It examines whether one investment strategy outperforms the

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other given the current geopolitical landscape. The study's key contributions include an empirical analysis of volatility and returns in renewable and non-renewable energy sectors, offering investors guidance on balancing risk and optimizing returns.

This paper proceeds as follows: Section 2 provides background information on the existing literature, Section 3 highlights the empirical findings, and Section 4 concludes the paper.

Literature Review

The global energy market has undergone substantial changes during the past several years, with the increasing participation of renewable energy in addition to conventional fossil fuels. This shift has introduced new dynamics in energy markets and investment portfolios that require greater insight into market integration, portfolio optimization, and risk management strategies.[8]

Recent studies have proved that renewable energy and conventional energy markets are highly connected. Zhang *et al.*[9] emphasize that renewable energy equities demonstrate a significant correlation with the returns of fossil energy under extreme market conditions, yet this relationship diminishes under normal market conditions. Xia *et al.*[10] also confirm the results by exhibiting asymmetric and significant impacts of energy price volatility on the return of renewable energy firms, particularly in European markets.

Such a relationship differs by various market conditions. Li *et al.*[11] discovered a positive correlation between the renewable energy and fossil energy markets in normal market conditions. In bear markets, however, it becomes extreme and contains strong asymmetrical dynamics. Jiang *et al.*[12] built on this by demonstrating that renewable energy shares have a net positive effect on the fossil energy markets, particularly in the oil and coal markets, while the effect is also highly periodic in the gas market.

Market integration patterns show wider variations in geographical terms. Bianconi and Yoshino[13] analysed 64 oil and gas companies in 24 nations, discovering that specific and common risk factors also pose a substantial influence on stock returns. Firm size and leverage were highlighted as key factors by the research, especially after the 2008 financial crisis.

Valadkhani[14] discovered that renewable energy ETFs outperformed fossil fuel ETFs in the US market, especially in risk-adjusted performance measures such as the Sortino and Sharpe ratios. According to the VIX index, the performance difference is more significant when the market uncertainty is greater.

The development of portfolio optimization techniques in energy markets is seen to reflect growing sophistication in methodology and approach. Kuang illustrated that although clean energy equities underperform overall equities, they outperform fossil fuel assets on a risk-adjusted return basis. The research also established that adding clean energy to a traditional asset enhances portfolio performance.

For the Chinese market, Bai *et al.*[15] proposed an enhanced portfolio approach that surpassed classical Markowitz approaches under varying market conditions. This was subsequently confirmed by Ma *et al.*[16]

Research has increasingly focused on energy portfolio risk management. Ahmad[17] found that crude oil serves as a better hedge for clean energy stocks than for technology stocks, particularly during periods of crisis. Galvani and Plourde[18] demonstrated that while energy futures reduce portfolio risk, they offer no significant improvement in energy stock returns.

Wang *et al.*[19] carried this research forward to commodity futures, discovering substantial gains from employing energy futures in portfolio diversification, especially within commodity portfolios.

The impact of policy decisions on renewable energy markets has been extensively documented. Antoniuk and Leirvik[20] discovered that policy events related to climate change have significantly influenced market returns. According to the research, policymakers must consider the reaction of the stock market to climate risk since investors quickly respond to climate news.

According to Masini and Menichetti,[21] investors trust mature technology more than policy intervention and are greatly affected by external advisers and peer pressure.

The advent of renewable energy markets can be encapsulated by changing investment patterns. Nautiyal *et al.*[22] discovered that energy-weighted portfolios have the most potential to provide the best returns in the short term, particularly in volatile times such as the global financial crisis and COVID-19. The green equities were determined by their study to be effective in hedging and risk management.

In emerging economies, the studies report controversial evidence. Artini and Sandhi[23] compared SME and manufacturing stock portfolios in Indonesia, India, and China and reported higher performance in Chinese and Indian markets compared to the Indonesian market. The geographical disparity in performance suggests the role of market-specific determinants in portfolio selection.

The literature has also considered the contribution of institutional drivers to the performance of energy markets. Antônio *et al.*[24] recommended careful consideration of market data. The results are consistent with Shachmurove's[25] previous research on Latin American markets, which called for careful consideration of risks and opportunities specific to each market.

There is recent proof of diverse methodological trends. Dai *et al.*[26] applied TVP-VAR methods in the investigation of volatility spillover among crude oil, gold, and Chinese new energy markets. Wang *et al.*[27] applied network analysis in dynamic spillover comprehension in the energy stock market, whereas Gurrib *et al.*[28] applied cryptocurrency analysis in energy portfolio optimization. The contrast of research methods indicates an ongoing enhancement in theoretical comprehension as well as empirical applications.

Shrimali[29] and Gargallo *et al.*[30] are of the opinion that the effectiveness of market integration and portfolio optimization will rely on building more robust policy platforms and risk management instruments. This will be critical in achieving investment targets and wider sustainability objectives.

Methods

The paper has used descriptive statistics, scatter plot graphics, t-tests, and regression analysis.

Pairwise T-test:

The t-test aims to evaluate the null hypothesis (H_0), which typically shows that there is no difference between the means of the two groups being compared. The alternative hypothesis (H_1) implies that there is a significant difference.

H0: $\mu1 = \mu2$

H1: $\mu1 \neq \mu2$

The test statistics for a t-test are calculated using formula[31]

$$t = \frac{x1 - x2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

Regression Analysis:

The model offers a practical framework for evaluating investment stability by capturing how returns respond to shifts in volatility. Volatility serves as a proxy for financial risk, enabling the examination of how different stock portfolios influence market uncertainty, hence chosen as the dependent variable. This provides insights into sector-specific drivers of volatility and potential volatility spillovers across markets.

$Yt = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{1t} + \ldots + \beta_n X_{nt} + \varepsilon_t$

Where Y_t is the dependent variable for observation t, which refers to volatility.

β_0 is the constant term representing the expected value of the dependent variable when all independent variables are 0.

β_1 to β_n are coefficients for the independent variables, which include returns of renewables, non-renewables, the aggregate stock market index, composite energy portfolio, and the combined portfolio.

While keeping all other variables constant, each coefficient shows how much the dependent variable changes when the corresponding variable changes by 1 unit.

ε_t is the error term, which represents the difference between the actual value and the predicted value from the model.

Volatility Calculations:

The volatility of each financial instrument is measured by employing the 30-day rolling standard deviation of daily returns.

Portfolio Construction:

The 5 portfolios are constructed as follows:

Portfolio X represents equally weighted averages of the eight individual renewable stocks for both cumulative return and volatility.

Portfolio X = 1/8*(NEE + CWEN + HASI +NEXNY + BEP + FLNC + ADANIGREENNS + FSLR)

Portfolio Y represents equally weighted averages of the eight individual non-renewable stocks for both cumulative return and volatility.

Portfolio Y = 1/8*(XOM + CVX + PCCYF + SHEL + TTE + COP + BP + EQNR)

Portfolio Z represents the aggregate market index taken directly from the NASDAQ Composite index for both cumulative return and volatility.

Portfolio XY is the equally weighted combination of Portfolio X and Portfolio Y.

Portfolio XY = 1/2*(Portfolio X + Portfolio Y)

Portfolio XYZ is the equally weighted combination of Portfolios X, Y, and Z.

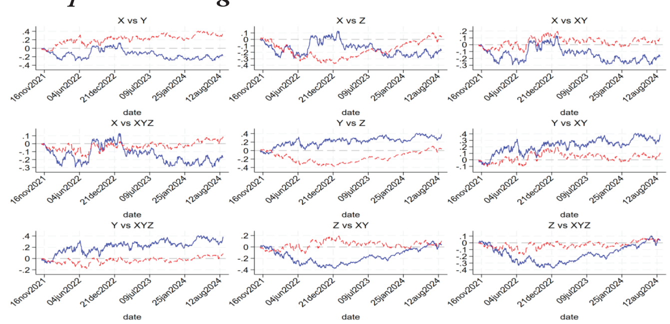
Portfolio XYZ = 1/3*(Portfolio X + Portfolio Y+Portfolio Z)

Result and Discussion

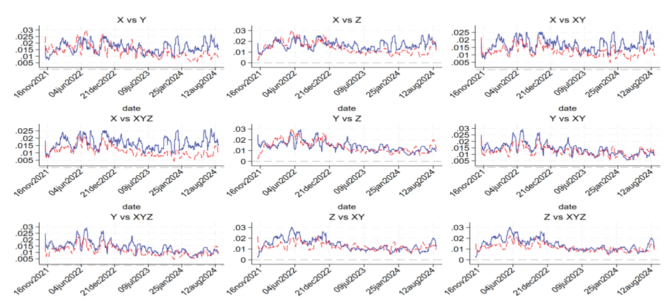
Data:

The data has been obtained from Yahoo Finance for a selected bundle of renewable energy companies (ticker symbols: NEE, CWEN, HASI, NEXNY, BEP, FLNC, ADANIGREENNS, and FSLR), non-renewable companies (ticker symbols: XOM, CVX, PCCYF, SHEL, TTE, BP, COP, and EQNR), along with the stock market index- NASDAQ Composite (ticker symbol: IXIC). The data covers the daily closing price for the selected period from 1/11/2021 to 30/8/2024. Within the selected period, there were 712 observations for all individual assets.

Empirical Findings:



Panel a. Cumulative Return



Panel b. Volatility

Figure 1: The line graphs show paired comparisons of changes in cumulative return (Panel a) and volatility (Panel b) for benchmark portfolios throughout the observation period. Both variables created asymmetrical patterns among portfolios, particularly in terms of cumulative returns.

Figure 1 presents the line graphics of cumulative return and volatility in Panel a and Panel b, respectively. In Panel a, we compared the cumulative return of portfolios X, Y, Z, XY, and XYZ. The order of average cumulative returns from best to worst is Y, XY, XYZ, X, and Z. Moreover, the average cumulative return of Y is much higher than the rest. Portfolio X did outperform the market significantly during the period from

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June to December 2022 before it started to decline and finally fell below market returns. In Panel b, we compared the volatility of portfolios X, Y, Z, XY, and XYZ. The order of ascending average volatility is XYZ, XY, Z, Y, and X. An asymmetry is observed in the risk-return relationship: portfolio X ranks 4th in cumulative return while portfolio Y ranks 1st. However, portfolio X is more volatile than Y, suggesting unfavorable risk-return dynamics, thus a less efficient investment choice.

Table 1 provides descriptive statistics for various cumulative return variables for Portfolio X, Y, Z, XY, and XYZ. This table includes the number of observations, mean return, standard deviation, and the maximum and minimum value of return. Several observations can be drawn from the comparisons of all portfolios. Portfolio Z, representing the market index, produced the lowest mean cumulative return, primarily due to a period of significant negative returns as indicated by a minimum value of -0.38. Although having a slightly higher maximum value in return, its mean return remains marginally lower than that of portfolio X. Portfolio Y demonstrates a dominant performance with the highest minimum, maximum, and mean value. This aligns with the positive impacts experienced by oil and gas companies, contrasted with the negative effects felt by the broader market, particularly the non-renewable energy sector, during the energy crisis and the Ukraine war. Moreover, we can see that diversification hugely decreases the magnitude of negative returns by more than 0.1 for both portfolios compared to the market itself. Positive returns are also mostly preserved as maximums remain closer to the market value. The significance of diversification is evident in the production of a notably higher mean return compared to the original market average.

Table 1: Includes the descriptive statistics of cumulative return for all portfolios.

Variable	Obs	Mean	Std. Dev.	Min	Max
cumulative return x	712	-.142	.102	-.297	.103
cumulative return y	712	.218	.107	-.085	.408
cumulative return z	712	-.164	.123	-.38	.108
cumulative return xy	712	.038	.063	-.118	.198
cumulative return xyz	712	-.030	.049	-.179	.088

Table 2 provides the pairwise t-test analysis between the five portfolios. According to the pairwise t-test analysis, all comparisons are statistically significant at the 1 percentage level. This suggests that the patterns in cumulative return among all individual comparisons demonstrate statistical differences. Therefore, cumulative return is an important indicator that distinguishes renewable energy stocks from non-renewable energy stocks.

Table 2: Presents the Paired t-test results of cumulative return between the five benchmark portfolios

Comparisons	Observations	Mean	Standard Error	Standard deviation	Base (mean)	Diff	t value	p value
vs C_X								
C_Y	712	.217799	.0039931	.1065486	-.1423138	-.347	-58.1	**0.000**
C_Z	712	-.1644995	.004624	.1233836	-.1423138	.036	3.1	**0.002**
C_{XY}	712	.0377426	.0023743	.0633533	-.1423138	-.174	-58.1	**0.000**
C_{XYZ}	712	-.0296714	.0018455	.0492446	-.1423138	-.105	-28.1	**0.000**
vs C_Y								
C_Z	712	-.1644995	.004624	.1233836	.217799	.039	64.6	**0.000**
C_{XY}	712	.0377426	.0023743	.0633533	.217799	.186	58.1	**0.000**
C_{XYZ}	712	-.0296714	.0018455	.0492446	.217799	.254	76.03	**0.000**
vs C_Z								
C_{XY}	712	.0377426	.0023743	.0633533	-.1644995	-.191	-34.9	**0.000**
C_{XYZ}	712	-.0296714	.0018455	.0492446	-.1644995	-.127	-34.9	**0.000**

Table 3 provides descriptive statistics for various volatility variables used in the analysis. The volatility statistics contrast sharply with the trends observed in cumulative returns. Portfolio X offers the highest mean volatility, indicating the largest fluctuations in stock prices. With reference to our previous cumulative return figures, we can infer that it experiences more frequent and pronounced downward price movements compared to other portfolios. This signals a loss of confidence among investors, especially in the renewable energy sector, in reaction to the crises. Despite a huge divergence in returns, portfolios Y and Z offer similar volatilities. This finding suggests that portfolio Y may be a more attractive investment, assuming that volatility is accepted as an accurate measure of risk. As expected, the diversified portfolios (XY & XYZ) have produced significantly lower mean volatility values compared to other benchmark portfolios. Additionally, the reduction in overall portfolio volatility in further diversification shows that renewable energy, non-renewable energy, and the market index are not perfectly correlated assets.

Table 3: Includes the descriptive statistics of volatility for all portfolios.

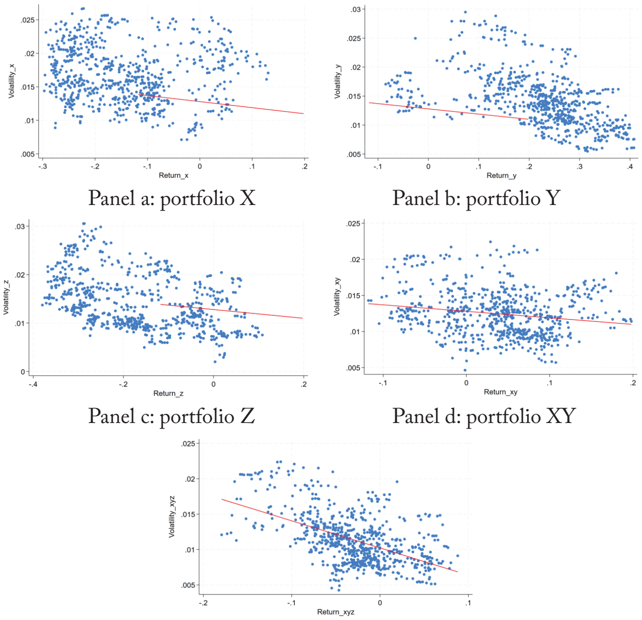
Variable	Obs	Mean	Std. Dev.	Min	Max
volatility x	711	.0167	.0041	.0071	.0267
volatility y	711	.0141	.0045	.0055	.0295
volatility z	711	.014	.0055	.002	.0306
volatility xy	711	.0124	.0032	.0046	.0224
volatility xyz	711	.0114	.0036	.0042	.0224

Table 4 provides the pairwise t-test analysis between the five portfolios. According to the pairwise t-test analysis, all comparisons are statistically significant at the 1 percentage level except the comparison between portfolio Y & portfolio Z. This suggests that the patterns in volatility among most individual comparisons are also statistically different. Therefore, like cumulative return, volatility is another important indicator that distinguishes renewable energy stocks from non-renewable energy stocks.

Table 4: Present the Paired t-test results of volatility between the five benchmark portfolios.

Comparison	Observations	Mean	Standard Error	Standard deviation	Base (Mean)	Diff	t value	p value
vs V_X								
V_Y	711	.0140936	.0001704	.0045449	.0167218	.0030201	13.1644	**0.0000**
V_Z	711	.0140433	.000206	.0054931	.0167218	.0030726	13.3459	**0.0000**
V_{XY}	711	.01245	.0001201	.0032017	.0167218	.0044918	38.1254	**0.0000**
V_{XYZ}	711	.0113569	.0001341	.0035759	.0167218	.0056245	40.5681	**0.0000**
vs V_Y								
V_Z	711	.0140433	.000206	.0054931	.0004634	.0003872	0.2937	0.3845
V_{XY}	711	.01245	.0001201	.0032017	.0004634	.0018541	15.3357	**0.0000**
V_{XYZ}	711	.0113569	.0001341	.0035759	.0004634	.0029519	24.9652	**0.0000**
vs V_Z								
V_{XY}	711	.01245	.0001201	.0032017	.0140433	.0019109	9.8479	**0.0000**
V_{XYZ}	711	.0113569	.0001341	.0035759	.0140433	.0029127	23.2979	**0.0000**

The Relationship between risk and return:



Panel a: portfolio X

Panel b: portfolio Y

Panel c: portfolio Z

Panel d: portfolio XY

Panel e: portfolio XYZ

Figure 1: The scatter plot graphic between volatility and return shows an overall negative correlation between the two variables, implying unconventional risk-return dynamics.

Figure 2 illustrates the relationship between volatility and cumulative return for portfolios X, Y, Z, XY, and XYZ. Results indicate a negative relationship between volatility and cumulative return for all cases. A strongly negative correlation is seen in portfolio XYZ, whereas portfolios X, Y, Z, and XY show a slight negative correlation. They may not imply that higher volatility is associated with higher returns. The observed negative relationship can be attributed to the heightened economic and geopolitical uncertainty during the energy crisis and the Ukraine War. Risk-averse sentiments are more common in periods of crisis, prompting widespread selloffs across sectors. This behavior may increase market volatility while simultaneously driving down returns, thereby resulting in the temporary appearance of a negative risk-return dynamic. It may guide investors in their portfolio construction and risk management strategies. Understanding that increased volatility does not always lead to higher returns may discourage energy investors from taking more risk in hopes of greater returns.

The regression analysis in Table 5 indicates that the cumulative return has a consistently negative and statistically significant impact on the volatility of portfolios X, Y, Z, XY, and XYZ, with p-values below 0.05 across all models. The maximum impact of return on volatility can be seen for the combined portfolio with the largest coefficient of -0.0384.

Table 5: Presents the regression analysis between volatility and returns among all portfolios.

VARIABLES	(1) Volatility_x	(2) Volatility_y	(3) Volatility_z	(4) Volatility_xy	(5) Volatility_xyz
Return_x	-0.0039**				
	(0.0015)				
Return_y		-0.0219***			
		(0.0016)			
Return_z			-0.0198***		
			(0.0014)		
Return_xy				-0.0090***	
				(0.0019)	
Return_xyz					-0.0384***
					(0.0026)
Constant	0.0162***	0.0189***	0.0108***	-0.0006***	0.0102***
	(0.0003)	(0.0004)	(0.0003)	(0.0001)	(0.0001)
Observations	711	711	711	711	711
R-squared	0.0091	0.2619	0.1974	0.0320	0.2798

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Evidence from individual companies:

To further understand the relationship between risk and return and to provide more robust empirical evidence, we have attained additional cumulative return and volatility data from individual companies, as presented in Tables 6 and 7.

Table 6: Includes the descriptive statistics for various cumulative return variables used in the analysis.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Renewable Energy Companies					
cumulative return NEE	712	-.18	.128	-.468	.088
Cumulative return CWEN	712	-.22	.157	-.524	.102
cumulative return HASI	712	-.557	.194	-.83	.047
Cumulative return NEXNY	712	-.185	.11	-.446	.066
cumulative return BEP	712	-.306	.148	-.559	.000
cumulative return FLNC	712	-.694	.177	-.868	.019
cumulative return ADG~S	712	.34	.519	-.522	1.695
cumulative return FSLR	712	.018	.292	-.524	.791
Panel B: Non-Renewable Energy Companies					
cumulative return XOM	712	.426	.185	-.103	.689
cumulative return CVX	712	.282	.124	-.024	.556
cumulative return PCCYF	712	.036	.23	-.334	.656
cumulative return SHEL	712	.207	.13	-.103	.523
cumulative return TTE	712	.118	.109	-.155	.372
cumulative return COP	712	.302	.141	-.088	.653
cumulative return BP	712	.079	.093	-.155	.295
cumulative return EQNR	712	.08	.158	-.19	.502

Table 7: Includes the descriptive statistics for various volatility variables from the 16 individual company stocks used in the analysis.

Variable	Obs	Mean	Std. Dev.	Min	Max
Panel A: Renewable Energy Companies					
volatility NEE	711	.0166	.0065	.0029	.0404
volatility CWEN	711	.0188	.006	.0104	.0434
volatility HASI	711	.0328	.0115	.0006	.0674
volatility NEXNY	711	.0234	.0132	0	.0674
volatility BEP	711	.0186	.0058	.0072	.0362
volatility FLNC	711	.0518	.015	.0192	.1025
volatility ADG~S	711	.0298	.0156	.0065	.0824
volatility FSLR	711	.0301	.01	.011	.0703
Panel B: Non-Renewable Energy Companies					
volatility XOM	711	.0169	.0052	.007	.0331
volatility CVX	711	.0155	.0055	.0041	.0315
volatility PCCYF	711	.024	.0099	0	.0701
volatility SHEL	711	.0154	.0065	.0052	.0345
volatility TTE	711	.0161	.006	.0014	.0387
volatility COP	711	.0194	.0076	.0065	.0481
volatility BP	711	.0171	.0068	.0058	.0451
volatility EQNR	711	.0205	.0058	.0079	.0362

Risk-return dynamics in individual companies:

From the individual company figures on volatility and cumulative returns, we gain detailed insights into the risk and return patterns within renewable and non-renewable energy stocks. In terms of risk, non-renewable energy stocks (XOM, CVX, PCCYF, SHEL, TTE, COP, BP, EQNR) generally exhibit lower volatility with standard deviations of around 0.004 to 0.005, suggesting greater price stability. On the other hand, renewable stocks show higher volatility individually; three

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companies (HASI, FLNC, ADANIGREENNS) have a standard deviation exceeding 0.01, indicating higher risk and more frequent price swings.

The risk-return relationship is significantly different between renewable and non-renewable energy companies. Non-renewable stocks in general offer higher returns with lower risk, reflecting consistent performance and predictable growth. In contrast, renewable energy stocks, despite higher volatility, have mostly negative returns. An anomaly is ADANIGREENNS, a renewable energy stock that demonstrates both high volatility and high returns.

For brevity, we cannot include all graphics and pairwise t-tests for individual companies against the portfolios. However, all empirical evidence is available on request.

Conclusion

The paper investigates the performance of renewable and non-renewable energy portfolios by examining volatility and cumulative returns. The findings highlight that portfolio Y, consisting of eight non-renewable energy companies, demonstrates a higher cumulative return compared to the renewable energy portfolio X and the broader market index portfolio Z. However, the higher return comes with increased volatility, indicating greater risk associated with non-renewable energy investment. In contrast, renewable energy stocks, represented by portfolio X, show the highest volatility despite producing similar returns to the market.

The results suggest that investors face distinct risk-return trade-offs when investing in renewable vs non-renewable energy sectors. Non-renewable energy stocks may appeal to investors seeking higher returns and are willing and able to tolerate higher risks. Renewable energy appears to be less efficient under the traditional risk-return framework. However, the perception is skewed to an extent by the data period, during which the energy crisis disproportionately benefited oil and gas producers. Despite this, the analysis implies that renewable energy investment could play a valuable role in diversifying portfolios.

However, several limitations should be acknowledged. The analysis is based on a relatively short time frame (2021-2024), which may limit the generalizability of the conclusions to longer-term market dynamics. Additionally, the selection of representative stocks is limited in both range and number, potentially omitting important variations across the energy sector. More comprehensive research would consider renewable energy production methods beyond solar and wind power, such as hydroelectric, geothermal, and bioenergy.

Looking ahead, a changing geopolitical landscape will continue to play a decisive role in shaping future energy markets. The Ukraine war, growing tensions in the Middle East, and concerns over supply chain dependencies have revealed strategic vulnerabilities of fossil fuel-dominated energy systems. In response, many countries are accelerating the transition toward domestic renewable energy production to achieve energy security. Such geopolitical considerations will increasingly shift capital allocation to favor more diversified and resilient portfolios with significant portions of clean energy assets. This topic continues to be an intersection of energy policy, market volatility, and global politics, deserving of future attention in academic research and investment strategies.

Future research might explore the longer-term performance of this portfolio as the renewable energy sector matures and global policies shift towards greener initiatives, as well as incorporating ESG factors as elements of risk and performance. This study provides a basis for understanding how geographical, economic, and environmental changes impact the performance of energy sector stocks, guiding investors in their portfolio allocation decisions within the energy market.

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References

1. Sharpe, W. F. Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *J. Finance* **1964**, *19* (3), 425–442.
2. Markowitz, H. Portfolio Selection. *J. Finance* **1952**, *7* (1), 77–91.
3. Jensen, M. C. Risk, the Pricing of Capital Assets, and the Evaluation of Investment Portfolios. *J. Bus.* **1969**, *42* (2), 167–247.
4. Ferson, W.; Schadt, R. W. Measuring Fund Strategy and Performance in Changing Economic Conditions. *J. Finance* **1996**, *51* (2), 425–461.
5. Beja, A. On Systematic and Unsystematic Components of Financial Risk. *J. Finance* **1972**, *27*, 37–45.
6. Pindyck, R. S. Volatility in Natural Resource Prices: A Review. J. *Environ. Econ. Manage*. **1999**, *37* (1), 128–150.
7. Guay, W.; Harford, J. The Cash-Flow Permanence and Information Content of Dividend Increases versus Repurchases. *J. Financ. Econ*. **2000**, *57* (3), 385–415.
8. Kuang, P. Clean Energy Investment and Portfolio Diversification. *J. Sustainable Finance Invest.* **2021**, *11* (3), 234–252.
9. Zhang, Y.; Sun, X.; Chen, W. Renewable Energy Market Integration: Evidence from Global Equity Markets. *Energy Econ*. **2023**, *120*, 106564.
10. Xia, Y.; Wang, Y.; Zhang, R. Energy Price Volatility and Renewable Energy Investment: An Asymmetric Analysis. *Econ. Model*. **2019**, *84*, 88–102.
11. Li, J.; Tang, X.; Liu, P. Fossil Fuel and Renewable Energy Markets: A Behavioral Perspective. *Energy Res. Soc. Sci*. **2022**, *91*, 102768.
12. Jiang, H.; Wu, Y.; Zhao, L. The Interplay of Renewable and Non-Renewable Energy Stocks: A Global Perspective. *J. Energy Mark*. **2021**, *14* (2), 75–96.
13. Bianconi, M.; Yoshino, J. A. Risk and Return in the Global Energy Sector. *Int. Rev. Econ. Finance* **2014**, *34*, 99–112.
14. Valadkhani, A. The Performance of Renewable Energy ETFs in the US Market. *Renew. Sustain. Energy Rev*. **2024**, *179*, 113459.
15. Bai, X.; Zhang, Y.; Liu, W. A Robust Portfolio Approach for the Chinese Energy Market. *J. Financ. Quant. Anal*. **2019**, *54* (2), 419–442.
16. Ma, F.; Li, T.; Zhao, Y. Revisiting Portfolio Optimization in Energy Markets. *Energy Econ*. **2023**, *123*, 107654.
17. Ahmad, W. Oil as a Hedge for Renewable Energy Stocks: A Time-Varying Analysis. *Appl. Energy* **2017**, *207*, 27–37.
18. Galvani, V.; Plourde, A. Futures Markets and Energy Stock Performance. *J. Futures Mark*. **2010**, *30* (5), 450–475.
19. Wang, Z.; He, K.; Liu, J. Commodity Futures and Portfolio Diversification. *J. Commod. Mark*. **2022**, *25*, 100182.

20. Antoniuk, Y.; Leirvik, T. Stock Market Responses to Climate Policy Shocks. *J. Sustainable Finance Invest.* **2024**, *14* (1), 109–125.
21. Masini, A.; Menichetti, E. Investor Preferences in Renewable Energy Markets. *Energy Policy* **2013**, *56*, 1–12.
22. Nautiyal, S.; Kaushik, G.; Singh, R. Energy Portfolios and Market Shocks: Evidence from the Global Financial Crisis and COVID-19. *J. Energy Finance Dev*. **2024**, *18*, 102345.
23. Artini, A.; Sandhi, N. Comparative Analysis of SME and Manufacturing Stocks in Emerging Markets. *J. Emerg. Mark*. **2020**, *14* (3), 257–273.
24. Antônio, D. R.; Almeida, R. P.; Lopes, A. Market Information and Energy Sector Performance. *J. Energy Econ.* **2015**, *48*, 356–368.
25. Shachmurove, Y. Latin American Energy Markets: Risks and Opportunities. *J. Int. Financ. Mark. Inst. Money* **1998**, *8* (3–4), 343–359.
26. Dai, J.; Wang, P.; Liu, X. TVP-VAR Analysis of Energy Market Spillovers. *Energy Econ*. **2022**, *111*, 106569.
27. Wang, Y.; Guo, Z.; Zhang, Q. Network Analysis of Energy Stock Spillovers. *Energy Policy* **2020**, *139*, 111252.
28. Gurrib, I.; Kamalov, F.; Rezgui, S. Cryptocurrency and Energy Market Interactions. *J. Financ. Data Sci*. **2020**, *6*, 1–14.
29. Shrimali, G. Market Integration and Renewable Energy Policy. *Renew. Energy* **2019**, *130*, 1150–1161.
30. Gargallo, P.; Salvador, M.; Ventura, S. Energy Portfolios and Risk Management. *J. Risk Finance* **2022**, *23* (2), 178–199.
31. Gujarati, D. N. *Basic Econometrics*, 4th ed.; McGraw-Hill: New York, 2002.

Author

Jeremy Cheung is a rising senior studying at Reading School (Reading, England). He plans to major in economics and has various other experiences in economic research. He is passionate about using this knowledge to create lasting social impact.

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