The impact of fossil fuels price on Weighted Average Cost of Capital (WACC) within energy transition projects in the future

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ABSTRACT

This study concentrates on evaluating the influence of fossil fuel price fluctuations on the Weighted Average Cost of Capital (WACC) in energy transition projects in the future. Through the analysis of historical price trends of fossil fuel prices, the research explores how market perceptions and price dynamics affect financing strategies. Long Short-Term Memory (LSTM) and Gaussian regression process(GRP) networks are utilized to prognosticate fossil fuel prices from 2025 to 2100. And a Stacking Regressor which includes Ridge, Decision Tree Regressor, Support Vector Regression, K Neighbors Regressor, and Random Forest Regressor is used to evaluate the impact of fossil fuel price on the WACC. Additionally, this study highlights geographic disparities by examining how fossil fuel-importing and -exporting countries respond to price fluctuations. Ultimately, the findings indicate that fossil fuel prices exert a relatively significant impact on nuclear, hydro, and biomass projects. Furthermore, regional differences are pronounced; fossil fuel-importing regions such as European countries and China demonstrate a higher R^2 value along with a broader spectrum of influential projects. In contrast, fossil fuel-exporting nations in the Middle East exhibit a lower model fit.

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1 INTRODUCTION

The urgency of global warming leads to the need for energy transition to achieve the Sustainable Development Goals (SDGs)([36]). Since energy consumption is the main source of global greenhouse gas emissions([5]), transforming global energy systems is crucial to mitigate climate change and achieve these goals. In response to the challenges, numerous initiatives have been launched, as prior research([29]) has proved the importance of environmental innovation in reducing ecological pressures. However, the energy transition is not only about implementing a more efficient energy system([8]); it also requires managing the environmental and social impacts to ensure sustainability([**rontiers2024**]). Consequently, the economic costs caused by transition projects need taking into account, especially for developing countries([49]). And a critical financial indicator in assessing the viability of such projects is the Weighted Average Cost of Capital (WACC), which indicates the average cost of a company or a countries' sources of capital([6]).

Previous studies have identified several key factors influencing the WACC, demonstrating that the capital cost of energy transition projects is the result of combined effects of various issues. Specifically, investors' risk perception and expectations directly impact WACC by dictating the required rate of return([3]). Strong policy signals([61]), such as the implementation of Renewable Portfolio Standards, can also enhance investor trust, reducing the perceived risk and thereby influencing WACC. Additionally, changes in technology costs([50]) and capital intensity, particularly for renewable projects, also significantly affect WACC, as technological advancements can potentially enhance resource utilization and their competitiveness([21]). For example, mature technologies benefit from lower costs due to reduced risks, while emerging ones face higher costs due to market uncertainties. Country risk([41]), which encompasses expectations of policy, economic and market risks in specific countries, is also a critical affecting factor, since higher country risk typically leads to higher required returns from investors. On the other hand, the accumulation of financing experience([4]) can reduce financial institutions' risk assessments of new technologies, leading to a decrease in WACC. In summary, these factors collectively influence WACC, impacting corporate financing costs and investment decisions.

In addition to the factors previously mentioned, fossil fuel prices may also influence WACC for energy transition projects. As previous studies demonstrate([2];[17]), volatility in fossil fuel prices affects the market risk and capital costs of energy companies, which may have impacts on the WACC. Specifically, changes in fossil fuel prices may raise the uncertainty and risk associated with energy projects([17]), influencing WACC and potentially suppressing investment in renewable energy projects. Aiming at exploring the impact of fossil fuels price changes in future decades, particularly with the accomplishment of the 1.5°C Climate Goal([56]), the research question of the study is: **How do fluctuations in fossil fuel prices influence the WACC for energy transition projects in the future, and how do these effects differ between fossil fuel importing and exporting countries?** Specifically, this study will explore how changes in fossil fuel prices affect WACC, particularly focusing on the differing economic contexts of importing(Europe and China) and exporting(Middle East) countries and its impact on the financial feasibility of renewable energy projects.

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2 CALCULATION OF WACC

For the WACC data, this study mainly uses [6]'s dataset, which contains their prediction for the WACC for different regions from 2020 to 2100 with the assumption of the of the accomplishment 1.5°C Climate Goal([56]). The calculation begins with analyzing past financial data at the enterprise level, using [40] and [27]'s method to calculate the cost of debt and equity, and incorporating the leverage ratio and tax rate to determine each company's WACC. This involves considering the costs of debt and equity, along with the tax impact. The formulas are as followed:

(a) **Firm-level WACC Calculation Formula:**

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

- $WACC_{it}$: weighted average cost of capital for firm i at time t.
- L_{it} : leverage ratio of firm i at time t.
- r_{Dit}: the cost of debt for firm i at time t.
- r_{Eit}: cost of equity for firm i at time t.
- TaxRate_{it}: tax rate for firm i at time t.

(b) **Leverage Ratio Calculation Formula:**

$$L_{it} = \frac{\text{Total Debt}_{it}}{\text{Total Debt}_{it} + \text{Total Equity}_{it}}$$

(c)**Cost of Debt Calculation Formula:**

$$r_{Dit} = \frac{\text{Interest Expense}_{it}}{\text{Total Debt}_{it}}$$

(d)**Cost of Equity Calculation Formula:**

$$r_{Eit} = \frac{\text{Total Cash Dividends Paid}_{it}}{\text{Total Equity}_{it}}$$

And the national WACC is then derived by weighting and averaging each company's WACC based on its share of the national market revenue, reflecting the country's overall financing cost and capital structure with the following formula. More WACC calculation example can be found in ([10] and [27]).

(e)**Country-level WACC Calculation Formula:**

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

- $WACC_{ct}$: weighted average cost of capital for country c at time t.
- Revenue_{it}: revenue of firm i at time t.
- $\text{Total Revenue}_{ct}$: total revenue of country c at time t.

After that, [6]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, illustrating the impact of global financial condition changes on financing costs.

(f) **Adjustment for WACC over Time (LRN Scenario)**:

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

- CoC_{tnT}: cost of capital for country n at time t and technology T.
- $\text{CoC}_{0n,T}$:initial cost of capital for country n and technology T.
- $Y_{tn,T}$: cumulative technology deployment of country n at time t and technology T.
- $Y_{0n,T}$: initial technology deployment of country n and technology T.
- bT:parameter based on the learning rate.

Utilizing the aforementioned data and assumptions, the study([6]) employs a suite of climate-energy-economy models, including IMACLIM, IMAGE, and WITCH, to simulate the variations in WACC under different climate policies and their implications for the energy transition. The modeling exercises project WACC values from 2020 to 2100 for various countries and energy technologies, considering factors such as cost of capital convergence (CoC-convergence), and the impact of additional climate policy measures.

3 PREDICTION OF FOSSIL FUEL PRICE

3.1 Long short term memory model(LSTM)

Studis ([46] and [38])have presented the role of machine learning model in fossil fuel predicting, especially LSTM. LSTM ([48]) is a recurrent neural network, which is proficient in handling sequence data with long-term dependencies. It uses a forget gate to decide the remaining of past information, an input gate to decide the receiving of new information, and an output gate to decide the output([33]). This design allows the model to flexibly control the flow of information. When using the LSTM for carbon price forecasting([60]), the optimal average coefficient of determination reached 0.982, and the average absolute percentage error (MAPE) was 0.555. These results indicate that LSTM is effective at capturing the multidimensional factors that influence fossil fuel prices and providing stable and reliable prediction results when dealing with complex time series data.

3.2 Gaussian regression process (GRP)

Previous study([31]) highlights the advantages of the GRP([44]) over other models in predicting fossil energy market prices. Specifically, GRP achieved an average root mean square error (RMSE) of 0.0434, the lowest among all compared models, indicating its superior prediction accuracy. In contrast, the average RMSE values for support vector regression (SVR)([57]) were 0.0445, regression tree (RT)([43]) 0.0498, k-nearest neighbor (kNN)([9]) 0.0642, and deep feed forward neural network (DFNN)([26]) 0.0640. These results clearly demonstrate the superiority of GRP in predicting future oil prices, particularly in terms of accuracy.

Specifically, the Gaussian regression process (GRP)([44]) used for predicting fossil fuel prices is based on a multivariate Gaussian process. The core of this approach lies in defining a probability distribution function $f(x)$, which follows a Gaussian process:

$$f(x) \sim GP(m(x), K(x, x))$$

Here([31]), $m(x)$ is the mean function, representing the expected value of $f(x)$; $K(x, x')$ is the covariance function (kernel function), which describes the correlation between random variables. Specifically, the mean function and covariance function are defined as follows:

$$m(x) = E[f(x)]$$
$$K(x, x') = E[(f(x) - m(x))(f(x') - m(x'))^T]$$

In this study, the chosen kernel function is the Gaussian kernel, which is given by:

$$k(x, x') = \exp[-\gamma \|x - x'\|^2]$$

Here, γ is a constant parameter that controls the width of the Gaussian kernel, thereby influencing the smoothness and flexibility of the model. Through Bayesian optimization([18]), the parameters of the GRP model were optimized, enabling the model to more accurately capture local variations in fossil energy market prices.

3.3 A combined model

Due to the efficiency and accuracy of LSTM and GRP, this study constructs a combined model involving both two algorithm to predict the fossil fuel prices from 2025 to 2100. The detailed steps are as followed:

First, the model preprocesses the original time series data, including removing missing values and outliers, and mapping the data to the range of 0 to 1 through normalization . Then, it uses an LSTM network for time series modeling. The model processes the input sequence through recurrent units. And in the model, each time step (the past 90 days of data) is the input, and LSTM generates predicted values for future time points by learning the nonlinear relationships and long-term patterns in those data.

After generating initial predictions, the model further added Gaussian noise to simulate the random fluctuations and uncertainty that may exist in real data. Therefore it enhances the robustness of the prediction results and makes them closer to reality. Then, the model inputs the noisy predicted results into the GPR model, which could generate predicted values and corresponding uncertainties based on input data points. In this case, GPR performs regression modeling by inputting the future date (in numerical form) as the independent variable and the LSTM's predicted results as the dependent variable. It not only smoothens the LSTM's predictions but also generates uncertainty estimates for each predicted point.

Based on the predicted values and standard deviations from the GPR output, the model further calculates the 0.95 confidence interval for each predicted point using the formula "predicted value ± 1.96 × standard deviation", providing a credible range for the prediction results. The upper and lower bounds of the confidence interval reflect the uncertainty of the prediction results.

4 DATA

To estimate the impact of fossil fuel prices on the WACC of energy transition projects in different regions, this study collects current and historical fossil fuel prices (coal, natural gas, and oil) from both previous research ([23])and dataset from World Bank.

Additionally, for the WACC values, this study focuses on data under the assumption of the 1.5°C goals from [6]'s dataset . Specifically, we select China+ and Europe to represent fuel-importing countries; Middle East to represent fuel-exporting countries , and the WACC of all transition countries to represent the world-wide capital cost within energy transition projects .

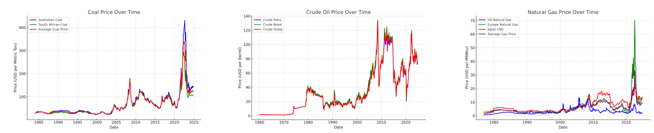

Figure 1: Historical fossil fuel price

5 METHOD

5.1 Prediction

Initially, this study collects historical fossil fuel prices (oil, natural gas, and coal) data from the World Bank dataset. Subsequently, we apply the combined model described in the previous section(3) to forecast oil, natural gas, and coal prices from 2025 to 2100. Specifically, monthly prices are predicted using both the LSTM([48]) and GRP([31]) models based on data from the preceding 90 months. The annual price is then calculated as the average of these monthly predictions.

5.2 Explore the impact of fossil fuel

To find the impact of fossil fuel, this study utilized the dataset generated by the previous prediction(3) and dataset form([6]), which includes WACC values of various energy transition projects (e.g., wind, nuclear, coal) and associated fossil fuel prices across time. Through Stacking Regressor([11]) analysis, this study evaluates how fluctuations in fossil fuel prices affect the WACC of diverse energy transition projects.

In our regression analyses, fossil fuel price (oil, natural gas, coal) was selected as the independent variable, while WACC served as the dependent variable. We conducted separate analyses for different energy types, including onshore, offshore, nuclear, carbon capture and storage (CCS), biomass, solar, and hydro. To develop a robust predictive model, we employed a Stacking Regressor model([11]), which is an ensemble learning technique that integrates predictions from multiple base learners. It utilizes five base learners: Ridge, Decision Tree Regressor, Support Vector Regression, K Neighbors Regressor, and Random Forest Regressor. Specifically, Ridge regression addresses the issue of multicollinearity through L2 regularization, which helps prevent overfitting. Decision tree regression is adept at capturing nonlinear relationships by dividing the data space into several regions for prediction, making it suitable for complex nonlinear problems. Support Vector Regression seeks the best regression plane in high-dimensional space, making it applicable to complex data. And K-nearest neighbor regression makes predictions by finding the nearest neighbor samples, not relying on distribution assumptions of the data. Additionally, Random forest regression builds multiple decision trees and averages their prediction results, demonstrating strong anti-overfitting capabilities.

To further enhance the model's performance, the code employs Randomized Search CV for hyperparameter tuning. By randomly selecting different combinations of hyperparameters within a broad parameter space, it can help identify the optimal model configuration, thereby improving prediction accuracy. The tuned hyperparameters include the regularization strength of ridge regression, the maximum depth of decision trees, the C value and epsilon value of SVR, etc. Ultimately, stacked regression combines the predictions of multiple base learners through linear regression as the meta-learner to make the final prediction. This ensemble method fully exploits the strengths of each base learner, reduces the potential bias of a single model, and thus provides more accurate and robust evaluation to the impact of fossil fuel fluctuations on WACC of energy transition projects.

6 RESULT

6.1 Fossil Fuel Price Prediction

As shown in figure (2), according to the prediction, from 2025 to 2100, the prices of fossil fuel (natural gas, oil, and coal) are expected to exhibit distinct trends. Natural gas prices are anticipated to be the most volatile, fluctuating within a range of approximately 6 to 18 dollars per unit, without a clear long-term upward or downward trajectory. This volatility reflects significant uncertainty in market supply and demand dynamics. Oil prices are predicted to follow a clear long-term downward trend, decreasing from around 76 dollars per barrel in early 2025 to approximately 62 dollars per barrel by 2100, while also experiencing periodic short-term fluctuations. Coal prices are projected to initially rise from about 125 dollars per unit to around 130 dollars per unit before stabilizing, entering a phase of relatively high but stable fluctuations.

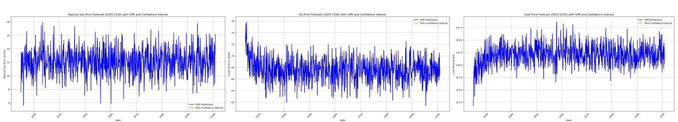

Figure 2: Fossil Fuel Price Forecasts

6.2 Transition Countries

In the analysis of the impact of fossil energy prices on the WACC of energy transition projects in overall transitional countries, this study finds that the prices of fossil energy have relative important influence on nuclear, biomass and hydropower projects among transition countries(3). Specifically, nuclear projects show a high correlation when facing fluctuations in the prices of oil, coal and natural gas, with R^2 values of 0.368, 0.504 and 0.291 respectively. These results indicate that the capital costs of nuclear projects are largely driven by the prices of fossil energy. Meanwhile, the RMSE and MAE values of these projects are relatively low, at 0.008, 0.007 and 0.009, which demonstrates the high accuracy of the model's predictions.

Similarly, biomass energy projects also demonstrate sensitivity to fluctuations in fossil fuel prices, with R^2 values of 0.368, 0.504, and 0.291 under the influence of oil, coal, and natural gas prices respectively. And the RMSE and MAE values of these projects are also low, at 0.008, 0.006, and 0.008, indicating the reliability of the predictive model. Additionally, hydropower projects also exhibit a certain degree of sensitivity when confronted with fluctuations under the influence of coal, oil, and natural gas prices, with R^2 values of 0.504, 0.367, and 0.215.

Figure 3: The Impact Of Fossil Fuel Price On WACC In Transition Countries

6.3 Europe

Under the influence of oil prices, the performance of various energy transition projects varies significantly. Offshore wind power and solar energy exhibit strong predictive capabilities, with R^2 values of 0.793 and 0.786 respectively(4), indicating high sensitivity to changes in oil prices. Their RMSE (0.000839, 0.000587) and MAE (0.000661, 0.000479) values are relatively low, demonstrating good model fit and low prediction error. Nuclear and hydropower projects also show moderate predictive capability, with R^2 values of 0.418 for both, and similarly low RMSE and MAE values, indicating reasonable accuracy.

Under the influence of coal prices, offshore wind power continues to perform well, with an R^2 value of 0.605, although this is lower than its performance under oil prices. Solar energy shows a significant correlation with an R^2 of 0.520, which is lower than its R^2 of 0.786 under oil prices but still indicates a strong association. Nuclear and hydropower projects have R^2 values of 0.311 under coal prices, suggesting some sensitivity.

Natural gas has a relatively minor impact on energy transition projects. However, nuclear, hydropower, and biomass projects exhibit some correlation with natural gas prices, with R^2 values around 0.3, which are relatively high compared to other projects.

6.4 China+ Regions

As presented in 5, this study finds that the fluctuation of oil prices has a relatively significant impact on the capital costs of nuclear, hydro, and biomass energy projects (all R^2 approximately 0.385). In contrast, the influence on onshore, offshore, and CSS projects is negligible (with R^2 values close to 0). The RMSE and MAE for nuclear, hydro, and biomass energy projects are also relatively low—both at approximately 0.001. This result indicates that the

Figure 4: The Impact Of Fossil Fuel Price On WACC In Europe

capital costs of these projects remain stable and predictable in response to fluctuations in oil prices. Additionally, the impact of coal price fluctuations mirrors that of oil prices; its effect on the capital costs of nuclear, hydro, and biomass energy projects is evident (all R^2 approximately 0.476). Furthermore, the influence of natural gas prices on solar energy projects is particularly pronounced (R^2 = 0.883), with RMSE and MAE values recorded at 0.000441 and 0.000411 respectively.

Overall, in China+ regions, fluctuations in fossil fuel prices have differing impacts on the capital costs of energy transition projects. Nuclear, biomass, and solar energy projects exhibit higher sensitivity to these price changes, whereas onshore and offshore wind projects show lower sensitivity.

Figure 5: The Impact Of Fossil Fuel Price On WACC In China+

6.5 Middle East

Regarding oil prices, the R^2 values for Nuclear, Hydro, and Biomass projects are approximately 0.392, with MAE values around 0.075(6). These results demonstrate strong predictive capabilities and indicate a significant correlation between their capital costs and oil prices. In the analysis of coal prices, Nuclear, Hydro, and Biomass projects continue to perform well, with R^2 values of 0.337, 0.335, and 0.336 respectively. Their RMSE and MAE values are approximately 0.010 and 0.008, indicating good predictive accuracy and a correlation between their capital costs and coal price changes. Additionally, CCS projects show some correlation with an R^2 value of 0.166, RMSE of 0.010, and MAE of 0.009.For natural gas prices, the performance of Nuclear, Hydro, and Biomass projects is relatively weaker, with R^2 values of 0.152, 0.179, and 0.151 respectively. Although their RMSE and MAE values remain low, their predictive accuracy is lower compared to that observed under oil and coal price fluctuations.

Figure 6: The Impact Of Fossil Fuel Price On WACC In Middle East

7 DISCUSSION

7.1 Regional Commonality

As shown in the results section, in most energy transition countries(3,5,46), fossil fuel prices have a significant impact on the WACC of nuclear, hydro, and biomass projects. The fluctuations of fossil fuel price influence market competitiveness, raw material expenses, and investor expectations([45]). An increase in fossil fuel prices enhances the comparative advantage of low-carbon energy sources, thereby stimulating financing and investment in renewable projects([35]). However, this also introduces greater market uncertainty and risk premiums. Conversely, a decrease in fossil fuel prices renders traditional energy sources more competitive, diminishing interest in renewable energy investments and raising the cost of capital for such projects.

Nuclear energy projects are characterized by substantial initial capital investments and extended construction periods([51]), with relatively fixed cost structures. In the context of rising fossil fuel prices, the production capital costs for traditional energy sources increase correspondingly. The relative stability of long-term operating costs for nuclear energy, coupled with its insensitivity to fluctuations in fossil fuel prices([39]), attracts greater investment into the sector, thereby reducing financing costs and capital expenditures. Conversely, when fossil fuel prices decline, traditional energy sources regain their cost advantage. Given the high initial capital outlay and prolonged construction timelines of nuclear projects([55]), they may face challenges in maintaining cost competitiveness. Furthermore, the success and feasibility of nuclear energy projects heavily rely on government policy support and subsidies([20]). Particularly during periods of high energy prices, governments may enhance subsidies for nuclear energy projects to stimulate investment in low-carbon technologies.

Similarly, hydropower projects are also typically large-scale, capital-intensive infrastructure initiatives with extended construction periods. Investors' expectations regarding capital costs are closely tied to fluctuations in fossil fuel prices([30]). Specifically, when fossil fuel prices rise, the relative competitiveness of hydropower projects increases, particularly in regions with limited access to abundant fossil fuel resources([59]). As a clean and sustainable energy source, hydropower may attract increased policy support and government subsidies, thereby reducing its capital costs. Conversely, when fossil fuel prices decline, the investment appeal of hydropower projects diminishes([42]). Investors may choose energy projects that offer higher short-term returns, which could potentially lead to an increase in the capital costs of hydropower projects. Moreover, the construction of hydropower facilities is constrained by natural resource availability and environmental conditions, resulting in uncertainty into capital expenditures([24]).

Additionally, the production of biomass energy primarily depends on the collection, transportation, and processing of biomass feedstocks (such as crop residues, wood, and forestry by-products)([28]). The prices of these raw materials are directly influenced by fluctuations in the energy market([7]). Compared to other renewable energy projects (such as wind and solar power), the costs associated with biomass energy are more sensitive to fluctuations in fossil fuel prices(3). Since the procurement of raw materials and fuels for biomass energy is closely tied to market prices for fossil fuels([34]). While the "fuel" required for other transition projects is essentially free and has a relatively fixed cost, unaffected by market volatility. Furthermore, biomass energy technology is still in its developmental stages([37]). Consequently, its cost structure is more likely to be influenced by technological advancements and economies of scale. Compared to mature technologies with established economies of scale, such as wind and solar power, the cost structure of biomass energy is more susceptible to changes([37]), especially in response to fluctuations in fossil fuel prices. Generally, biomass energy exhibits greater cost volatility in response to energy market changes due to its reliance on raw materials, particularly during periods of significant fossil fuel price fluctuations.

7.2 Regional Differences

7.2.1 Europe. Europe exhibits a consistently high R^2 value (0.3297 on average) in transition projects, indicating that the WACC responds robustly to fluctuations in fossil fuel prices(4). Furthermore, Europe has a higher proportion of non-zero R^2 projects(4), implying that a greater number of projects are sensitive to and can be explained by variations in fossil fuel prices. Additionally, Europe's lower RMSE and MAE values suggest that these projects have smaller prediction errors, thereby demonstrating higher stability and accuracy.

As a major importer of fossil fuels, particularly oil and natural gas, Europe is highly susceptible to fluctuations in fossil fuel prices ([47]). During energy transition, fossil fuel prices directly affect Europe's energy costs, economic stability, and project financing structures ([32]). Consequently, there is a strong correlation between the WACC of energy transition projects and fossil fuel prices. Moreover, Europe's energy transition projects benefit from a high degree of technological maturity and innovation ([14]), especially in wind and solar energy. These innovations enhance the projects' ability to efficiently and flexibly respond to changes in fossil fuel prices when addressing capital costs and financing needs. The European energy market([13]) is also characterized by its maturity and stability, shaped by long-standing renewable energy policies such as carbon trading systems, energy taxes, and subsidy programs. These policies, along with well-developed infrastructure ([12]) and market mechanisms, ensure that the energy market accurately reflects fossil fuel price fluctuations. It enables energy transition projects to better capture the impact of energy price changes on capital costs, thus making the WACC more responsive to fossil fuel price movements.

7.2.2 China+ region. The mean R^2 value for the China+ region (0.2195) (5)is lower than that of Europe (0.3297)(4), yet it remains above the global average. Notably, the R^2 value for natural gas in solar projects within the China+ region reaches 0.8839, indicating an exceptionally strong model fit and highlighting a robust correlation. Furthermore, the China+ region exhibits smaller RMSE and MAE values, suggesting higher accuracy and stability in predictive models.

The initial reason behind China's relatively high correlation between fossil fuel price and WACC of transition projects is the high reliant on imports of its energy market ([52]). As one of the world's largest importers of fossil fuels([58]), China's energy prices are significantly influenced by international market volatility. Secondly, the Chinese energy market is characterized by substantial government intervention. The government plays a pivotal role in setting energy prices ([19]), ensuring supply, and regulating market rules. Specifically, through subsidies and price controls, the government maintains market stability for fossil fuels([22]). These interventions reduce the uncertainty associated with energy prices, thereby minimizing the direct impact of price fluctuations on energy transition projects. Consequently, while China's energy transition still depends on fossil fuels, government intervention contributes to a lower R^2 value compared to more market-driven European countries.

7.2.3 Middle East. The data from the Middle East region exhibit a relatively low model fit, with an average R^2 of only 0.135(6), lower than that observed in other regions. Additionally, prediction errors (RMSE and MAE) in this region are generally higher. This suggests that the capital cost of energy transition projects in the Middle East is less influenced by fluctuations in fossil fuel prices.

The economies of fossil fuel exporting countries in the Middle East have long relied on oil and gas revenues, which reduce their urgency for energy transition ([25]). Rather than domestic market needs, the energy transitions in the region are driven more by international pressure and sustainability concerns ([54]). Abundant fossil fuel resources and stable exporting revenues slow the pace of energy transition([15]), keeping policies and investments focused on fossils. Consequently, fossil fuel price volatility has minimal impact on the capital costs of energy transition projects. Additionally, Middle Eastern energy markets are somewhat insulated from global oil and gas markets. Governments use price controls and reserve management to stabilize domestic markets([53]), mitigating the effects of global price fluctuations. This stability means changes in fossil fuel prices do not significantly affect consumers or enterprises([15]), further reducing its impact on capital costs of energy transition projects. In contrast, renewable technologies like solar and wind power require large initial investments and face higher price volatility([16]), suppressing their competitiveness. As a result, even if fossil fuel prices fluctuate, demand for renewable projects remains stable, minimizing the effect on capital cost.

8 CONCLUSION AND INTELLECTUAL MERIT

This research utilizes machine learning models to study how fossil fuel price fluctuations affect the Weighted Average Cost of Capital of energy transition projects in the future. Based on previous studies([6]), this study takes advantage of machine learning techniques (LSTM ([48]), GPR([31]), and Stacking Regressor([11])). By combining these methods with regional analysis (7), the research offers a unique, interdisciplinary way to understand the financial and behavioral impacts of fossil fuel price volatility, contributing to a deeper understanding of WACC dynamics in renewable energy.

Future research orientations could be centered on exploring the commonalities and particularities of diverse factors in shaping the WACC for energy transition projects. Although this study simply concentrates on the role of fossil fuel price, future endeavors might investigate how the piece could interact with factors like policy frameworks ([61]) and natural resource endowment ([1]) to have a joint impact on capital costs. Additionally, the combined impact of fossil fuel price fluctuations and capital-intensive technologies ([50] and [21]) to WACC could also be significant.

In the long run, research can be focused on collecting more extensive datasets to identify novel and emerging factors that influence energy transition costs. For example, exploring the potential of innovation and scientific investment (1) or refining project financing structures (1) could disclose new approaches to lower the WACC, thereby expediting energy transition projects. These studies will not only deepen our understanding on financial dynamics of energy transitions but also contribute to the sustainable development goals([36]).

9 CODE AVAILABLILITY

All the Data, code, and images are available in our **Github Repositories**. (Please click 'Github Repositories' to get the code,data, and images.)

Table 1: Influential factors on capital cost of energy transition ([3];[4]; [41];[60])

Factor	Description
Country Risk Premium	Political and economic stability could affect capital costs.
Technology Risk Premium	The additional return demanded by investors to compensate for the risks of adopting of new technologies.
Financing Experience Curve	Experience reduces costs for capital-intensive tech.
Policy Support	Subsidies and targets lower capital costs for low-carbon tech.
Market Maturity	Mature markets have lower capital costs.
Capital Intensity	The high ratio of capital investment to labor investment required for clean energy technologies.
Natural Resource Endowment	Abundant resources may not be fully exploited.
Carbon Emission Prices	Carbon pricing increases fossil fuel costs.
Project Financing Structure	Renewable rely on project financing cost.
Technology Maturity	Mature tech has lower costs; emerging tech higher.
Innovation and Investment	Innovation and Investment could accelerate cost reductions.

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