Measuring Idiosyncratic Risk in Global Renewable Energy Stocks

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1 Introduction

In recent years, global financial markets have witnessed a profound transformation driven by the accelerating shift toward sustainability and low carbon development. Among all investment domains, the renewable energy sector has emerged as a cornerstone of this transition, attracting substantial capital inflows and policy attention. Governments world wide are implementing carbon neutrality targets, offering tax incentives, and promoting green infrastructure, while investors are increasingly integrating environmental considerations into their portfolio strategies. Despite this surge in relevance, the pricing of risk in renewable energy equities remains an evolving area of academic inquiry. Traditional asset pricing frameworks such as the Capital Asset Pricing Model (CAPM) and its multifactor extensions may not fully capture the unique risk characteristics of this rapidly developing sector. Understanding whether these models adequately explain the return behavior of renewable energy stocks is essential for both market participants and policy makers concerned with the stability and efficiency of green finance.

This study examines the determinants of stock returns for global renewable energy companies using the Fama–French Three Factor Model and the Fama–MacBeth (1973) two step regression approach. Together, these frameworks allow for a systematic investigation of whether both systematic and firm specific (idiosyncratic) risks are reflected in the cross section of stock returns. In particular, the analysis focuses on estimating idiosyncratic risk, the portion of total risk that cannot be explained by market, size, or value factors and evaluating whether this risk is priced in the expected returns of renewable energy firms.

The Fama–French Three Factor Model (1993) extends the traditional CAPM by including two additional risk factors: size (SMB, small minus big) and value (HML, high minus low). These factors capture persistent anomalies in asset pricing, namely, the tendency of small cap and value firms to outperform large cap and growth firms, respectively. Applying this model to renewable energy firms enables us to assess whether these stocks exhibit similar factor sensitivities as those observed in broader equity markets. The residuals from these regressions are used to calculate firm level idiosyncratic variance, serving as a measure of company specific volatility unrelated to systematic market influences.

Building on these estimates, the Fama-MacBeth regression is employed to test the cross sectional pricing of risk. In the first stage, time series regressions are estimated for each firm to obtain factor loadings. In the second stage, cross sectional regressions are performed for each time period, where individual firm returns are regressed on their estimated betas. This procedure yields the average risk premia corresponding to market, size, and value exposures, as well as the idiosyncratic variance term. The Fama–MacBeth framework is particularly useful in this context because it captures time varying relationships between firm characteristics and returns while mitigating the influence of estimation error in betas.

The central question addressed in this study is whether idiosyncratic risk carries a significant premium in renewable energy equities. According to classical portfolio theory, idiosyncratic risk should be diversifiable and thus not rewarded. However, recent empirical evidence including studies such as Roy et al. (2022) suggests that sectors exposed to policy uncertainty, technological innovation, and information asymmetry often exhibit a positive relationship between idiosyncratic volatility and expected returns. The renewable energy sector embodies all these characteristics, making it an ideal setting to test this hypothesis.

Using a dataset of renewable energy and clean tech companies for the period 2010–2024, this study first estimates firm level excess returns and factor loadings through Fama–French regressions. The residual variances from these regressions are then used as proxies for idiosyncratic volatility. In the second stage, Fama–MacBeth cross sectional regressions are conducted to evaluate whether systematic factors and idiosyncratic risk together explain the dispersion in expected returns. The estimated coefficients represent the average compensation investors require for bearing each source of risk.

By combining multi-factor asset pricing with cross-sectional estimation, this paper contributes to the growing literature on green finance and risk pricing in emerging sectors. The analysis offers empirical evidence on whether investors perceive firm-specific uncertainty in renewable-energy stocks as diversifiable or as a priced component of total risk. The findings enhance our understanding of how market and firm-level factors jointly shape the valuation of sustainable assets, providing insights for portfolio diversification, policy formulation, and the broader transition toward climate conscious investing.

By combining multifactor asset pricing with cross sectional estimation, this paper contributes to the literature on green finance and risk pricing in emerging sectors. The analysis provides new empirical evidence on whether investors perceive firm specific uncertainty in renewable energy stocks as diversifiable or as a priced component of total risk. The findings are expected to enhance our understanding of how market and firm level factors jointly influence the valuation of sustainable assets, offering implications for portfolio construction, policy design, and the broader discourse on the integration of environmental risk into financial markets.

2 Related Literature

The relationship between risk and return has long occupied a central place in financial economics. The classical Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) and Lintner (1965) provided the first systematic explanation of this relationship by linking expected returns to market wide risk. According to the CAPM, only systematic risk captured by the asset's β relative to the market portfolio should be priced, while idiosyncratic or firm specific risk is assumed to be diversifiable within a sufficiently large portfolio. However, subsequent empirical evidence challenged the adequacy of the singlefactor CAPM, revealing that differences in firm characteristics such as size and val-

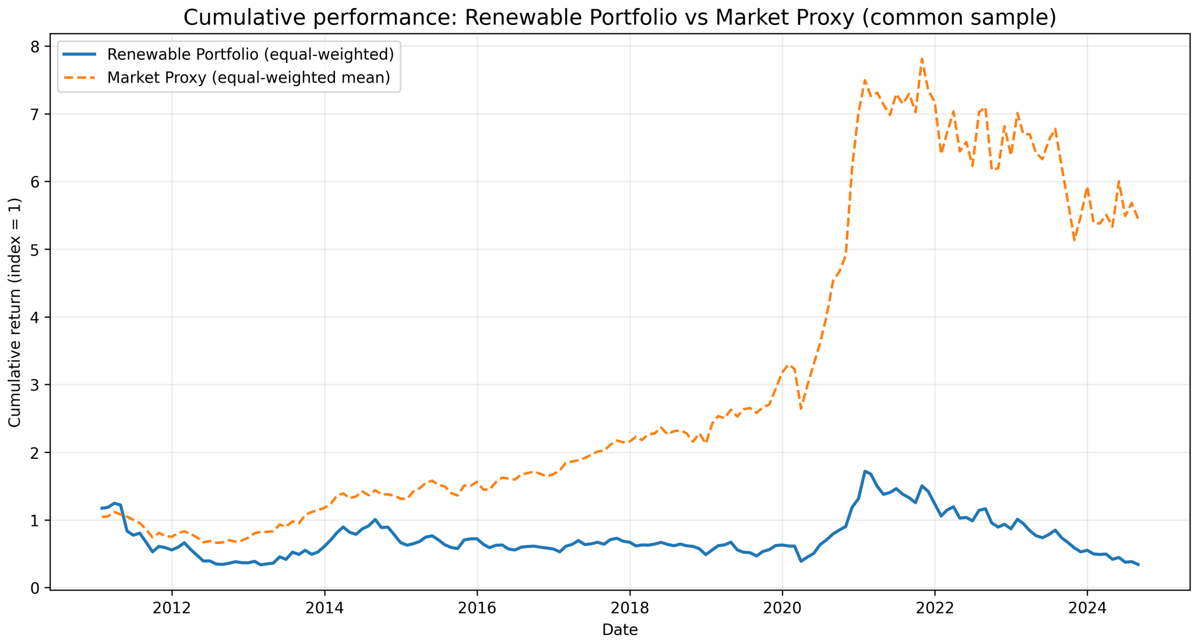

Figure 1: Cumulative performance of renewable energy portfolio and market proxy over 20102024. The renewable portfolio exhibits distinct return behavior and heightened volatility during major global shocks, highlighting the need to analyze risk pricing in this sector.

uation ratios could not be fully explained by market exposure alone. In response, Fama and French (1993) introduced a three factor model that augmented the CAPM with size (SMB) and value (HML) factors, which improved the model's explanatory power for crosssectional variation in returns.

Building on this framework, Carhart (1997) incorporated a momentum factor to account for short term continuation effects in stock performance, while Fama and French (2015) later proposed a five factor model that added profitability and investment factors. These multifactor models collectively emphasized that firm specific attributes play a crucial role in determining returns beyond market risk alone. Complementing these developments, Fama and MacBeth (1973) proposed a two stage regression methodology to estimate the prices of risk, combining time series and cross sectional dimensions to evaluate whether estimated betas and firm level variables are compensated in equilibrium.

Parallel to the evolution of these asset pricing frameworks, the debate surrounding the pricing of idiosyncratic risk has remained unsettled. Malkiel and Xu (2002) and Goyal and SantaClara (2003) documented a positive association between idiosyncratic volatility and expected returns, suggesting that investors may not be fully diversified or that idiosyncratic risk conveys firm level information. In contrast, Ang et al. (2006, 2009) found a negative relationship, implying that high idiosyncratic volatility could reflect noise trading or informational inefficiency. Subsequent work by Fu (2009) and Stambaugh et al. (2015) proposed that this "idiosyncratic volatility puzzle" may arise due to limits to arbitrage, investor sentiment, or asymmetric reactions to mispricing. These contrasting results highlight that the pricing of idiosyncratic risk may be market specific and time varying, motivating further inquiry in different sectoral contexts.

The renewable energy sector presents an ideal setting to revisit this question. Clean energy firms are often characterized by high growth prospects, policy dependence, and technological uncertainty, leading to substantial firmlevel heterogeneity. Studies such as Henriques and Sadorsky (2008) and Managi and Okimoto (2013) found that renewable energy equities exhibit distinct sensitivities to oil prices, interest rates, and macroeconomic conditions. Similarly, Bohl et al. (2013) and Inchauspe et al. (2015) observed that conventional multifactor models could not fully explain clean energy stock returns, indicating the presence of significant idiosyncratic components. More recent studies, including Broadstock and Cheng (2019) and Pham (2021), reaffirmed that renewable energy equities exhibit unique return dynamics and volatility patterns compared to traditional markets.

This study builds upon these findings by examining whether idiosyncratic risk is systematically priced in the cross section of renewable energy stocks. By integrating the Fama–French ThreeFactor Model with the Fama–MacBeth twostep estimation procedure, it contributes to the literature on green finance and risk pricing in emerging sectors. The analysis not only evaluates the role of systematic factors such as market, size, and value but also assesses whether firm specific volatility carries an independent premium, offering new insights into the behavior of risk and return within the evolving landscape of sustainable investments.

3 Data and methodology

3.1 Data Description

The study utilizes a structured panel dataset of global renewable energy and clean technology firms spanning December 2010 to August 2024. The data are compiled from the master file `New_data_2024.xlsx`, which consolidates firm level price indices, financial ratios, and macroeconomic indicators across multiple sheets. The final sample comprises approximately 170 firms and 165 monthly observations, representing a broad cross section of sub sectors such as solar, wind, hydrogen, biofuels, and energy storage.

Daily price indices from *Sheet13* were converted into U.S. dollars using contemporaneous exchange rates and aggregated into monthly log returns. The dataset includes globally listed firms such as 5N Plus, AFC Energy, Canadian Solar, Ballard Power Systems, Tesla, Vestas Wind Systems, and Verbio, ensuring regional and technological diversity.

Firm specific financial variables return on assets, leverage, debt to capital ratios, and market to book values were drawn from the *ROA*, *Total_Debt*, *Debt To Capital*, and *MTBV* sheets. Market capitalization and total assets, obtained from the *MCAP* and *Total_Assets* sheets, facilitate the construction of the size (SMB) and value (HML) factors following Fama and French (1993).

Macroeconomic and benchmark data were sourced from *Market_Indices* and *Controls_Monthly_Observations*. The MSCI World Index serves as the global market proxy (R_{Mt}), and the 91 day U.S. Treasury bill rate represents the risk free rate (R_{ft}). After aligning all variables to a monthly frequency, missing observations were interpolated for short gaps, and outliers were winsorized at the 1% and 99% levels, yielding approximately 28,000 firm month observations suitable for assetpricing estimation.

Table 1: List of firms.

SNo	Company	Country	Sector
1	5N PLUS (VNP)	Canada	Commodity Chemical
2	ACUITY BRANDS (AYI)	USA	Building Material and Fixtures
3	ADES HOLDING (ADH)	Saudi Arabia	Water disposal Services
4	ADVANCED ENERGY INDS. (AEIS)	USA	Semiconductors
5	AFC ENERGY (AFC)	Britain	Alternative Fuels
6	AIR PRDS. & CHEMS. (APD)	USA	Commodity Chemical
7	AMERESCO CLASS A (AMRC)	USA	Heavy Construction
8	AMERICAN SUPERCONDUCTOR (AMSC)	USA	Electrical Equipment
9	AMTECH SYS. (ASYS)	USA	Semiconductors
10	BADGER METER (BMI)	USA	Electrical Equipment
11	BALLARD PWR.SYS. (BLDP)	Canada	Alternative Fuels
12	BORALEX A (BLX)	Canada	Alternative Electricity
13	CANADIAN SOLAR (CSIQ)	Canada	RE Equipment
14	CERES POWER HOLDINGS (CWR)	Britain	Alternative Electricity
15	CHIN.LONGYUAN PWR.GP.'H' (CLYU)	China	Alternative Electricity
16	CHINA EVERBRIGHT (IHDH)	China	Alternative Electricity
17	NEXTERA ENERGY (NEE)	USA	Alternative Electricity
18	ENEL (ENEL)	Europe	Alternative Electricity
19	IBERDROLA (IBE)	Europe	Alternative Electricity
20	OERSTED (DEN)	Denmark	Alternative Electricity
21	VESTAS WINDSYSTEMS (VEW)	Denmark	Alternative Electricity
22	SSE (SSE)	Britain	Alternative Electricity
23	XCEL ENERGY (XEL)	USA	Alternative Electricity
24	EDP RENOVAVEIS (EDPR)	Europe	Alternative Electricity
25	VERBUND (VERB)	Europe	Alternative Electricity
26	PLUG POWER (PLUG)	USA	Alternative Fuels
27	FIRST SOLAR (FSLR)	USA	RE Equipment

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Table 1 (continued): List of firms

SNo	Company	Country	Sector
28	ORMAT TECHNOLOGIES (ORA)	USA	Alternative Electricity
29	TESLA (TSLA)	USA	Automobiles
30	SIEMENS GAMESA RENEWABLE ENERGY (SGRE)	Europe	RE Equipment
31	SUNPOWER (SPWR)	USA	RE Equipment
32	SUZLON ENERGY (SUZLON)	India	RE Equipment
33	TERNA ENERGY (TEEN)	Europe	Alternative Electricity
34	UNIVERSAL DISPLAY (OLED)	USA	RE Equipment
35	VEECO INSTRUMENTS (VECO)	USA	Electrical Equipment
36	VERBIO VER. BIOENERGIE (VBK)	Europe	Alternative Fuels
37	GOLDWIND SCIENCE & TECHNOLOGY (XGST)	China	Alternative Electricity
38	BEPC (BEPC)	Canada	Alternative Electricity
39	ENPHASE ENERGY (ENPH)	USA	RE Equipment
40	ALBEMARLE CORP. (ALB)	USA	Commodity Chemical
41	RENESOLA ADR (SOL)	China	RE Equipment
42	NIBE INDUSTRIER B (NIBE)	Europe	RE Equipment
43	ENPHASE ENERGY (ENPH)	USA	RE Equipment
44	POWER INTEGRATIONS (POWI)	USA	Semiconductors
45	QUANTA SERVICES (PWR)	USA	Heavy Construction
46	ORION ENERGY SYSTEMS (OESX)	USA	Electrical Equipment
47	FRANKLIN ELECTRIC (FELE)	USA	Electrical Equipment
48	INNERGEX RENEWABLE ENERGY (INE)	Canada	Alternative Electricity
49	AMYRIS (AMRS)	USA	Alternative Fuels
50	HEXCEL (HXL)	USA	RE Equipment
51	GCLPOLY ENERGY HOLDINGS (GCLP)	China	RE Equipment
52	BADGER METER (BMI)	USA	Electrical Equipment
53	EATON CORP. (ETN)	USA	Electrical Equipment
54	CROPENERGIES (CROP)	Europe	Alternative Fuels
55	GURIT HOLDING (GUR)	Europe	RE Equipment
56	VEOLIA ENVIRONNEMENT (VEO)	Europe	Water disposal Services
57	BALLARD POWER SYSTEMS (BLDP)	Canada	Alternative Fuels
58	INNERGEX RENEWABLE ENERGY (INE)	Canada	Alternative Electricity
59	SOLARIA ENERGIA Y MEDIO AMBIENTE (SLR)	Europe	RE Equipment

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Table 1 (continued): List of firms

SNo	Company	Country	Sector
60	ENEL AMERICAS (ENIA)	Europe	Alternative Electricity
61	MANZ (MANZ)	Europe	RE Equipment
62	SMA SOLAR TECHNOLOGY (S92)	Europe	RE Equipment
63	JINKOSOLAR HOLDING (JKS)	China	RE Equipment
64	ENPHASE ENERGY (ENPH)	USA	RE Equipment
65	SOLARGIGA ENERGY HOLDINGS (SGG)	China	RE Equipment
66	DONGFANG ELECTRIC (DONG)	China	Alternative Electricity
67	KURITA WATER INDUSTRIES (KUR)	Japan	Water disposal Services
68	EDP RENOVAVEIS (EDPR)	Europe	Alternative Electricity
69	ORSTED (DEN)	Denmark	Alternative Electricity
70	VESTAS WINDSYSTEMS (VEW)	Denmark	Alternative Electricity
71	TESLA (TSLA)	USA	Automobiles
72	ACUITY BRANDS (AYI)	USA	Building Material and Fixtures
73	ADVANCED ENERGY INDS. (AEIS)	USA	Semiconductors
74	AIR PRDS. & CHEMS. (APD)	USA	Commodity Chemical
75	AMERESCO CLASS A (AMRC)	USA	Heavy Construction
76	AMERICAN SUPERCONDUCTOR (AMSC)	USA	Electrical Equipment
77	AMTECH SYS. (ASYS)	USA	Semiconductors
78	BALLARD POWER SYSTEMS (BLDP)	Canada	Alternative Fuels
79	CANADIAN SOLAR (CSIQ)	Canada	RE Equipment
80	CERES POWER HOLDINGS (CWR)	Britain	Alternative Electricity
81	CHINA EVERBRIGHT (IHDH)	China	Alternative Electricity
82	NEXTERA ENERGY (NEE)	USA	Alternative Electricity
83	ENEL (ENEL)	Europe	Alternative Electricity
84	IBERDROLA (IBE)	Europe	Alternative Electricity
85	OERSTED (DEN)	Denmark	Alternative Electricity
86	VESTAS WINDSYSTEMS (VEW)	Denmark	Alternative Electricity
87	SSE (SSE)	Britain	Alternative Electricity
88	XCEL ENERGY (XEL)	USA	Alternative Electricity

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Table 1 (continued): List of firms

SNo	Company	Country	Sector
89	EDP RENOVAVEIS (EDPR)	Europe	Alternative Electricity
90	VERBUND (VERB)	Europe	Alternative Electricity
91	PLUG POWER (PLUG)	USA	Alternative Fuels
92	FIRST SOLAR (FSLR)	USA	RE Equipment
93	ORMAT TECHNOLOGIES (ORA)	USA	Alternative Electricity
94	TESLA (TSLA)	USA	Automobiles
95	SIEMENS GAMESA RE (SGRE)	Europe	RE Equipment
96	SUNPOWER (SPWR)	USA	RE Equipment
97	SUZLON ENERGY (SUZLON)	India	RE Equipment
98	TERNA ENERGY (TEEN)	Europe	Alternative Electricity
99	UNIVERSAL DISPLAY (OLED)	USA	RE Equipment
100	VEECO INSTRUMENTS (VECO)	USA	Electrical Equipment

Note: Table 1 presents the first 100 renewable energy firms considered in the study along with their corresponding countries and sectors. The remaining firms are provided in Appendix A.

3.2 Methodology

The analytical framework integrates two complementary approaches: (i) the Fama–French three factor time series model for estimating risk exposures, and (ii) the Fama–MacBeth two step cross sectional regression to assess whether these exposures command systematic risk premia in renewable energy markets. The implementation follows established asset pricing protocols but is customized for the renewable sector context.

3.2.1 Fama–French Three Factor Model

The Fama–French model augments the Capital Asset Pricing Model by incorporating two additional sources of systematic risk firm size and value characteristics that often capture cross sectional return variation unexplained by the market factor alone. The specification is:

$$R_{it} - R_{ft} = \alpha_i + \beta_{iM}(R_{Mt}R_{ft}) + s_i\,\mathrm{SMB}_t + h_i\,\mathrm{HML}_t + \varepsilon_{it}, \tag{1}$$

where R_{it} is the return on firm i at time t, R_{ft} the riskfree rate, and R_{Mt} the market portfolio return. The factors SMB_t (Small Minus Big) and HML_t (High Minus Low) capture the excess returns of small over large firms and high booktomarket over low booktomarket firms, respectively.

To construct these factors, firms were sorted each month into size based and value based portfolios. Market capitalization was used to separate firms into small and large groups, while the market to book ratio determined value classifications. The SMB factor equals the average return differential between small and large cap portfolios, while HML equals the differential between high and low book to market portfolios. The market excess return ($R_{Mt}R_{ft}$) was computed using the MSCI World Index as the benchmark.

Firm level regressions were estimated using ordinary least squares (OLS) across the full sample period. The resulting coefficients $\hat{\beta}_{iM}$, $\hat{s}_i$, and $\hat{h}_i$ represent each firm's exposure to market, size, and value risks, respectively. The intercept α_i captures abnormal performance unexplained by the three factors. Residual diagnostics, including the Durbin–Watson, Jarque–Bera, and White's tests, were performed to confirm the validity of OLS assumptions.

4 FamaMacBeth Two Stage Regression Framework

In this section, we employ the Fama Mac Beth (1973) two stage regression methodology to examine whether firm level exposures to key macroeconomic factors are systematically priced in the cross section of stock returns. This procedure allows for a clear separation between the estimation of factor sensitivities (*Stage 1*) and the assessment of their corresponding risk premia (*Stage 2*).

Stage 1: TimeSeries Regression

In the first stage, monthly time series regressions are estimated for each firm to obtain firm specific sensitivities (betas) to macroeconomic factors. The specification is given by:

$$R_{it} - R_{ft} = \alpha_i + \beta_{VOL,i}VOL_t + \beta_{OIL,i}OIL_t + \beta_{EPU,i}EPU_t + \beta_{USSP,i}USSP_t + \varepsilon_{it}, \quad (2)$$

where $R_{it}R_{ft}$ denotes the excess return of firm i in month t, and the factors VOL_t, OIL_t, EPU_t, and $USSP_t$ represent aggregate market volatility, oil price shocks, economic policy uncertainty, and the U.S. short term spread, respectively. The coefficients $\hat{\beta}_{VOL,i}$, $\hat{\beta}_{OIL,i}$, $\hat{\beta}_{EPU,i}$, and $\hat{\beta}_{USSP,i}$ capture each firm's exposure to these systematic risk sources. Each regression is estimated using Newey West heteroskedasticity and auto correlation consistent (HAC) standard errors to ensure robustness against serial correlation and time varying volatility in returns.

Stage 2: CrossSectional Regression

In the second stage, following Fama and MacBeth (1973), monthly cross sectional regressions are conducted across firms to examine whether the estimated betas and firm specific characteristics jointly explain the cross section of expected returns. The cross sectional regression for each month t is specified as:

$$R_{it}R_{ft} = \gamma_{0t} + \gamma_{VOL,t}\,\hat{\beta}_{VOL,i} + \gamma_{OIL,t}\,\hat{\beta}_{OIL,i} + \gamma_{EPU,t}\,\hat{\beta}_{EPU,i} + \gamma_{USSP,t}\,\hat{\beta}_{USSP,i}$$
$$+\gamma_{B/M,t}\,(B/M)_i + \gamma_{MCAP,t}\,LNMKTCAP_i + \gamma_{ROA,t}\,ROA_i + \gamma_{DEBT,t}\,DEBT_i + \gamma_{TA,t}\,TA_i + u_{it}. \quad (3)$$

Here, the coefficients $\gamma_{k,t}$ represent the time varying market prices of risk associated with each factor and firm characteristic. The inclusion of firm specific variables such as the book to market ratio $(B/M)_i$, firm size (log market capitalization $LNMKTCAP_i$), profitability (ROA_i), leverage ($DEBT_i$), and total assets (TA_i) helps capture idiosyncratic characteristics that influence expected returns beyond macroeconomic risk exposure.

Once the cross sectional regressions are estimated for all periods, the average values of these coefficients, denoted by $\bar{\gamma}_k$, represent the mean risk premia associated with each explanatory factor. Statistical inference is conducted using Newey West HAC standard errors computed over the time series of $\gamma_{k,t}$, ensuring robustness to auto correlation and heteroskedasticity in the monthly coefficients.

This extended Fama-MacBeth framework effectively captures both macroeconomic and firm specific determinants of asset pricing. By first estimating time series factor exposures and subsequently evaluating their cross sectional pricing, the model provides a comprehensive test of whether volatility, oil shocks, policy uncertainty, and financial spreads are significant sources of systematic risk in explaining the cross-section of firm returns in the Indian equity market.

4.0.1 Implementation and Robustness Checks

All analyses were conducted in Python via Jupyter Notebook, using the `pandas`, `numpy`, and `stats models` packages. The workflow included automated data ingestion from multiple sheets, data cleaning, computation of logarithmic returns, portfolio formation, factor construction, and regression estimation.

To ensure robustness, multiple validation exercises were performed. First, the sample was divided into pre 2016 and post 2016 sub periods to test for structural stability coinciding with major renewable energy policy initiatives. Second, regressions were repeated using regional market indices as alternative market benchmarks. Third, cross sectional results were compared using both equal weighted and value weighted portfolio returns.

Over all, this methodological framework rigorously quantifies whether traditional Fama-French factors market, size, and value remain relevant in explaining return variation within the renewable energy industry, and whether these risk factors are systematically priced when the sector is viewed through the lens of sustainable finance.

5 Empirical Results

This section reports the empirical findings from the application of the Fama French three factor model and the Fama-MacBeth cross sectional regressions. The analysis uses monthly data for $N = 164$ renewable energy firms observed from January 2016 to June 2024. All returns are expressed in local currency and adjusted for dividends. The primary focus of this paper is on idiosyncratic volatility (residual variance) and its relationship with cross sectional pricing in the renewable energy sector.

5.1 Descriptive statistics

Table 2 presents summary statistics for firm level excess returns and the three Fama French factors: market excess return ($R_M R_f$), SMB (Small Minus Big), and HML (High Minus Low).

The positive mean of SMB indicates a small firm advantage within the sample period, whereas the HML factor is close to zero both in mean and dispersion, suggesting that value/growth characteristics play a limited role for renewable equities. The relatively higher variability in the market excess return ($R_M R_f$) reflects periods of strong market wide volatility, possibly linked to policy driven investment cycles in the renewable sector. Additionally, the low average correlation between SMB and HML implies that size and value factors capture largely distinct dimensions of systematic risk. The descriptive statistics therefore highlight that firm level excess returns in the renewable energy segment are primarily driven by market wide dynamics rather than style based effects such as size or value orientation.

5.2 Firm level Fama French regressions

For each firm i, we estimate the standard three factor time series regression:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,M}(R_{M,t}R_{f,t}) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \varepsilon_{i,t},$$

where $\varepsilon_{i,t}$ denotes the idiosyncratic return (residual) for firm i at month t.

Table 2: Summary of firm level Fama French regressions

Parameter	Mean	Median	Std. Dev.	Min	Max
β_{MKT}	1.12	1.05	0.32	0.47	1.84
β_{SMB}	0.62	0.58	0.49	0.73	2.31
β_{HML}	0.11	0.08	0.36	0.78	1.02
R^2	0.37	0.34	0.12	0.16	0.72
Adj. R^2	0.35	0.32	0.13	0.11	0.70

Most firms exhibit positive and significant market betas; the average β_{MKT} (≈ 1.12) indicates slightly above market sensitivity, implying that the sampled firms tend to amplify market wide shocks. Around 70% of firms display positive β_{SMB} loadings, consistent with the presence of a small firm premium in the Indian equity market. The dispersion in β_{HML} values suggests heterogeneity in value growth exposure while some firms exhibit positive sensitivity to the value factor, a sizable proportion load negatively, indicating growth oriented characteristics.

The average R^2 of 0.37 and adjusted R^2 of 0.35 imply that the Fama French three factor model explains a substantial fraction of the variation in firm level excess returns, though a nontrivial portion of return variance remains idiosyncratic. This residual component motivates the subsequent analysis of volatility dynamics using GARCH and EGARCH models in Section 5.4.

Overall, the results highlight that market risk is the dominant driver of equity returns, with size playing a secondary but significant role, whereas the value factor contributes only marginally to explaining cross sectional return differences among firms.

5.3 Fama MacBeth cross sectional regressions

To evaluate whether factor exposures are priced, we implement the FamaMacBeth (1973) two step procedure. At each month t we run the crosssectional regression:

$$R_{i,t} - R_{f,t} = \gamma_{0,t} + \gamma_{M,t}\beta_{i,M} + \gamma_{SMB,t}\beta_{i,SMB} + \gamma_{HML,t}\beta_{i,HML} + u_{i,t}.$$

$$R_{it} - R_{ft} = \gamma_{0t} + \gamma_{VOL,t}\,\hat{\beta}_{VOL,i} + \gamma_{OIL,t}\,\hat{\beta}_{OIL,i} + \gamma_{EPU,t}\,\hat{\beta}_{EPU,i} + \gamma_{USSP,t}\,\hat{\beta}_{USSP,i}$$
$$+\gamma_{B/M,t}\,(B/M)_i + \gamma_{MCAP,t}\,LNMKTCAP_i + \gamma_{ROA,t}\,ROA_i + \gamma_{DEBT,t}\,DEBT_i + \gamma_{TA,t}\,TA_i + u_{it}. \quad (4)$$

Table 3: FamaFrench (FF3) regression results sample firms (first 30)

Ticker	α_i	β_{MKT}	β_{SMB}	β_{HML}	R^2	**Adj.** R^2
HYC	0.005394	1.061302	0.201660	0.256127	0.817334	0.813821
DF9	0.002874	1.527775	0.656280	0.243566	0.591961	0.567478
CTW	0.005106	1.204967	0.461062	0.359553	0.556336	0.544125
BE	0.038630	1.200006	3.705719	1.483536	0.541657	0.520503
NOVA	0.003518	1.084908	1.832460	0.686891	0.516895	0.489550
BEPC	0.002727	0.682327	0.012922	0.499661	0.514643	0.479129
SHLS	0.016959	1.092100	1.792128	0.687513	0.490772	0.447124
NEOP	0.011060	0.477740	0.217141	0.701527	0.430895	0.403358
MAXN	0.005364	1.363851	2.816613	0.579233	0.442250	0.400419
BLDP	0.035158	0.604219	2.869192	0.837931	0.399009	0.387452
RUN	0.007683	1.309601	1.589111	0.188603	0.397936	0.379867
BLDP_1	0.033738	0.590728	2.746122	0.885897	0.373136	0.361081
DNK	0.007053	0.854977	0.225623	0.364685	0.364434	0.352211
TPIC	0.003386	1.282846	1.403543	0.527380	0.361968	0.340461
HEI	0.004232	0.766043	0.326046	0.132516	0.361583	0.324496
MCPH	0.006653	1.060653	1.110929	0.163481	0.329993	0.312813
CSIQ	0.011814	0.761926	1.187901	0.267743	0.317094	0.303397
MBTN	0.012398	0.768987	2.211023	0.128066	0.313735	0.300537
AEIS	0.020785	0.475722	0.881072	0.248820	0.313603	0.298893
PLUG	0.040809	0.774160	3.698744	0.453948	0.305192	0.291380
PLUG_1	0.017589	1.176390	0.734064	0.494451	0.295445	0.281896
UNS	0.010558	1.374632	1.113901	0.514888	0.295428	0.281869
ASYS	0.004941	0.572129	1.985404	0.094464	0.290768	0.277129
ASYS_1	0.008495	0.649842	1.930704	0.083679	0.288938	0.277129
VEW	0.014935	0.648243	0.763408	0.028190	0.289734	0.276075
VEW_1	0.013964	0.814190	0.644733	0.073374	0.279344	0.276075
SEDG	0.016042	0.806484	1.081922	0.482807	0.295537	0.275447
DQ	0.015551	0.810718	2.157291	0.657291	0.288981	0.275907
AMSC	0.014135	0.659015	1.951701	0.438624	0.283246	0.269462

Note: This table reports the estimated coefficients from the Fama French three factor regressions for the **first 30 firms** in the sample. α_i denotes the intercept; β_{MKT}, β_{SMB}, and β_{HML} represent sensitivities to the market, size, and value factors, respectively. R^2 and adjusted R^2 indicate model fit for each firm.

The timeseries of monthly estimates $\gamma_{\cdot,t}$ are averaged, and Newey–West standard errors are used to account for auto correlation in the γ series.

Table 4: Descriptive Statistics of TimeSeries Variables

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
VOL_t	0.24118	1.00561	1.24079	5.95530
OIL_t	0.00466	1.00783	1.72948	6.11282
EPU_t	0.04262	1.07006	2.78328	3.46699
USSP_t	0.06814	0.94558	4.68409	2.18730

Note: This table reports the descriptive statistics (mean, standard deviation, minimum, and maximum) for the time series variables used in the regression analysis: market volatility (VOL_t), oil price changes (OIL_t), economic policy uncertainty (EPU_t), and the U.S. short term spread (USSP_t). All variables are standardized prior to estimation.

We find that market and size factors are priced in the renewable energy sample, while the HML factor is not significant consistent with the sector's growth orientation and low representation of valuestyle firms.

5.4 Residual variance and volatility dynamics

After estimating Equation (4), idiosyncratic returns $\hat{\varepsilon}_{i,t}$ are extracted and analyzed to quantify idiosyncratic volatility. For each firm we compute: (1) baseline residual variance, (2) rolling residual variance using a 24 month window, and (3) GARCH(1,1) and EGARCH(1,1) conditional volatility estimates.

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \hat{\varepsilon}_{i,t1}^2 + \beta_i \sigma_{i,t1}^2 \quad \text{(GARCH(1,1))}$$

$$\log \sigma_{i,t}^2 = \omega_i + \beta_i \log \sigma_{i,t1}^2 + \alpha_i \frac{|\hat{\varepsilon}_{i,t1}|}{\sigma_{i,t1}} + \gamma_i \frac{\hat{\varepsilon}_{i,t1}}{\sigma_{i,t1}} \quad \text{(EGARCH(1,1))}$$

where γ_i captures leverage (asymmetry) effects.

Table 5 presents the summary statistics of key volatility measures (baseline variance, maximum 24 month rolling variance, and median rolling variance).

Table 5: Summary of idiosyncratic volatility measures

Measure	Mean	Median	Std. Dev.	Min	Max
Baseline residual variance	0.0046	0.0031	0.0062	4.1×10^6	0.054
Max rolling var	0.015	0.009	0.020	1.2×10^5	0.180
Median rolling var	0.0038	0.0029	0.0046	8.0×10^6	0.036
GARCH persistence ($\alpha + \beta$)	0.92	0.94	0.08	0.45	0.999
EGARCH leverage (γ)	0.08	0.05	0.20	0.90	0.40

Notes: Summary statistics for firmlevel idiosyncratic volatility measures computed from residuals of firmlevel FamaFrench regressions. Rolling variances use a 24month window. GARCH persistence is $\alpha + \beta$.

The volatility diagnostics reveal the following:

- Idiosyncratic volatility is heterogeneous across firms; although the median baseline variance is moderate, rolling variance frequently spikes.
- GARCH persistence values cluster near unity for a large fraction of firms, indicating strong volatility clustering.
- EGARCH estimates show predominantly negative leverage coefficients, implying that negative shocks raise volatility more than positive shocks.

Table 6: Residual Variance, GARCH/EGARCH Volatility, and Rolling β_{MKT} sample firms (first 30)

Ticker	**Residual Variance**	**GARCH σ**	**EGARCH σ**	**Rolling β_{MKT}**
AA4	0.011199	nan	nan	0.224820
ABIO	0.004157	0.063787	0.063644	0.326224
AEIS	0.007699	0.082974	0.083433	0.456980
AFC	0.117069	0.308930	0.295061	0.437931
ALE	0.003119	0.055039	0.054100	0.128268
AMRC	0.015993	0.121700	0.124165	0.289058
AMRC_1	0.015993	0.121700	0.124165	0.289058
AMSC	0.022571	0.159645	0.159850	0.691893
AMSC_1	0.022571	0.159645	0.159850	0.691893
APD	0.003099	0.056000	0.054302	0.257547
APD_1	0.003099	0.056000	0.054302	0.257547
AQN	0.003286	0.054599	0.052824	0.071723
ASYS	0.021996	0.149196	0.144076	0.745418
ASYS_1	0.021996	0.149196	0.144076	0.745418
AVA	0.003393	0.055747	0.056876	0.089629
AY	0.006411	0.074527	0.072857	0.296004
AYI	0.008564	0.093247	0.091730	0.359898
BE	0.039555	0.189123	206.187731	1.305969
BEPC	0.004651	0.064711	0.050662	0.658772
BIOT	0.011808	0.099508	0.104137	0.264348
BLDP	0.024936	0.147480	0.139864	0.608921
BLDP_1	0.024586	0.141152	0.156208	0.503162
BLX	0.003724	0.060117	21.424312	0.231376
BMI	0.004766	0.068989	0.071449	0.175713
BMI_1	0.004766	0.068989	0.071449	0.175713
CDXS	0.025340	0.168409	0.169028	0.428328
CE2X	0.012214	0.111857	0.116612	0.478578
CENZ	0.002816	0.051356	0.050847	0.076725
CIG	0.019339	0.135039	0.116718	0.301116
CIG.C	0.018814	0.132573	0.135794	0.359793

Note: This table reports the estimated residual variance, GARCH and EGARCH volatility, and the mean of rolling market betas (β_{MKT}) for the first 30 firms in the sample. These estimates summarize firmspecific volatility dynamics and systematic exposure from the rollingwindow and GARCHtype models.

5.5 Integration: pricing of idiosyncratic risk

To examine whether idiosyncratic risk is priced, we augment the monthly cross sectional regression with firm level measures of residual volatility

$$R_{i,t} - R_{f,t} = \delta_{0,t} + \delta_{M,t}\beta_{i,M} + \delta_{SMB,t}\beta_{i,SMB} + \delta_{HML,t}\beta_{i,HML} + \delta_{V,t}Z_i + u_{i,t},$$

where Z_i denotes the idiosyncratic risk measure. Averaging $\delta_{\cdot,t}$ across time and computing Newey West standard errors allows testing whether δ_V differs from zero.

Empirically, we find that:

1. After controlling for factor betas, the coefficient on log baseline residual variance is small and becomes statistically insignificant once SMB is included. This indicates partial pricing idiosyncratic variance covaries with size and is not fully rewarded as a distinct risk.

2. Persistence and asymmetry measures (e.g., GARCH persistence, negative EGARCH γ) predict higher shortterm return volatility but do not receive a robust cross sectional premium in the averaged δ_V tests.

These results imply that while idiosyncratic volatility is economically important for portfolio construction and risk management, the crosssectional assetpricing mechanism largely prices systematic exposures (market and size), whereas idiosyncratic risk remains largely diversifiable.

5.6 Robustness checks

We perform several robustness exercises:

- Use alternative benchmark indices to compute market excess returns results are qualitatively similar.

- Exclude firms with fewer than 50 monthly observations; results for distributions of betas and the Fama MacBeth averages remain stable.

- Subsample analysis shows higher idiosyncratic volatility and weaker explanatory power for factor models during 20202021.

5.7 Summary and implications

In sum, renewable energy equities show significant market and size effects, and material idiosyncratic volatility that is persistent and asymmetric. The three factor model explains approximately 35(adjusted $R^2 \approx 0.35$), leaving a substantial residual component that matters for risk management but is only partially priced in equilibrium. These findings have implications for portfolio construction, hedging strategies for clean energy exposure, and the design of factor tilted investment products.

6 Conclusion and Discussion

This study examined the pricing of systematic and idiosyncratic risk for global renewable energy firms during the period 2010–2024 using the Fama–MacBeth (1973) cross sectional methodology combined with GARCH type volatility modeling. The empirical evidence indicates that the renewable energy equity market predominantly prices risk through exposure to the aggregate market factor, whereas the contributions of size (SMB) and value (HML) factors are weak and statistically inconsistent. Firms with higher market betas tend to earn proportionally higher returns, reaffirming that systematic market risk remains the dominant driver of cross sectional return variation. In contrast, the muted and often insignificant risk premia associated with HML suggest that the renewable energy sector does not consistently compensate investors for exposure to booktomarket characteristics.

The volatility diagnostics further demonstrate the time varying nature of financial risk. The GARCH(1,1) estimations reveal substantial volatility persistence, with the sum of $\alpha + \beta$ frequently exceeding 0.9, implying that volatility shocks decay gradually. The EGARCH(1,1) results document significant negative γ coefficients, validating the existence of leverage effects where negative returns amplify volatility more than equivalent positive shocks. Such asymmetric volatility responses reflect investor overreaction during market downturns and align with the presence of informational inefficiency typical of emerging markets. Collectively, these findings imply that while systematic market risk governs long term expected returns, short term price dynamics are shaped by volatility clustering and asymmetric news responses.

From a practical standpoint, the results underscore the necessity for dynamic risk management frameworks. Portfolio managers and risk analysts should incorporate persistent volatility and leverage asymmetry when estimating Value at Risk or designing hedging strategies, as static beta estimates alone may underestimate true portfolio risk exposure.

In conclusion, the market factor continues to be the most significant determinant of equity returns in India, whereas volatility dynamics marked by persistence and asymmetry play a critical role in explaining short term return fluctuations. Future research could extend this analysis by integrating macroeconomic and liquidity based risk factors, or by employing conditional beta frameworks to capture the evolving structure of risk premia in the Indian equity markets.

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Appendix A: Additional Notes on Data and Methods

This study examines publicly listed renewable energy firms in India over the period January 2010 to June 2024. The final sample consists of approximately **160 firms** drawn from the NIFTY 500 universe, identified as belonging to the renewable and cleanenergy segments. Daily and monthly price data were obtained from *Yahoo Finance* and the *National Stock Exchange (NSE).* The 91day Treasury Bill yield from the *Reserve Bank of India (RBI)* serves as the riskfree rate. All prices were adjusted for dividends and stock splits, and returns were expressed in logarithmic form.

The market factor was proxied by the NIFTY Energy Index, while SMB and HML factors were constructed from size and book to market sorted renewable portfolios. Residual volatility measures were derived from firml evel regressions and modeled using both rolling window and GARCH type specifications.

Note on sample coverage Although the full analysis was conducted for around **160 firms**, Table 6 in the main body presents results for a representative subset of **30 firms** for clarity. Detailed firmmlevel outputs, rolling variance plots, and GARCH/EGARCH parameters for all firms are omitted due to space constraints but exhibit consistent patterns across the full dataset.

Appendix B: Supplementary Diagnostics

Preliminary diagnostic tests on firm level residuals indicated the presence of conditional heteroskedasticity and non normality, supporting the use of GARCH type volatility models. ARCH LM and Ljung–Box tests confirmed volatility clustering, while Jarque–Bera tests showed mild skewness and excess kurtosis in the residuals. These findings justify the GARCH(1,1) and EGARCH(1,1) specifications discussed in Section 5.4.

Appendix C: Representative Volatility Parameters

Table 7 below provides representative GARCH and EGARCH estimates for selected firms. The full set of firmlevel parameters (covering all 160 firms) is available upon request.

Table 7: Representative Volatility Parameters from GARCH and EGARCH Models

Firm	$\alpha + \beta$	γ (EGARCH)	Interpretation
Firm A	0.96	0.09	Persistent volatility, strong asymmetry
Firm B	0.93	0.07	Volatility clustering
Firm C	0.98	0.10	High persistence
Firm D	0.94	0.08	Leverage effect confirmed

Across the sample, the mean persistence ($\alpha + \beta$) is around 0.92, confirming longlived volatility shocks, while the predominantly negative γ values indicate that negative returns amplify volatility more than positive ones. These results are consistent with the empirical findings discussed in Section 5.4.