Fossil Fuel Prices and Capital Cost: A Machine Learning Driven Study on Energy Transition

Shilin Ou[1], Luyao Zhang[1]*, Ming-Chun Huang[1]*
[1]Duke Kunshan University, Suzhou, China
shilin.ou@dukekunshan.edu.cn, luyao.zhang@dukekunshan.edu.cn, mingchun.huang@dukekunshan.edu.cn

Abstract

Financial risk assessment plays a vital role in accelerating the global energy transition and achieving the 1.5°C climate target. This study develops a three-stage machine learning framework to analyze the impact of fossil fuel price volatility on the weighted average cost of capital (WACC) for energy transition projects. First, a hybrid Long Short-Term Memory-Gaussian Regression Process (LSTM-GRP) model forecasts fossil fuel prices, followed by an LSTM-based inflation predictor. In the final stage, an AutoML (AutoGluon) regression model evaluates how variations in fossil fuel prices and inflation influence WACC across nine energy sectors and multiple global regions.

The results show that the WACC in energy-importing regions like Europe (R^2=0.67) and China(R^2=0.64) is highly sensitive to price shocks, making their decarbonization pathways vulnerable to external market instability. Conversely, the energy-exporting countries in Middle East (R^2=0.54) exhibit lower sensitivity, indicating a fiscal cushion that may reduce the economic impetus for transition. The findings demonstrate how energy price volatility shapes financing conditions and investment risks for renewable energy deployment. This approach integrates AI-driven forecasting with climate finance modeling, providing an interpretable and data-driven tool to support policy design, green investment strategies, and climate-resilient energy planning.

Introduction

The urgency of mitigating global warming necessitates a rapid energy transition to achieve the Sustainable Development Goals (SDGs) (Messerli et al. 2019). Since energy consumption is the primary source of global greenhouse gas emissions (Bogdanov et al. 2021), a transformation of energy systems is essential. This transition is not solely a technological endeavor (Chen et al. 2019); it also encompasses critical economic dimensions (Anonymous 2024), Among which the weighted average cost of capital (WACC) is a critical metric (Stewart and Shirvan 2022). It represents the average return required by capital providers, balancing the costs of debt and equity financing (Bachner, Mayer, and Steininger 2019). The environmental consequences of this financial indicator are profound; modeling shows that high capital costs in developing economies can reduce green energy production by 35% and delay the achievement of net-zero emissions by a full decade(Ameli et al. 2021).

A pernicious challenge for the energy transition is its inherent vulnerability to shocks from the legacy fossil fuel system it seeks to replace. Volatility in global oil, gas, and coal prices propagates through the financial system, influencing inflation, interest rates, and investor risk perception, thereby destabilizing the WACC for capital-intensive renewable projects(Melodia and Karlsson 2022). This financial vulnerability translates directly into environmental risk, as it can slow the pace of decarbonization(Egli, Steffen, and Schmidt 2019). Existing research has successfully elucidated the impact of fossil fuel price volatility on market risk for energy companies (Dobrowolski et al. 2022a; Ayinde and Adeyemi 2024). However, less attention has been devoted to evaluating its influence on WACC within the context of energy transition projects. Additionally, the varied impacts of fossil fuel price volatility across different energy sectors and regions have not been fully explored.

Therefore, this study focuses on the upcoming decade and seeks to answer the following questions:

- How do fossil fuel price fluctuations affect the WACC of energy transition projects, influencing the pace of renewable energy deployment?
- How do these price dynamics affect capital costs across regions, particularly between fuel-importing and fuel-exporting countries, and how should financing strategies for low-carbon projects be shaped?

Literature review

Calculation of WACC

For the WACC data, this study mainly uses previous study's (Calcaterra et al. 2024) dataset, which contains their predictions for the WACC for different regions. The calculation begins with analyzing past financial data at the enterprise level, calculating the cost of debt and equity, and incorporating the leverage ratio and tax rate to determine each company's WACC as follows(Polzin et al. 2019; Kling et al. 2021) :

$$WACC_{it} = L_{it} \times r_{Dit} \times (1 - \text{TaxRate}_{it}) + (1 - L_{it}) \times r_{Eit}$$

where $WACC_{it}$ represents the weighted average cost of capital for firm i at time t, L_{it} is the leverage ratio, r_{Dit}

*Joint corresponding authors.

is the cost of debt, r_{Eit} is the cost of equity, and $TaxRate_{it}$ is the tax rate for firm i at time t.

And the national WACC is then derived by weighting and averaging each company's WACC based on its share of the national market revenue. (Egli, Steffen, and Schmidt 2019; Kling et al. 2021).

$$WACC_{ct} = \sum_i \left(\frac{\text{Revenue}_{it}}{\text{Total Revenue}_{ct}} \right) \times WACC_{it}$$

Where $WACC_{ct}$ represents the weighted average cost of capital for country c at time t, $Revenue_{it}$ is the revenue of firm i at time t, and Total $Revenue_{ct}$ is the total revenue of country c at time t.

After that, previous study(Calcaterra et al. 2024) introduces a time dimension and financial learning, simulating how technological progress and experience accumulation can lower WACC by reducing technological risks and the required safety margin. The CoC-convergence scenario examines the trend of WACC in developing countries converging towards levels seen in developed countries.

$$\text{CoC}_{tnT} = \text{CoC}_{0n,T} \times \left(\frac{Y_{tn,T}}{Y_{0n,T}} \right)^{-bT}$$

Where CoC_{tnT} is the cost of capital for country n at time t and technology T, $CoC_{0n,T}$ is the initial cost of capital, $Y_{tn,T}$ is the cumulative technology deployment, $Y_{0n,T}$ is the initial technology deployment , and bT is a parameter.

Utilizing the aforementioned data and assumptions, it can employ a suite of climate-energy-economy models to simulate the WACC across various regions and energy sectors.

Impact of Fossil Fuel Prices on WACC Components

Previous subsection outlines calculating $WACC_{it}$ using firm-level data, in which the cost of equity (r_{Eit}) and the cost of debt (r_{Dit}) are not static. They are profoundly influenced by broader market dynamics, among which fossil fuel prices play a critical role (Melodia and Karlsson 2022).

The cost of equity(r_{Eit}) is estimated using the Capital Asset Pricing Model (CAPM), defining the expected return as:

$$r_{Eit} = r_{f,t} + \beta_i(r_{m,t} - r_{f,t})$$

Where $r_{f,t}$ is the risk-free rate at time t, β_i is the firm's systematic risk, and $(r_{m,t} - r_{f,t})$ is the equity risk premium (ERP).

Fossil fuel price could influence each component of the CAPM equation. The substitution effect shows that higher fossil fuel prices enhance the economic competitiveness of renewable energy projects, lowering their perceived risk and thus the overall required return, r_{Eit} (Melodia and Karlsson 2022). Additionally, the impact on systematic risk (β_i) is ambiguous. Renewable assets can act as a hedge against fossil fuel price volatility due to their zero fuel cost, implying a lower β(Millischer et al. 2024). Conversely, if investors focus on substitution logic, renewable energy stock prices may correlate with oil prices, leading to a higher β (Lieberman 2009). On the other hand, persistent fossil fuel price volatility highlights climate transition risks, leading investors to demand a "brown penalty" for fossil fuel assets and offer a "green premium" for renewables, effectively lowering the required ERP for green projects (Shrimali 2021).

Similarly, the cost of debt(r_{Dit}) is also susceptible to fossil fuel price shocks, which are a major driver of inflation, often compelling central banks to raise policy rates (Vrînceanu et al. 2020). This directly increases the economy-wide risk-free rate ($r_{f,t}$), which serves as a benchmark for all borrowing and raises r_{Dit} for capital-intensive renewable projects (Kjellevoll and Wilberg 2023). At the project level, high fossil fuel prices can improve the value of a renewable project's fixed-price Power Purchase Agreement (PPA), reducing its credit risk and potentially lowering the credit spread component of r_{Dit} (Duma, Cabré, and Kruger 2023). This is supported by growing evidence of a "green premium" in debt markets, where lenders offer more favorable terms to renewable projects.

Therefore, the final calculated $WACC_{it}$ for a renewable energy firm is a function not only of its internal financial structure (L_{it}) but also of these external pressures that alter the fundamental costs of its capital (r_{Eit} and r_{Dit}). The interplay of these mechanisms is summarized in the table below.

Table 1: Theoretical Channels of Fossil Fuel Price Transmission to Renewable Energy WACC

Price Signal	Affected Component	Transmission Channel
Level Increase	r_E (Cost of Equity)	Substitution Effect
Level/Volatility	r_E (Cost of Equity)	Market Correlation
Volatility Increase	r_E (Cost of Equity)	Hedging Property
Volatility Increase	r_E (Cost of Equity)	Climate Risk Pricing
Volatility Increase	r_D (Cost of Debt)	Macroeconomic Contagion
Level Increase	r_D (Cost of Debt)	Off-taker Stability
Level Increase	r_D (Cost of Debt)	PPA Contract Value
Volatility Increase	r_D (Cost of Debt)	Debt Market "Green Premium"

Ultimately, the net impact on the WACC of renewable energy projects hinges on the relative magnitude of these opposing forces: the project-level advantages stemming from higher fossil fuel prices versus the detrimental consequences of macroeconomic contagion.

Methodology

This study proposes a three-stage approach to assess the impact of fossil fuel price fluctuations on WACC for energy transition projects. The first stage predicts fossil fuel prices using a hybrid LSTM-GRP model, and the second stage calculates the corresponding inflation rates.

After that, the third stage evaluates the impact of fossil fuel prices on WACC using AutoGluon model based on performance metrics of R², MAPE, and RMSE.

Stage1: Prediction of Fossil Fuel Prices

Since previous studies have proved the proficiency of Long Short-Term Memory (LSTM) in handling sequence data with long-term dependencies (Al-Selwi et al. 2024; Lindemann et al. 2021), and the advantages of Gaussian Regression Process (GRP) (Lahmiri 2024; Rasmussen 2003) in predicting fossil energy prices. This study uses a hybrid model combining LSTM and GRP to predict fossil fuel prices (coal, oil, and natural gas) from 2026 to 2035(Figure 1).

Step 1.1: LSTM Model The primary forecasting model is a LSTM network designed to learn intricate non-linear patterns from historical time-series data. To represent the cyclical nature of monthly patterns, we transform the month of the year, m, into two continuous sinusoidal features :

$$m_{\sin} = \sin\left(\frac{2\pi m}{12}\right), \quad m_{\cos} = \cos\left(\frac{2\pi m}{12}\right) \tag{1}$$

The model architecture integrates a convolutional layer for local pattern extraction, followed by bidirectional LSTM and GRU layers to capture long-range temporal dependencies. An attention mechanism is subsequently applied, enabling the model to dynamically weight the importance of different time steps in the input sequence during prediction generation. The model predicts the price for the next time step, and this prediction is then used to update the feature set for the subsequent step, which is fed back into the model to generate the next forecast.

Step 1.2: Forecast Refinement with Gaussian Process Regression The point estimates generated by the LSTM model are subsequently refined using a GRP model. We employ a composite kernel to model the underlying price function:

$$k(t,t') = C \cdot \exp\left(-\frac{\|t-t'\|^2}{2l^2}\right) + \sigma_n^2 \delta(t,t') \tag{2}$$

where C is the constant kernel and l is the length-scale parameter.

This kernel incorporates a Radial Basis Function component that encodes the assumption of smoothness in the underlying function space. Given the initial predictions from the LSTM model, represented as the vector $\mathbf{y}_{DL}$. The GRP computes a predictive mean, serving as the price P_e for Stage 3, which is calculated as:

$$P_e = K(t,X)[K(X,X) + \sigma_n^2 I]^{-1}\mathbf{y}_{DL} \tag{3}$$

where $K(t,X)$ is the vector of covariances between the test point t and the training inputs X, and $K(X,X)$ is the covariance matrix of the training inputs.

Stage2: Calculation of Inflation Rate

Inclusion of Inflation Rate as a Covariate In the model, the inflation rate is included as a crucial covariate. As a macroeconomically sensitive indicator, WACC is directly influenced by the prevailing interest rate environment, and the inflation rate is a primary basis for central banks to adjust monetary policies (Dobrowolski et al. 2022b). Additionally, fossil fuel prices themselves are closely correlated with the macroeconomic inflation levels (Kang, Park, and Suh 2020).

Forecasting Framework This study adopts a methodology proven to be accurate in predicting inflation rate (Paranhos 2025), which models the inflation rate as a non-linear function fitting problem :

$$y_{z+h} = G(x_z; \Theta_h) + \epsilon_{z+h} \tag{4}$$

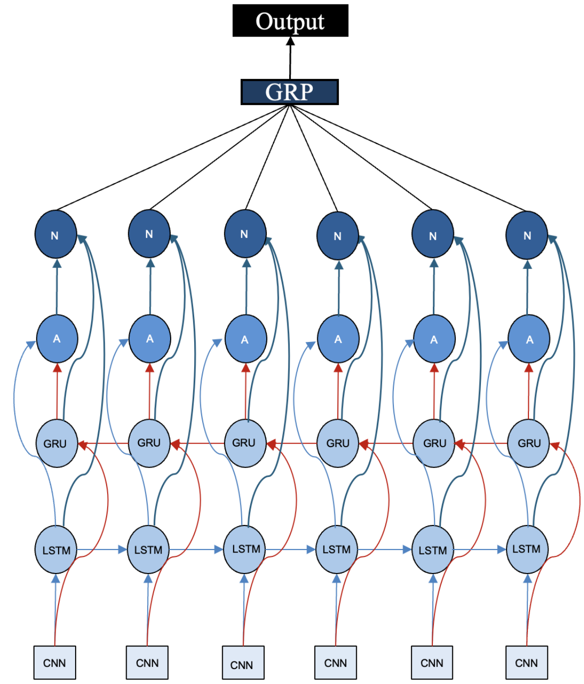

Figure 1: Architecture for Price-Prediction model: It includes a network with CNN, LSTM/GRU, attention(A), and Normalization(N) layer, which is then smoothed by a GRP.

where y_{t+h} is the inflation rate at a future horizon h, and x_t is the vector of predictor variables containing relevant macroeconomic indicators and their lags.

The function $G(\cdot)$ combines an LSTM structure with a fully connected feed-forward (FF) network:

$$G(x_z; \Theta_h) = g_{FF}(\text{LSTM}(x_z; \Theta_{LSTM}); \Theta_{FF}) \tag{5}$$

In this architecture, the LSTM first processes the sequential input data to extract a set of dynamic factors. Subsequently, the feed-forward takes these dynamic factors as input to generate the final inflation forecast.

To address the high sensitivity of neural network training to random parameter initializations, we can employ an Ensemble Learning strategy for model optimization.

Specifically, the final forecast is calculated by averaging the outputs of N independently trained models, each with a different initialization:

$$\hat{y}_{ens,z+h} = \frac{1}{N}\sum_{n=1}^{N} \hat{y}_{n,z+h} \tag{6}$$

where $\hat{y}_{n,z+h}$ is the prediction from the n-th model.

The parameters Θ_h for all models are estimated by minimizing MSE:

$$\hat{\Theta}_h = \arg\min_{\Theta_h} \left\{ \frac{1}{z-h} \sum_{z=1}^{z-h} (y_{z+h} - G(x_z; \Theta_h))^2 \right\} \tag{7}$$

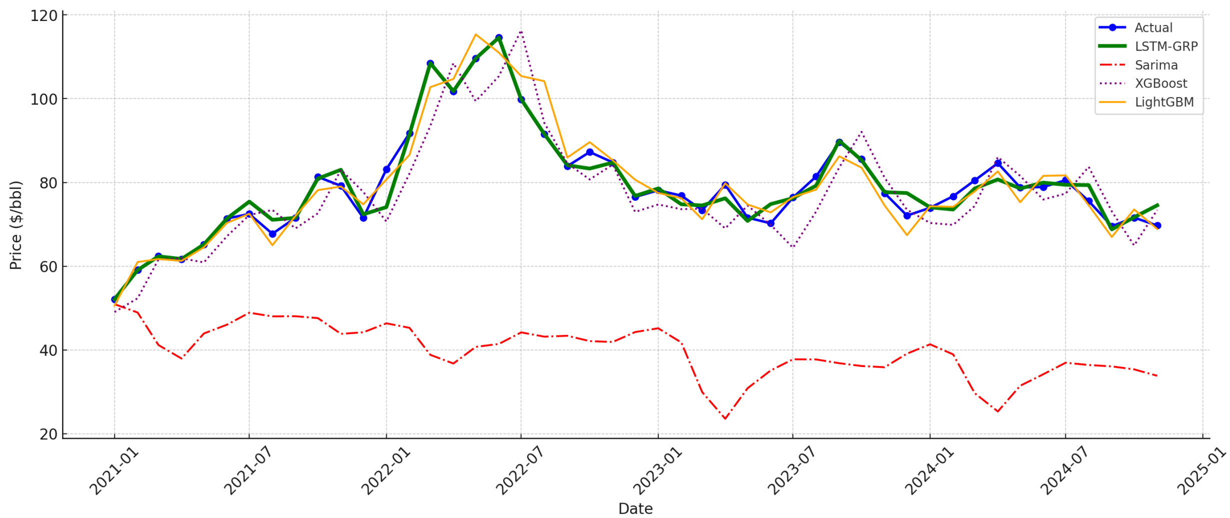

Figure 2: Accuracy of Prediction Model: forecast results of oil prices from 2021 to 2024, using different models (LSTM-GRP, SARIMA, XGBoost, LightGBM).

Stage3: Evaluation of WACC Based on Fossil Fuel Price

To quantify the impact of fossil fuel price fluctuations on the WACC, we employed an Automated Machine Learning (AutoML) model, which can automate model selection, hyperparameter tuning, and ensembling.

Modeling Design This assessment model involves three fossil fuel prices (Coal, Natural Gas, and Oil) and nine types of energy transition projects. To isolate variables, we constructed and trained a total of $3 \times 9 = 27$ independent regression models. In each model, the independent variables consist of an energy price and the contemporaneous inflation rate, while the dependent variable is the WACC for the project. This approach aims to find a function f for each project type p and energy source e, such that:

$$\mathrm{WACC}_p = f(P_e, \hat{y}_{ens,t}) + \epsilon \tag{8}$$

where $WACC_p$ is the capital cost for a specific project, P_e is the price, $\hat{y}_{ens,t}$ represents the inflation rate, and ϵ is the irreducible error term.

Automated Modeling with AutoGluon We selected the AutoGluon-Tabular framework to perform training and optimization. Since it could enhance model robustness and accuracy through the following two techniques:

- **j-fold Cross-Validation Bagging**: It trains multiple base models h_j on different subsets of the training data created via cross-validation. The final result, $\hat{y}_{\text{bag}}$ is the average of output of all base models:

$$\hat{y}_{\text{bag}}(x) = \frac{1}{J}\sum_{j=1}^{J} h_j(x) \tag{9}$$

- **Auto Stacking**: Let the set of base models be $\{h_m\}_{m=1}^{M}$. A higher-level meta-model, H, is trained on the out-of-fold predictions of these base models. The final result, $\hat{y}_{\text{stack}}$, is generated by this meta-model, which learns the optimal way to combine the base model outputs:

$$\hat{y}_{\text{stack}}(x) = H(h_1(x), h_2(x), \ldots, h_M(x)) \tag{10}$$

Through this automated process, we generated an optimized model for each of the 27 regressions, best adapted to its data characteristics.

Model Performance Evaluation Although AutoGluon has built-in optimization targets during its training process, we conducted an independent performance evaluation for each final model after training was complete. The evaluation metrics included R^2, MAPE, and RMSE. These three metrics were chosen to provide a comprehensive assessment of the model's performance from different perspectives: R^2 measures the extent to which the model explains the variance in WACC, MAPE intuitively reflects the average percentage of prediction deviation, and RMSE quantifies the dispersion of errors between predicted and actual values. Together, these metrics provide a comprehensive and robust basis for evaluating the predictive power of fossil fuel prices on WACC.

Accuracy of the Prediction models

To validate the accuracy of the LSTM-GRP model, this study employed four models (LSTM-GRP, SARIMA, XGBoost, and LightGBM) to forecast WTI crude oil prices from 2021 to 2024 using data from 1982 to 2020. The predictions generated by these models were subsequently compared with actual oil prices, as shown in Figure (2). Evaluation metrics revealed that the LSTM-GRP model outperformed the other models, achieving a coefficient of determination of 0.966. Additionally, the LSTM-GRP model exhibited lower RMSE and MAE values of 2.105 and 1.6342, respectively. Additionally, the accuracy of forecasting the inflation rate has been examined in previous studies(Paranhos 2025).

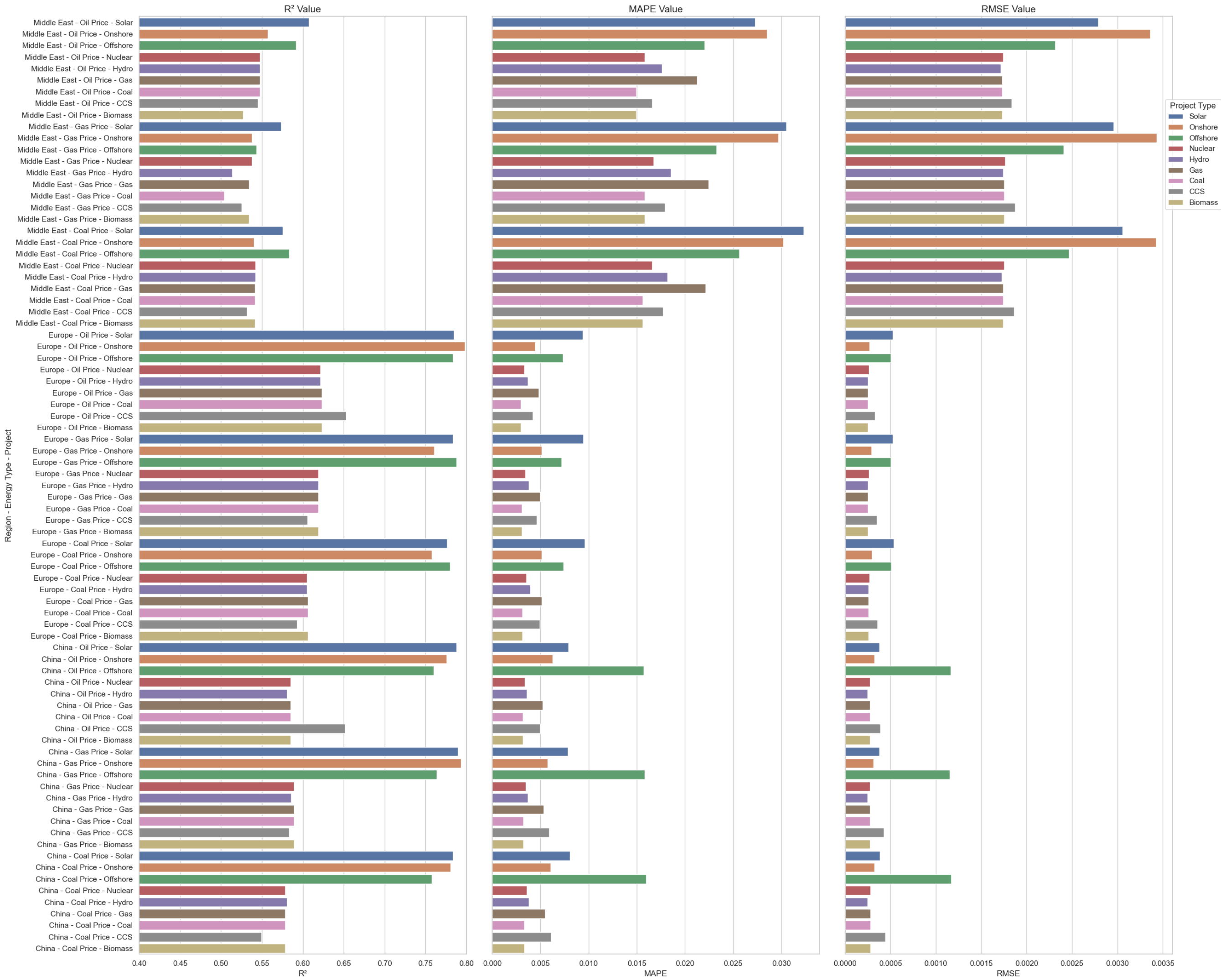

Figure 3: Model Performance for Each Project:Comparison of R², MAPE, and RMSE for estimating WACC across various regions and energy transition projects.

Results

As shown in Figure 3, the experiment results demonstrate that fossil fuel price fluctuations differentially impact various energy transition projects. Solar and wind(both onshore and offshore) projects demonstrate the highest sensitivity, with average R^2 values all exceeding 0.7. In contrast, other projects, including hydropower, biomass, and coal, exhibit a lower level of sensitivity. Their average R^2 values are generally 0.5, suggesting that their capital costs are likely driven more by other, non-fossil-fuel-price factors.

From a regional perspective, the impact of fossil fuel prices exhibits clear geographical characteristics. In major energy-importing regions like Europe and China, the influence is considerably more pronounced, with average R^2 values of 0.67 and 0.65. Conversely, the impact is markedly weaker in the Middle East, an energy-exporting region, where the average R^2 value is only 0.54. This disparity is also reflected in the prediction error, as the Middle East's average MAPE (0.0209) is substantially higher than that of Europe (0.0050) and China (0.0061), implying greater uncertainty in capital cost.

Discussion

Regional Differences

Europe As shown in Figure3, the WACC of European energy transition projects will continue to be influenced by the volatility of fossil fuel prices(R²=0.67). This conclusion is supported not only by the high R² calculated by this study, but also by the structural characteristics of Europe's energy system (Román-Collado and Casado Ruíz 2024), limitations in policy regulation (European Commission 2023b,a), and the amplification of external risks (OECD 2021).

Structural Dependence and Policy Limitations Despite Europe's global leadership in renewable energy technology promotion, its short-term reliance on fossil fuel imports remains difficult to reverse ((Li and Leung 2021)). Data indicates that the proportion of fossil fuel imports in Europe increased from 70% in 2018 to 82% in 2024(Table2). This allows global price fluctuations to directly affect the energy market and, consequently, capital costs. Furthermore, the elasticity coefficient of WACC volatility with respect to import ratios in Europe is 0.48—the highest globally(Egli, Steffen, and Schmidt 2019), underscoring Europe's heightened sensitivity to price transmission.

On the other hand, the regulatory effectiveness of the EU Emissions Trading System exhibits diminishing marginal returns. Research shows that for every 10-euro increase in carbon prices per ton, WACC sensitivity decreases by 0.15 R^2 points. However, when carbon prices exceed 100 euros per ton, the smoothing effect diminishes by 40% (Bouzarovski and Tirado Herrero 2017; EEA 2022). Additionally, the diffusion of technological innovation faces constraints due to infrastructure bottlenecks (European Commission 2023a). For example, Germany experienced a wind power curtailment rate of up to 6% in 2023 due to grid congestion, weakening the optimization potential of accumulated wind power patents on capital costs (Schmidt et al. 2019)

External Shocks and Financial Risks Geopolitical risks further amplify the impacts of price fluctuations: during the 2022 Russia-Ukraine conflict, European natural gas prices surged by 380%, causing a 58-basis-point spike in the WACCs of offshore wind projects. Model simulations indicate that similar crises could raise WACC peaks by an additional 70 basis points (IEA 2022; Cooper 2017).

Moreover, international capital flows supporting Europe's energy transition amplify risk transmission effects. With 62% of green bonds denominated in US dollars, Fed interest rate hikes may add 25-40 basis points to financing costs (Ehlers and Packer 2017). A $10-per-barrel increase in oil prices triggers a $120-million outflow from European clean energy ETFs, further elevating financing costs (Flammer 2021).

Table 2: Fossil Energy Import Ratios (2018-2024)

Year	Middle East	China	Europe
2018	0%	60%	70%
2019	0%	62%	72%
2020	0%	60%	75%
2021	0%	58%	73%
2022	0%	55%	78%
2023	0%	60%	80%
2024	0%	58%	82%

China The WACC of China's energy transition projects also exhibits correlation with international fossil energy prices(R^2=0.64). It could be mainly driven by structural dependence, policy intervention, and energy heterogeneity.

Import Dependence As one of the world's largest fossil energy importers(Table2), China's energy security and price stability rely heavily on international markets (Sun, Li, and Shang 2022; Wang et al. 2023). In 2022, import dependence for crude oil and natural gas reached 73.5% and 42% respectively (EEA 2022). This vulnerability causes international price fluctuations to quickly affect domestic markets through the "imported inflation-financing premium" mechanism. For example, a $10 per barrel rise in Brent crude oil prices raises WACC for photovoltaic projects by 12-18 basis points (Ben-Salha et al. 2022).

Government Intervention To mitigate the risks of price fluctuations, the Chinese government has developed a distinctive energy price management system (Glocker and Wegmüller 2024; He and Lin 2017). By implementing a "price corridor," the government has constrained thermal coal price fluctuations to within ±15%. From 2021 to 2023, the standard deviation of China's thermal coal prices was only $7.2 per ton, markedly lower than the $18.5 per ton observed in the European API2 index during the same period (Glocker and Wegmüller 2024). Fiscal subsidies have also played a critical role; in 2023, $44 billion in fossil energy subsidies reduced the volatility of WACC for China's energy transition projects to 3.1%, equivalent to just 53% of the volatility in market-oriented countries.

Middle East The data from the Middle East region exhibit a relatively low model fit, with an average R^2 of 0.54 (Figure3), lower than that observed in other regions. This phenomenon can be attributed to its unique position as a fossil fuel exporter, the specific institutional framework, and the entrenched technological path dependence.

Economic Structure In the Middle East, revenues from fossil fuel exports constitute 68% of total fiscal income (World Bank 2023; Fattouh and El-Katiri 2013a), and their economies are highly dependent on the stable cash flow generated by oil and gas trade (Karanfil and Omgba 2023). For example, Saudi Arabia secures its revenue through long-term export contracts, which account for 82% of its trade volume (GECF 2023). Additionally, it leverages sovereign wealth funds, such as the Public Investment Fund (PIF) with assets exceeding $700 billion, to directly invest in renewable energy projects, thereby mitigating market financing risks. 76% of green hydrogen and photovoltaic projects in the Middle East are financed through sovereign guarantees(IRENA 2023), resulting in a WACC with a risk premium of only 1.2%, significantly lower than that in Europe (3.5%). This "fiscal cushion" ensures the rigidity of capital costs; even if international oil prices fluctuate from $80 per barrel to $60 per barrel, the WACC for Saudi photovoltaic projects varies by merely 0.3% (S&P Global Ratings 2024).

Institutional Design Middle Eastern governments use a three-tier framework to reduce the impact of fossil fuel price volatility on energy transition costs(Surkov and Simonov 2023), creating a "policy isolation layer."

1. Dual-track system: Low domestic energy prices (Saudi gasoline at $0.6 per liter, one-third of U.S. rates) suppress alternative energy demand (Fattouh and El-Katiri 2013b). Subsidies enhance renewable energy competitiveness; for instance, Gulf countries' fossil fuel subsidies account for 8.2% of GDP (IMF 2023). Long-term agreements, like Dubai Solar Park's 20-year fixed electricity price (4.5 cents/kWh), decouple capital costs from short-term price fluctuations.

2. Strategic reserves and production adjustments: Middle East oil reserves cover 214 days of demand (IMF 2023). Governments stabilize prices by adjusting production.

3. Sovereign guaranties: Using the Barakah nuclear power plant in the United Arab Emirates as an example, 90% of its funding originates from state-owned banks, maintaining a stable debt cost of 3.2%. The correlation coefficient R^2 between its financing costs and oil price fluctuations is only 0.02 (OECD 2019).

Environmental Implications of Financial Sensitivity

The regional disparities in WACC sensitivity identified in our results (Figure3) are not merely financial metrics; they are proxies for the stability and velocity of decarbonization, linking financial market to tangible climate outcomes.

For energy-importing regions like Europe and China (average $R^2 = 0.67$ and 0.65), the strong correlation means that financial risk translates directly into environmental risk. The resulting uncertainty in financing costs can deter or delay the large-scale, capital-intensive investments. Consequently, the pace of their energy transition becomes hostage to the instability of the very markets they aim to exit, jeopardizing the deployment required to align with a 1.5°C trajectory.

Conversely, the weaker correlation in the Middle East (average $R^2 = 0.54$) presents a different environmental paradox. The financial stability afforded to renewable projects by a "fiscal cushion" from fossil fuel revenues mutes the urgent market-based incentive to transition. While this de-risks individual projects, it can foster a decarbonization pace driven by deliberate policy choices rather than pressing economic necessities. This decoupling may lead to a slower transition, as the region remains insulated from market signals.

Ultimately, our findings reveal that the financial mechanisms shaping climate outcomes are divergent across the globe. It frames the topic for the next subsection: designing policy that can either mitigate market volatility to ensure a stable transition (as needed in Europe and China) or create sufficient incentives to overcome economic inertia (as in the Middle East).

Climate Finance & Policy

In Europe, the WACC for renewable energy projects is highly sensitive to fluctuations in fossil fuel prices. The high R^2 and low MAPE values(0.67 and 0.004) indicate that renewable investments remain exposed to energy price volatility. To meet the 1.5°C climate target, European policymakers could prioritize developing financial instruments such as green bonds, subsidies, and climate risk insurance. These mechanisms can stabilize financing costs, reduce investor risk, and stimulate greater private investment in renewable energy.

China's energy transition exhibits moderate sensitivity (R^2=0.64), partly due to government policies. While this intervention brings short-term stability, it may obscure the actual cost competitiveness of renewable energy and potentially deter private sector investment. To align with the 1.5°C climate target, policymakers could consider gradually introducing more market-driven price mechanisms, complemented by targeted green finance initiatives to reduce capital costs. Utilizing state-supported low-interest loans to lower WACC can serve as an effective strategy to incentivize private investment in clean energy while preserving broader economic stability.

The Middle East's low sensitivity to fossil fuel price fluctuations is indicated by the R^2 of 0.54. It presents a potential risk due to the region's heavy dependence on fossil fuel revenues. To ensure long-term economic resilience and align with global decarbonization objectives, policymakers could prioritize the diversification of the energy mix through increased investment in renewable energy. In this context, sovereign wealth funds can serve as a strategic vehicle by providing long-term, low-cost capital for renewable energy projects, thereby reducing overall financing costs. These funds can strategically allocate capital toward renewable energy infrastructure, enhancing financial stability and mitigating project-related risks.

Conclusion & Future Work

This study introduces a three-stage machine learning model to assess the effects of fossil fuel price volatility on the WACC of energy transition projects. The findings emphasize that achieving the 1.5°C target requires region-specific climate finance solutions. Policymakers and investors need to tailor their strategies to address the unique challenges posed by fossil fuel price volatility. Since it can promote renewable energy investments that remain financially viable and resilient amid global market shifts.

While this study provides some insights into the financial dynamics of the energy transition, further research is also needed. Initially, some datasets and assumptions rely on secondary sources. Future work could enhance the robustness of these findings by incorporating firm-level financial data. Additionally, future work could transition from quantifying predictive sensitivity to formal causal inference, using techniques like Granger causality or Structural Equation Models to handle policy variables, financial mechanisms, and technological learning rates. Finally, the framework itself can be enhanced by benchmarking against advanced architectures like Transformers and leveraging our GRP model's predictive variance to conduct full uncertainty quantification and stress-testing.

Acknowledgments

The Duke Kunshan University Education Development Foundation supports the research. The research results of this article are also sponsored by the Kunshan Municipal Government research funding.

References

Al-Selwi, S. M.; Hassan, M. F.; Abdulkadir, S. J.; Muneer, A.; Sumiea, E. H.; Alqushaibi, A.; and Ragab, M. G. 2024. RNN-LSTM: From applications to modeling techniques and beyond—Systematic review. *Journal of King Saud University - Computer and Information Sciences*, 36(5): 102068.

Ameli, N.; Dessens, O.; Winning, M.; Cronin, J.; Chenet, H.; Drummond, P.; Calzadilla, A.; Anandarajah, G.; and Grubb, M. 2021. Higher cost of finance exacerbates a climate investment trap in developing economies. *Nature Communications*, 12(1): 4046.

Anonymous. 2024. Sustainable Energy Transition for Renewable and Low Carbon Grid Electricity Generation and Supply. *Frontiers in Energy Research*.

Ayinde, T. O.; and Adeyemi, F. A. 2024. Fossil fuel prices and economic policy uncertainty– A regime-switching approach. *Energy and Climate Change*, 5: 100140.

Bachner, G.; Mayer, J.; and Steininger, K. W. 2019. Costs or benefits? Assessing the economy-wide effects of the electricity sector's low carbon transition – The role of capital costs, divergent risk perceptions and premiums. *Energy Strategy Reviews*, 26: 100373.

Ben-Salha, O.; Hakimi, A.; Zaghdoudi, T.; Soltani, H.; and Nsaibi, M. 2022. Assessing the impact of fossil fuel prices on renewable energy in China using the novel dynamic ARDL simulations approach. *Sustainability*, 14(16): 10439.

Bogdanov, D.; Ram, M.; Aghahosseini, A.; Gulagi, A.; Oyewo, A. S.; Child, M.; Caldera, U.; Sadovskaia, K.; Farfan, J.; De Souza Noel Simas Barbosa, L.; Fasihi, M.; Khalili, S.; Traber, T.; and Breyer, C. 2021. Low-cost renewable electricity as the key driver of the global energy transition towards sustainability. *Energy*, 227.

Bouzarovski, S.; and Tirado Herrero, S. 2017. The energy divide: Integrating energy transitions, regional inequalities and poverty trends in the European Union. *European urban and regional studies*, 24(1): 69–86.

Calcaterra, M.; Aleluia Reis, L.; Fragkos, P.; Briera, T.; de Boer, H. S.; Egli, F.; Emmerling, J.; Iyer, G.; Mittal, S.; Polzin, F.; et al. 2024. Reducing the cost of capital to finance the energy transition in developing countries. *Nature Energy*, 1–11.

Chen, B.; Xiong, R.; Li, H.; Sun, Q.; and Yang, J. 2019. Pathways for sustainable energy transition. *Journal of Cleaner Production*, 228: 1564–1571.

Cooper, A. C. 2017. Building a socio-technical energy research community: Theory, practice and impact. *Energy Research & Social Science*, 26: 115–120.

Dobrowolski, Z.; Drozdowski, G.; Panait, M.; and Apostu, S. A. 2022a. The weighted average cost of capital and its universality in crisis times: Evidence from the energy sector. *Energies*, 15(18): 6655.

Dobrowolski, Z.; Drozdowski, G.; Panait, M.; and Apostu, S. A. 2022b. The Weighted Average Cost of Capital and Its Universality in Crisis Times: Evidence from the Energy Sector. *Energies*, 15(18).

Duma, D.; Cabré, M. M.; and Kruger, W. 2023. Risk mitigation and transfer for renewable energy investments. *Stockholm Environment Institute*, 3(7): 1–26.

EEA. 2022. Trends and projections in Europe 2022. Technical report, European Environment Agency.

Egli, F.; Steffen, B.; and Schmidt, T. S. 2019. Bias in energy system models with uniform cost of capital assumption. *Nature communications*, 10(1): 4588.

Ehlers, T.; and Packer, F. 2017. Green bond finance and certification.

European Commission. 2023a. Renewable Energy Directive. Technical Report COM(2021) 129 final, European Commission, Brussels. https://energy.ec.europa.eu/topics/renewable-energy/renewable-energy-directive-targets-and-rules/renewable-energy-directive_en.

European Commission. 2023b. What is the EU ETS? Technical Report COM(2021) 129 final, European Commission, Brussels. https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/what-eu-ets_en.

Fattouh, B.; and El-Katiri, L. 2013a. Energy subsidies in the Middle East and North Africa. *Energy Strategy Reviews*, 2(1): 108–115. Strategy Options and Models for the Middle East and North Africa (MENA) Energy Transition.

Fattouh, B.; and El-Katiri, L. 2013b. Energy subsidies in the middle East and North Africa. *Energy Strategy Reviews*, 2(1): 108–115.

Flammer, C. 2021. Corporate green bonds. *Journal of financial economics*, 142(2): 499–516.

GECF. 2023. GECF Annual Gas Market Report 2023.

Glocker, C.; and Wegmüller, P. 2024. Energy price surges and inflation: Fiscal policy to the rescue? *Journal of International Money and Finance*, 149: 103201.

He, Y.; and Lin, B. 2017. The impact of natural gas price control in China: A computable general equilibrium approach. *Energy Policy*, 107: 524–531.

IEA. 2022. Europe's energy crisis: Implications for the global energy transition. Technical report, IEA.

IMF. 2023. Fossil Fuel Subsidies: 2023 Update. Technical report, International Monetary Fund. Accessed: 2025-04-04.

IRENA. 2023. *Renewable Energy Statistics 2023*. Abu Dhabi: International Renewable Energy Agency. ISBN 978-92-9260-537-7.

Kang, H.; Park, J.; and Suh, H. 2020. The rise of part-time employment in the great recession: Its causes and macroeconomic effects. *Journal of Macroeconomics*, 66: 103257.

Karanfil, F.; and Omgba, L. D. 2023. The energy transition and export diversification in oil-dependent countries: The role of structural factors. *Ecological Economics*, 204: 107681.

Kjellevoll, V.; and Wilberg, S. S. 2023. *The Impact of ESG Perfomance on the Cost of Capital in Energy and Natural Resources Companies*. Master's thesis, NTNU.

Kling, G.; Volz, U.; Murinde, V.; and Ayas, S. 2021. The impact of climate vulnerability on firms' cost of capital and access to finance. *World Development*, 137: 105131.

Lahmiri, S. 2024. Fossil energy market price prediction by using machine learning with optimal hyper-parameters: A comparative study. *Resources Policy*, 92: 105008.

Li, R.; and Leung, G. C. 2021. The relationship between energy prices, economic growth and renewable energy consumption: Evidence from Europe. *Energy Reports*, 7: 1712–1719.

Lieberman, D. 2009. Renewable energy as a hedge against fuel price fluctuation.

Lindemann, B.; Müller, T.; Vietz, H.; Jazdi, N.; and Weyrich, M. 2021. A survey on long short-term memory networks for time series prediction. *Procedia CIRP*, 99: 650–655. 14th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 15-17 July 2020.

Melodia, L.; and Karlsson, K. 2022. Energy price stability: The Peril of fossil fuels and the promise of renewables. *Roosevelt Institute*, 11.

Messerli, P.; Murniningtyas, E.; Eloundou-Enyegue, P.; Foli, E. G.; Furman, E.; Glassman, A.; Hernández Licona, G.; Kim, E. M.; Lutz, W.; Moatti, J.-P.; et al. 2019. Global sustainable development report 2019: the future is now–science for achieving sustainable development.

Millischer, L.; Fu, M. C.; Volz, U.; and Beirne, J. 2024. *Do Renewables Shield Inflation from Fossil Fuel-Price Fluctuations?* International Monetary Fund.

OECD. 2019. *The Economics of Long-term Operation of Nuclear Power Plants*. Paris: OECD Publishing. ISBN 9789264992054.

OECD. 2021. *Financing climate objectives in cities and regions*. OECD Publishing.

Paranhos, L. 2025. Predicting inflation with recurrent neural networks. *International Journal of Forecasting*.

Polzin, F.; Egli, F.; Steffen, B.; and Schmidt, T. S. 2019. How do policies mobilize private finance for renewable energy?—A systematic review with an investor perspective. *Applied Energy*, 236: 1249–1268.

Rasmussen, C. E. 2003. Gaussian processes in machine learning. In *Summer school on machine learning*, 63–71. Springer.

Román-Collado, R.; and Casado Ruíz, V. 2024. Key effects contributing to changes in energy imports in the EU-27 between 2000 and 2020: A decomposition analysis based on the Sankey diagram. *Energy Economics*, 140: 108009.

Schmidt, O.; Melchior, S.; Hawkes, A.; and Staffell, I. 2019. Projecting the future levelized cost of electricity storage technologies. *Joule*, 3(1): 81–100.

Shrimali, G. 2021. Financial Performance of Renewable and Fossil Power Sources in India. *Sustainability*, 13(5).

S&P Global Ratings. 2024. GCC Corporate And Infrastructure Outlook 2024: Holding Up Against Refinancing Needs.

Stewart, W.; and Shirvan, K. 2022. Capital cost estimation for advanced nuclear power plants. *Renewable and Sustainable Energy Reviews*, 155: 111880.

Sun, G.; Li, J.; and Shang, Z. 2022. Return and volatility linkages between international energy markets and Chinese commodity market. *Technological Forecasting and Social Change*, 179: 121642.

Surkov, A. N.; and Simonov, A. G. 2023. Middle East Energy Policy Transformation: Saudi Case. In *Sustainable Development Risks and Risk Management: A Systemic View from the Positions of Economics and Law*, 463–467. Springer.

Vrînceanu, G.; Horobeț, A.; Popescu, C.; and Belaşcu, L. 2020. The influence of oil price on renewable energy stock prices: an analysis for entrepreneurs. *Studia Universitatis Vasile Goldiș Arad, Seria Științe Economice*, 30(2): 24–35.

Wang, X.; Wang, J.; Wang, W.; and Zhang, S. 2023. International and Chinese energy markets: Dynamic spillover effects. *Energy*, 282: 128724.

World Bank. 2023. Middle East and North Africa Economic Update.

Appendix: Reproducibility Checklist

This appendix outlines the necessary data, models, and configurations required for replication, organized according to the study's three-stage methodology. The resources and instructions are available on the project's GitHub repository: https://github.com/GreenComp-ERC/ImpactOfFossilFeulPrice .

General Configuration

- **Environment:** Python 3.11.4, AutoGluon 1.4.0, TensorFlow 2.5.0+, Keras 2.4.3+.
- **Hardware:** Experiments were run on macOS (Darwin) with an Apple (arm64) 10-core CPU and 16GB RAM. See `System Configuration Report.ipynb` for details.

Stage 1: Fossil Fuel Price Prediction

- **Data:** Historical fossil feul prices from the World Bank. Files: `Average_Coal_Price.xlsx`, `Average_Gas_price.xlsx`, `Average_oil_price.xlsx`.
- **Code:** `Price_Prediction.ipynb` (model) and `Price_Data_Processing.ipynb` (processing).

Stage 2: Inflation Rate Prediction

- **Data:** Macroeconomic indicators colected by this study: `comprehensive_economic_data.xlsx` and `worldBank_Inflation.csv`.
- **Code:** `Prediction_Inflation.ipynb`.

Stage 3: WACC Impact Evaluation (AutoGluon)

- **Data:** `Euope_WACC.xlsx`, `China_WACC.xlsx`, and `Middle_EAST_WACC.xlsx`.
- **Code:** `Impact_FossilFuel.ipynb`.
- **Evaluation:** Metrics (R^2, MAPE, RMSE) were calculated and stored in `Result.xlsx`.

Table 3: Model Hyperparameter

Stage 1		Stage 2		Stage 3	
Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
time_step	12	Imputer Neighbors	3	Scaler	MinMaxScaler
scaler	(0,1)	Scaler	StandardScaler	Time Limit	600 seconds
Conv1D Filters	80	Lookback / Time Step	4	Bagging Folds	10
Conv1D Kernel Size	3	Ensemble Size 'N'	5	Stacking	auto_stack=True
Dropout 1 Rate	0.3	LSTM 1 Units	32	Dynamic Stacking	True (auto-set)
Bidirectional LSTM Units	128	LSTM 1 Kernel Regularization	l2(0.01)	GBM: max_depth	3
Dropout 2 Rate	0.5	Dropout 1 Rate	0.3	GBM: learning_rate	0.01
GRU Units	64	BatchNormalization 1	Applied	GBM: num_boost_round	100
Dropout 3 Rate	0.5	LSTM 2 Units	16	CAT: depth	3
Hidden Dense Units	80	LSTM 2 Kernel Regularization	l2(0.01)	CAT: learning_rate	0.01
Learning Rate	0.0005	Dropout 2 Rate	0.3	CAT: iterations	100
Epochs	200	BatchNormalization 2	Applied	num_layers	1
Batch Size	32	Dense 1 Units	64	hidden_size	16
EarlyStopping Patience	20	Dense 1 Kernel Regularization	l2(0.01)	dropout	0.3
ReduceLROnPlateau Patience	10	Dropout 3 Rate	0.2	-	-
ReduceLROnPlateau Factor	0.2	Dense 2 Units	32	-	-
GPR n_restarts_optimizer	10	Random Seed	42	-	-
GRP alpha (Regularization)	0.01	Learning Rate	0.001	-	-
GPR random_state	42	Loss Function	mse	-	-
-	-	Epochs	300	-	-
-	-	Batch Size	8	-	-
-	-	Validation Split	0.2	-	-
-	-	EarlyStopping Patience	50	-	-
-	-	ReduceLROnPlateau Patience	20	-	-
-	-	ReduceLROnPlateau Factor	0.5	-	-

Table 4: Data Dictionary

Variable Name	Description	Role	Source / Data File
`Crude_oil_average`	Historical average crude oil price (proxy for all fuels)	Stage 1 Target	`Average_oil_price.xlsx`
`(Engineered Feat.)`	Cyclical time features (`Month_Sin`) & rolling averages	Stage 1 Feature	Generated from Stage 1 data
`Predicted_Price`	GRP-smoothed fuel price forecast (2024-2035)	Stage 1 Output → Stage 3 Input	`oil_price_forecast_to_2035.csv`
`FP_CPI_TOTL_ZG`	Inflation, consumer prices (annual %)	Stage 2 Target	`comprehensive_economic_data.xlsx`
`NY_GDP_MKTP_KD_ZG`	GDP growth (annual %)	Stage 2 Feature	World Bank
`SL_UEM_TOTL_ZS`	Unemployment, total (% of labor force)	Stage 2 Feature	World Bank
`FR_INR_RINR`	Real interest rate (%)	Stage 2 Feature	World Bank
`(Other Macro Feat.)`	13 other macro-indicators (e.g., M2, trade balance)	Stage 2 Features	World Bank, Yahoo Finance
`Onshore`	WACC for Onshore Wind projects	Stage 3 Target (iterated)	`_WACC.xlsx`
`Offshore`	WACC for Offshore Wind projects	Stage 3 Target (iterated)	`_WACC.xlsx`
`(Other Projects)`	WACC for Nuclear, Solar, CCS, Coal, Gas, etc.	Stage 3 Target (iterated)	`_WACC.xlsx`
`inflation rate`	Inflation rate (from Stage 2) as predictor	Stage 3 Feature	`_WACC.xlsx`
`Coal Price`	Fossil fuel price (from Stage 1) as predictor	Stage 3 Feature	`_WACC.xlsx`
`Gas Price`	Fossil fuel price (from Stage 1) as predictor	Stage 3 Feature	`_WACC.xlsx`
`Oil Price`	Fossil fuel price (from Stage 1) as predictor	Stage 3 Feature	`_WACC.xlsx`
R^2	R-squared score of the fitted Stage 3 model	Stage 3 Output	`_results.csv`
`MAPE`	Mean Absolute Percentage Error of the model	Stage 3 Output	`_results.csv`
`RMSE`	Root Mean Squared Error of the model	Stage 3 Output	`_results.csv`