

The Risk-Return Trade-Off of US Renewable Energy Sector

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Abstract. This study applies the Fama-French three-factor model to analyze the impact of market risk premium, size, and value factors on the stock returns of eight major renewable energy companies listed on the U.S. stock market. Employing linear regression analysis. The analysis indicates that while market trends heavily influence stock returns, the size and value factors' effects vary across different companies. This study contributes to understanding the financial performance of renewable energy firms and underscores the need for industry-specific risk management approaches to bolster investor confidence and facilitate sector growth. The results serve as a foundational reference for investors and policymakers interested in the renewable energy market's dynamics and its future development trajectory.

Keywords: Risk-return trade-off, Fama-French model, US renewable energy, volatility, Stock price analysis.

1. Introduction

As the global climate continues to warm and traditional energy sources dwindle, the international landscape is confronted with escalating uncertainties. The challenges of accelerating climate change and the prevailing energy crisis are formidable, demanding a unified response from humanity. In light of these challenges, a revolution in new energy is gaining momentum in the United States, embracing sustainable sources such as wind, solar, and tidal energy. These innovations are not just environmentally friendly but are also pivotal in ensuring energy security and sustainability for societies worldwide, with the added benefit of fostering world peace.

The expansion of the new energy industry in the US is heavily dependent on cutting-edge science and technology, coupled with substantial capital investment. This burgeoning industry represents a synergy of economic growth, scientific discovery, technological breakthroughs, and job creation, thus laying the groundwork for unprecedented developmental strides. By championing sustainable practices, the new energy sector exemplifies the progressive ideals of ecological balance, peace, and prosperity, inviting increased scholarly attention to its critical role in spearheading scientific and socio-economic advancement.

In the wake of the coronavirus pandemic, the global economy has experienced a downturn, reflected in part by stock market trends indicative of wavering confidence in consumer and producer behaviors. The new energy sector, an emergent force within the US economy, offers vast potential for development, boasting a resilient ecological footprint and an extensive supply chain. It is poised to enhance production scalability, rejuvenate the industrial framework, and stimulate economic resurgence. Despite the sector's potential, as evidenced in the heightened market focus during the first half of 2023, investment flows into associated industries like automobile manufacturing, electronic control motor production, and intelligent navigation systems have been comparatively subdued. A low volume ratio and market hesitancy, compounded by the instability triggered by the energy crisis, have dampened investor enthusiasm, impeding the production and market consumption dynamics within the new energy domain.

The US stock market serves as a crucial gauge of global economic sentiment and provides unique insights into the transformative new energy sector. This research seeks to bridge the knowledge gap by delving into the risk-return trade-off inherent in the US renewable energy market, with the goal of delineating a more lucid portrayal of the sector's economic promise. The importance of the new

energy sector to the US economy cannot be overstated; it is a beacon of innovation and a cornerstone of the transition to a greener economy.

This paper is structured to enhance understanding in this critical area, beginning with a comprehensive literature review in Section 2 that sets the stage for a deeper exploration of the sector's contributions to economic resilience and technological innovation. Section 3 details the data and methodology utilized in our study. Section 4 presents the empirical analysis of US new energy stocks employing the Fama-French three-factor model. Finally, Section 5 concludes by discussing the implications of our findings.

2. Literature review

The literature on the US renewable energy sector is extensive. Sadorsky (2012)[1] investigated the factors influencing the risk of renewable energy companies, finding that while company sales growth reduces risk, increases in oil prices heighten it. However, moderate positive oil price returns can be offset by sales growth, resulting in reduced systematic risk. Ferrer et al. (2018)[2] examined the interrelation between renewable energy stocks and crude oil prices, discovering that in the long run, crude oil prices do not significantly impact renewable energy companies, suggesting a separation of the two sectors. Nevertheless, a short-term connection was observed, indicating that investors view them as comparable assets.

Building on these studies, Dutta (2017)[3] noted a significant relationship between oil prices and renewable energy. Fluctuations in the oil market affect the new energy stock market, with uncertainties in oil stocks influencing the rate of return and volatility in the renewable energy stock or fund markets. Investors in the stock or ETF market are thus exposed to considerable risk. Specifically, higher oil prices indicate an increased demand for renewable energy sources. Continuous uncertainties regarding oil and fuel prices and production create incentives for people to seek substitutes [1]. In the early stages in the United States, the demand for traditional energy increased as people believed the international fuel supply chain was unstable, and America needed to reduce its dependence on energy imports [4]. With many uncertainties in the new energy department, the market preferred to increase domestic fuel and crude oil production to minimize the volatility of systematic risk. Due to a lack of investment confidence, investors and capital have not focused on renewable energy. After 2009, the Chinese and American governments invested in energy development, including new energy such as wind, hydro, and solar energy, and crude oil became irreplaceable [4]. In 2014, China emphasized an inspection in Shanghai, which showcased the development of new energy vehicles [5]. Unlike traditional vehicles, new energy vehicles use electricity as their source of energy, and their combustion emits gases that do not harm the environment. Analysis of some new energy vehicle companies revealed that overall sales began to grow significantly from 2016 [5].

Additionally, Bloomberg New Energy Finance's research on renewable market financing shows that the scale of finance along the new energy vehicles innovation chain has exhibited a compound growth rate over the past decades [6]. Moreover, particularly after the COVID-19 pandemic, the global economy is recovering from the downturn, and the energy crisis has led more investors to focus on global clean energy investment. Consequently, renewable energy investment is attracting more market attention. However, compared to traditional energy sources like fossil fuels, clean energy investments require higher upfront spending, although they level the cost of capital due to lower operating costs in the long run [7].

To analyze the new energy industry more directly, studies have sought to identify the link between the dynamic stock prices of new energy companies and other associated factors. Earlier studies have shown that CO₂ emissions significantly influence policymakers to set higher carbon permit prices, which increases the cost of fossil fuel production and stimulates capital flow into environmentally-friendly industries [8]. Currently, researchers believe that investors value company-specific information more than macroeconomic factors. Further literature explains the connection between

fossil fuel stock prices and new energy stock prices, suggesting that the latter is a primary measure for investors to gauge the development of new energy companies. This is because industry-wide backgrounds do not accurately reflect the fluctuations in the new energy industry; hence, micro-level company information such as stock price, rate of return, and volatility becomes a crucial criterion [9].

More recently, Geng et al. (2021)[10] analyzed the return and volatility network of global new energy companies, finding a high degree of information spillover, particularly in volatility. This study highlights an asymmetric effect where bad news contributes more to systematic risk than good news and identifies certain companies as key information transmitters. Geng et al. (2021)[10] inspired us to focus on Tesla, which, as a leading force in the new energy sector, has significantly influenced the industry with its innovations, products, and market success. Other works have focused on the broader new energy sector rather than individual companies. For instance, Dutta et al. (2020)[11] examined how volatility in the energy sector, as measured by the implied volatility index (VXXLE), affected clean energy exchange-traded funds (ETFs), revealing that clean energy asset returns are likely to decrease during periods of high volatility. Furthermore, studies on herding behavior, such as Chang et al. (2020)[12], observed strong herding spillovers from the US fossil fuel markets to renewable energy, especially before the Global Financial Crisis (2007-2009). They found that the US fossil fuel sector influenced Europe and Asia's renewable returns during COVID-19. More recently, Geng et al. (2021)[10] analyzed the return and volatility network of global new energy companies, finding a high degree of information spillover, particularly in volatility. This study highlights an asymmetric effect where bad news contributes more to systematic risk than good news and identifies certain companies as key information transmitters. Geng et al. (2021)[10] inspired us to focus on Tesla, which, as a leading force in the new energy sector, has significantly influenced the industry with its innovations, products, and market success. Other works have focused on the broader new energy sector rather than individual companies. For instance, Dutta et al. (2020)[11] examined how volatility in the energy sector, as measured by the implied volatility index (VXXLE), affected clean energy exchange-traded funds (ETFs), revealing that clean energy asset returns are likely to decrease during periods of high volatility. Furthermore, studies on herding behavior, such as Chang et al. (2020)[12], observed strong herding spillovers from the US fossil fuel markets to renewable energy, especially before the Global Financial Crisis (2007-2009). They found that the US fossil fuel sector influenced Europe and Asia's renewable returns during COVID-19. To measure the return on a company's stock, the most common approach is to analyze the corporate stock return to shareholders over a period. However, over a brief period, asymmetric information can impact the stock price to a certain extent, potentially causing it to underperform in terms of the company's return on equity [13]. A more efficient mechanism to measure the degree of stock market activity is the use of a time-varying method, focusing on the dynamism of stock returns in different periods [14]. Unlike autocorrelation tests and a battery of linear and nonlinear approaches, this method provides a more unbiased way to define financial performance in a brief period, lessening the impact of time length on the analysis. As previously mentioned, asymmetric information can affect stock price fluctuations, necessitating the consideration of factors beyond time, such as randomness and predictability. Some researchers have developed theoretical underpinnings and empirical methods to create an adaptive market framework to test various time returns and identify unexpected risks due to asymmetric information [15]. Additionally, Approximate Entropy is a statistical method for quantifying randomness, using the value of the statistic to indicate counting patterns. However, these methods, based on data in datasets or statistical estimators in experiments, lack timeliness and the authenticity of macro-observations and are not industry-specific [16].

In this regard, we apply the CAPM and Fama-French models to measure the undiversifiable and systematic risks of new energy companies like Tesla. The validity of the CAPM model has been extensively discussed over time, with some studies indicating difficulties in using the market portfolio in experiments and in addressing its statistical problems and limitations in the current stock market [17]. The classical CAPM model uses the risk-free rate, the expected return of the market, and market volatility (beta):

$$E(R_i) = R_f + \beta_i[E(R_m) - R_f] \quad (1)$$

where R_f is the risk-free interest rate, $E(R_m)$ is the expected return on the value-weighted market portfolio, and β_i is the slope of the regression of the security's excess return on the market's excess return, to capture the relationship between return and volatility (risk). Recently, researchers have summarized multiple investors' extrapolative expectations as data, and evidence showed that the CAPM model is consistent with the predictions of other models, including aggregate stock market prices. This model also matches empirical facts, which means we can compare the present data with the previous one and use the correlation to predict the market's subsequent return [18]. Andrew J. Patton and Allan Timmermann (2010)[19] applied the liquidity preference hypothesis and t-tests for monotonicity in financial variables to measure expected return with multiple market volatilities (beta). Moreover, considering the limitations of CAPM, we combine it with the Fama-French model, using average return, price ratio, size (market capitalization, price times shares outstanding), and errors in time-series regression to capture expected return [20]:

$$E(R_i) - R_f = \beta_i[E(R_m) - R_f] + s_iE(SMB) + h_iE(HML) \quad (2)$$

where $E(R_i) - R_f$ is the expected return on a portfolio in excess of the risk-free rate, $E(SMB)$ and $E(HML)$ stand for the small-minus-big and high-minus-low returns on portfolios, respectively, and β_i, s_i , and h_i are the sensitivities of the corresponding expected returns. In further studies, following the Miller-Modigliani proposition on profitability and investment strategies of companies, researchers added alpha and errors to the formula:

$$R_i - R_f = \alpha_i + \beta_i(R_m - R_f) + s_iE(SMB) + h_iE(HML) + \text{errors} \quad (3)$$

This accounts for a certain degree of unanticipated risk and statistical residuals. Some researchers even use it to explain the excess return of selected companies and to test stock prices during global crises like COVID-19. The Fama-French model achieves more accurate results in explaining statistical outcomes [21]. Meanwhile, the model confirmed that realized returns in low book-to-market value portfolios and high book-to-market value portfolios are correctly specified at the firm level and for market portfolio types [22]. Additionally, beyond factors of company types, like SMB and HML, it incorporates consumption growth and inflation, indicating that macroeconomic factors also play a role in expected return, measuring risk and return from two perspectives. The approach uses HML to forecast consumption growth, while SMB has significant explanatory power for inflation [23].

The new energy sector, particularly companies focusing on new energy vehicles, influences and is influenced by traditional energy prices and energy policies. These are considered sensitive factors, while some unexpected factors, such as global crises, represent unanticipated errors or alpha [24]. Furthermore, due to the varied scale of companies within the new energy vehicle industry, variables such as HML (high-minus-low book-to-market values) and SMB (small-minus-big market capitalizations) play a significant role in measuring expected returns. Sentiment analysis has been employed by researchers to consider financial operations, political events, rumors, news, and company dealings to identify the risk and return associated with new energy companies [25]. While such analysis tests the sensitivity of various factors, models like the CAPM (Capital Asset Pricing Model) and Fama-French provide a context for errors that do not relate to the current market or crises that cannot be measured or have never occurred before.

3. Data and methodology

The American new energy landscape showcases a range of dynamic companies that are making significant strides in innovation and influencing market trends, with their stocks actively traded on major exchanges. At the forefront is Tesla, Inc., renowned not only for its electric vehicles but also for its advancements in battery energy storage and solar technology, catalyzing change in the sustainable energy sector. NextEra Energy, Inc. stands as the preeminent producer of wind and solar

energy globally, spearheading the shift towards a more renewable energy grid. Sunrun Inc. is at the vanguard of residential solar and battery storage, propelling the domestic uptake of clean energy. Meanwhile, Enphase Energy, Inc. is transforming solar energy collection and management with its innovative microinverter technology. These industry leaders are not merely trailblazers in technological development; they are also significant contributors to the expansion of the clean energy sector, instrumental in forging America's path toward energy autonomy and environmental stewardship. Their stock market performance is indicative of the sector's economic promise and mirrors a rising investor trust in renewable energy's prospects. In our analysis, we examine the returns of these companies using metrics such as HML, SMB, and the Fama-French three-factor model, among others, to better understand the financial dynamics at play in the new energy market.

The Fama-French three-factor model is a comprehensive framework that builds upon the Capital Asset Pricing Model (CAPM) to elucidate stock returns through a more complex perspective. It suggests that, beyond the market risk accounted for in CAPM, two additional factors—size and value—also exert significant influence on stock returns. The theoretical equation for the model is:

$$E(R_i) = R_f + \beta_{i,m}(E(R_m) - R_f) + \beta_{i,s}SMB + \beta_{i,v}HML + \alpha_i \quad (4)$$

where $E(R_i)$ is the expected return on asset i , R_f is the risk-free rate, $\beta_{i,m}$ measures the asset's sensitivity to market returns $E(R_m)$, $\beta_{i,s}$ gauges the sensitivity to the size factor SMB (small minus big), $\beta_{i,v}$ reflects the sensitivity to the value factor HML (high minus low book-to-market), and α_i represents the asset's alpha, or abnormal return. Practically, regression analysis with stock returns as the dependent variable and the market, SMB, and HML factors as independent variables is employed to empirically test the model and estimate the factor loadings for a particular asset or portfolio.

The Fama-French model is pivotal in academic finance and practical investment strategy, offering a more nuanced understanding of risks and returns in equity markets than the CAPM alone. By factoring in size and book-to-market value, it accounts for a broader range of systematic risks that affect portfolio performance. This sophisticated model is invaluable to portfolio managers and individual investors for building diversified portfolios, asset pricing, and performance analysis. Its empirical validity over various periods and markets attests to its enduring applicability and has led to its widespread use in mutual fund evaluation, investment strategy formulation, and the academic investigation of market anomalies and efficiency.

In our comprehensive analysis of new energy stocks through the lens of the Fama-French three-factor model, we leverage the statistical capabilities of R and its specialized packages. Specifically, utilizing the tidyverse and scales packages, the script fetches Fama-French three-factor monthly and daily data directly from the French Data Library, which is then processed to match the specified date range from January 1, 2013, to December 31, 2023. The data includes market risk premium (market excess returns), size factor (SMB), and value factor (HML), normalized to appropriate percentage scales. Next, we use the quantmod package, which helps us to obtain stock data from Yahoo Finance. It pulls historical daily data for a selection of major U.S. energy companies: NextEra Energy, Inc. (NEE), Enphase Energy, Inc. (ENPH), SolarEdge Technologies, Inc. (SEDG), First Solar, Inc. (FSLR), Brookfield Renewable Partners L.P. (BEP), Plug Power Inc. (PLUG), Tesla, Inc. (TSLA), and Vestas Wind Systems A/S (VWDRY). Daily returns are computed for each stock. Linear regressions are run for each stock against the Fama-French factors to evaluate their influence on the stocks' daily returns.

4. Empirical analysis

In our analysis, we employ the Fama-French three-factor model, incorporating market risk premium, size factor, and value factor, to assess the daily and monthly returns of renewable energy companies, including Tesla and seven other U.S. stocks, following the methodology outlined earlier. We conduct a linear regression to analyze the rates of return for Tesla, Enphase Energy, Inc.,

SolarEdge Technologies, Inc., First Solar, Inc., Brookfield Renewable Partners L.P., Plug Power Inc., and Vestas Wind Systems A/S.

For each stock, we apply the Fama-French three-factor model's original formula in a linear regression framework:

$$E(R_i) - R_f = \beta_i[E(R_m) - R_f] + s_iSMB + h_iHML \quad (5)$$

Where $E(R_i) - R_f$ is the expected excess return of the stock, R_i is the actual return at a specific time, R_f is the risk-free interest rate, $E(R_m) - R_f$ represents the market risk premium, SMB is the size premium, HML is the value premium, and $\beta_i, s_i,$ and h_i are the stock's sensitivities to these factors. The regression equation we use is:

$$Y = \alpha + \beta X_1 + sX_2 + hX_3 + e \quad (6)$$

With Y as the excess return, $X_1, X_2,$ and X_3 as the independent variables representing the market, size, and value factors respectively, and e as the residual term. The regression results are summarized in Tables 1-8.

Table 1. Regression results for NextEra Energy (NEE)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	0.0001803	0.0002344	0.769	0.44180
β	0.6835482	0.0215417	31.731	$< 2e - 16^{***}$
s	-0.3288572	0.0388783	-8.459	$< 2e - 16^{***}$
h	-0.0719630	0.0278144	-2.587	0.00972**

Table 2. Regression results for Enphase Energy (ENPH)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	0.0017877	0.0008722	2.050	0.0405*
β	1.5022732	0.0801627	18.740	$< 2e - 16^{***}$
s	1.6194075	0.1446771	11.193	$< 2e - 16^{***}$
h	-0.5047641	0.1035052	-4.877	$1.14e - 06^{***}$

Table 3. Regression results for SolarEdge Technologies (SEDG)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	0.0009043	0.0007616	1.187	0.235
β	1.3619409	0.0655598	20.774	$< 2e - 16^{***}$
s	1.0653621	0.1204827	8.842	$< 2e - 16^{***}$
h	-0.3894917	0.0823040	-4.732	$2.36e - 06^{***}$

Table 4. Regression results for First Solat (FSLR)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	0.0005536	0.0005444	1.017	0.309
β	1.0806113	0.0500368	21.596	$< 2e - 16^{***}$
s	0.7653600	0.0903061	8.475	$< 2e - 16^{***}$
h	-0.0213208	0.0646070	-0.330	0.741

Table 5. Regression results for Brookfield Renewable Partners (BEP)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	$-4.144e - 05$	$2.959e - 04$	-0.140	0.8886
β	$7.281e - 01$	$2.720e - 02$	26.772	$< 2e - 16^{***}$
s	$8.029e - 02$	$4.908e - 02$	1.636	0.1020
h	$7.018e - 02$	$3.512e - 02$	1.999	0.0457*

Table 6. Regression results for Plug Power (PLUG)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	0.001875	0.001087	1.725	0.084668.
β	1.497278	0.099931	14.983	$< 2e - 16^{***}$
s	2.062470	0.180355	11.436	$< 2e - 16^{***}$
h	-0.446126	0.129030	-3.458	0.000553***

Table 7. Regression results for Tesla (TSLA)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	0.0015674	0.0005853	2.678	0.00745**
β	1.3912180	0.0537976	25.860	$< 2e - 16^{***}$
s	0.6551911	0.0970935	6.748	$1.82e - 11^{***}$
h	-0.7925873	0.0694629	-11.410	$< 2e - 16^{***}$

Table 8. Regression results for Vestas Wind Systems (VWDRY)

Coefficient	Estimate	Std. Error	t value	Pr (> t)
α	0.0010653	0.0004735	2.250	0.0245*
β	0.9314394	0.0435206	21.402	< 2e – 16***
s	0.0851427	0.0785456	1.084	0.2785
h	-0.0288682	0.0561933	-0.514	0.6075

The regression results for the eight renewable energy companies analyzed using the Fama-French three-factor model present a comprehensive view of the relationship between company stock returns and market factors. Across the tables, we observe varying degrees of sensitivity to the market risk premium (β), size premium (s), and value premium (h). First, for NextEra Energy (NEE), the results indicate a strong market factor (β) with a significant t-value, suggesting that the stock is highly responsive to market risk premium changes. However, the size and value factors are negatively related to the stock's returns, with size having a particularly strong inverse relationship. Second, Enphase Energy (ENPH) shows a significant positive relationship with both the market risk premium and the size factor, implying that the company's returns are influenced by market trends and it benefits from being a smaller-sized company within its sector. The negative coefficient for the value factor suggests that Enphase's stock price is less influenced by book-to-market value aspects.

Third, SolarEdge Technologies (SEDG) and First Solar (FSLR) both have significant positive β coefficients, indicating a strong relationship with the market risk premium. For SolarEdge, the size factor is also significant and positive, whereas for First Solar, the size factor is positively related but not at a significant level. Both companies show an insignificant relationship with the value factor, though SolarEdge's is negative. Fourth, Brookfield Renewable Partners (BEP) presents a unique case where the market factor is significant and strong, but the size and value factors are not statistically significant, although the value factor's t-value suggests a marginal significance level. Fifth, Plug Power (PLUG) shows a considerable positive β coefficient and a very significant size factor, reflecting high sensitivity to market movements and benefiting from being a smaller-sized company. However, the value factor is significantly negative, indicating an inverse relationship with the company's book-to-market value.

Sixth, for Tesla (TSLA), there's a very significant positive relationship with the market and size factors, while the value factor is strongly negative, implying Tesla's stock returns are less associated with the company's book-to-market value. Finally, Vestas Wind Systems (VWDRY) exhibits a significant positive market factor, but the size and value factors are not significant, with the value factor being negative, suggesting these aspects do not have a strong impact on the company's stock returns.

Overall, while market risk premium is a consistent significant predictor for the returns of these renewable energy companies, size and value factors vary in their influence, with some firms showing strong size effects and others indicating a significant relationship with the value factor. This suggests that while market trends are crucial, the impact of company size and value characteristics can differ widely across firms in the renewable energy sector.

We also summarize the R-squared, Adjusted R-squared, and F-statistics for the eight renewable energy companies.

Table 9. Summary of Regression Model Fit and Significance for Selected Renewable Energy Stocks

Company	R-squared	Adjusted R-squared	F-statistic	F-statistic p-value
NEE	0.2708	0.27	342.2	<2.2e-16
ENPH	0.1853	0.1844	209.5	<2.2e-16
SEDG	0.2266	0.2255	215.1	<2.2e-16
FSLR	0.1894	0.1885	215.3	<2.2e-16
BEP	0.2183	0.2174	257.2	<2.2e-16
PLUG	0.1447	0.1438	155.9	<2.2e-16
TSLA	0.2642	0.2634	330.8	<2.2e-16
VWDRY	0.1514	0.1505	164.4	<2.2e-16

The R-squared values range from a high of 0.2708 for NextEra Energy (NEE) to a low of 0.1447 for Plug Power (PLUG), indicating varying levels of model fit across different companies. Similarly, the Adjusted R-squared values follow suit, adjusting for the number of predictors in the model. The F-statistics are all significant at a p-value less than $2.2e - 16$, indicating that the models are statistically significant and that the independent variables collectively have a strong explanatory power for the variance in the companies' stock returns (Table 9).

5. Discussion

Our analysis focuses on Tesla and other pivotal players in the renewable energy sector to understand stock performance in the U.S. stock market. We assess the influence of market risk premium, size factor, and value factor on stock returns, employing the Fama-French three-factor model for linear regression analysis. While our approach provides substantial insights into the stock behaviors of eight major U.S. renewable energy firms, it is not exhaustive of the entire industry's investment landscape. Moreover, our model, constrained to market, size, and value factors, does not account for complex real-world elements such as policy shifts, environmental considerations, public sentiment, and unforeseeable events—all of which can also significantly impact stock prices.

Despite these limitations, the analysis serves as a valuable indicator of how market dynamics, industry scale, and external valuation factors currently influence renewable energy enterprises. Notably, market risk exerts a considerable effect on stock prices across the renewable energy sector, suggesting that industry-wide mutual impacts and a robust risk mitigation framework are critical. By enhancing investor confidence and fostering industry growth, we can improve corporate valuations, which in turn, may positively sway stock prices and propel industry advancement.

Echoing our empirical findings, the Fama-French model effectively captures the daily and monthly returns of renewable energy companies, substantiated by the regression results (Tables 1-8). The varying R-squared values—highlighted in our summary Table 9—illustrate the model's differential fit across companies, with the F-statistics confirming the statistical significance of the models. These results underscore the importance of market trends, while also revealing diverse impacts of size and value characteristics unique to each firm within the renewable energy sector.

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