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US-China Tensions and renewable energy markets: A Dynamic Bayesian Inference Approach

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Abstract

This paper examines the impact of US-China trade tensions on renewable energy markets from 2010-2024. Using a Dynamic Bayesian Inference approach, we quantify time-varying sensitivities of four NASDAQ renewable energy indices: Solar, Wind, Geothermal, and Green Economy. Our findings reveal significant heterogeneity in market responses. These results suggest that certain renewable sectors have developed effective resilience mechanisms to geopolitical risks.

Keywords: Dynamic Bayesian Inference, US-China trade tensions, renewable energy

JEL classification: C11, F51, Q40

1. Introduction

The escalating US-China trade tensions have emerged as a critical factor reshaping global markets, with potential implications for the global energy transition. Recent trade disputes between these renewable energy giants have resulted in global trade losses exceeding \$165 billion (Amiti et al., 2019), triggered significant trade diversions (Bown, 2021), and reduced collaborative R&D initiatives (Feder, 2019). Despite growing evidence that geopolitical risks increase volatility across financial and commodity markets (Gong & Xu, 2022; D. Zhang et al., 2023), the specific impacts on renewable energy markets remain poorly understood.

The clean energy sector has experienced rapid growth due to significant government investments driven by the Paris Agreement and green finance initiatives (Demiralay et al., 2023; D. Zhang et al., 2023). As leaders in the global energy transition, both the US and China dominate key segments such as battery technologies and solar panel manufacturing. Their dominance makes renewable energy markets particularly vulnerable to bilateral tensions, which can disrupt supply chains (Walmsley & Minor, 2020), increase costs, and delay critical projects (Wu et al., 2024). This vulnerability raises an important research question: How do US-China trade tensions affect different segments of renewable energy markets, and have these impacts evolved over time?

While existing studies have extensively examined the impacts of geopolitical risk on conventional markets, including equity markets (Ali et al., 2023; Balli et al., 2023), commodity markets (Go & Yong, 2024; Gong & Xu, 2022), bond markets (Liu et al., 2024), and cryptocurrency markets (Aysan et al., 2019; Plakandaras et al., 2021), the renewable energy sector has received comparatively little attention. Furthermore, traditional econometric approaches such as Markov regime-switching models and TVP-VAR-SV models often fail to capture the nuanced, time-varying sensitivities of individual renewable energy indices to geopolitical events.

To address this gap, we investigate the impact of US-China tensions on four renewable energy markets. Our Dynamic Bayesian Inference framework offers distinct advantages over conventional methods by allowing for adaptive estimation of market-specific characteristics such as volatility, persistence, and baseline evolution, thereby providing more granular insights into how these markets respond to geopolitical pressures. Furthermore, we estimate the predictive performance of our models across different market segments using cross-validation and error metrics, ensuring robustness and reliability. Finally, we examine how market responses to geopolitical tensions have evolved over time, with a particular focus on adaptation and resilience patterns.

Our analysis reveals significant heterogeneity in how renewable energy markets respond to US-China tensions. Solar energy demonstrates the most dramatic transformation, evolving from initial negative sensitivity to the strongest positive response, while geothermal exhibits declining sensitivity over time. These findings suggest that certain renewable sectors have developed resilience mechanisms to geopolitical risks, potentially through domestic capacity development and policy support, while others remain vulnerable to international tensions.

We contribute to existing literature in several important ways. First, we extend the emerging literature on geopolitical risk by documenting new evidence on how US-China trade tensions impact renewable energy markets complementing existing studies on conventional markets such as commodities, equities, and cryptocurrencies. Second, we offer methodological contribution which provides superior insights into time-varying market sensitivities, compared to traditional methods such as TVP-VAR-SV models (Ali et al., 2023), Markov regime-switching (Sheenan, 2023), copula models (Wu et al., 2025), and other traditional methods.

Third, we contribute to understanding the dynamics of energy market by documenting heterogeneous responses of energy markets to US-China trade dispute. Finally, our findings have important policy implications suggesting that targeted policy interventions and diversification strategies may help mitigate the adverse effects of geopolitical tensions on renewable energy markets and support the global transition to clean energy.

2. Method and Data

In order to analyze the impact of US-China tensions on renewable energy market we used four renewable energy indices including the NASDAQ OMX Green Economy Index, NASDAQ OMX Solar Energy Index, NASDAQ OMX Wind Energy Index, and NASDAQ OMX Geothermal Energy Index¹ spanning from October 2010 to February 2024.

Table 1: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Median	Min	Max	Skew.	Kurt.
Green_Econ	161	1785.99	714.92	1558.39	919.53	3549.43	0.81	-0.70
Geothermal	161	1049.48	237.41	987.32	729.34	1924.24	1.09	0.96
Solar	161	1627.85	1274.21	1063.90	301.60	4446.92	1.01	-0.63
Wind	161	1791.69	928.51	1712.81	444.86	4324.03	0.59	-0.38

Based on the descriptive statistics shown in Table 1, Green_Econ and Wind indices have similar average values (around 1,780), while Geothermal is much lower (about 1,050). Solar shows the highest variability, with a very large standard deviation (1,274) and the widest range, indicating substantial volatility. Geothermal is the most stable series, with the smallest dispersion. All series exhibit moderate positive skewness, meaning occasional high values; kurtosis values near zero indicate distributions close to normal, with no extreme tail behavior.

The U.S.–China Tension (UCT) index by Roger et al. (2024) is chosen because it provides a systematic, high-frequency, and text-based measure of geopolitical frictions that directly affect global supply chains and technology-intensive sectors such as renewable energy. Its construction follows the established Baker–Bloom–Davis methodology, ensuring transparency and replicability. Figure 1 shows the UCT index over time from 2010 to 2024.

¹ These indices were chosen because they provide sector-specific, transparent, and investable measures of renewable market activity. Each index captures a distinct technological segment allowing analysis of heterogeneous market sensitivities to US–China tensions.

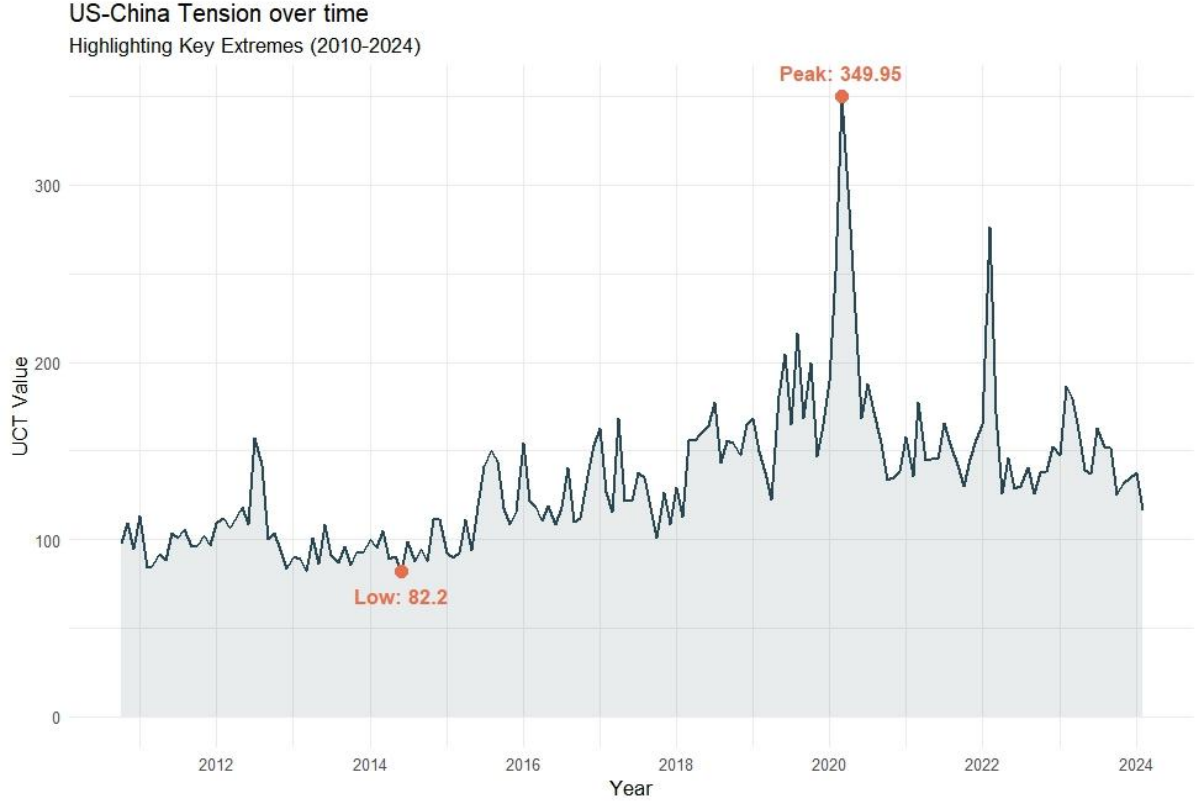


Figure 1. UCT index over time

This study employs a Dynamic Bayesian Inference Approach. We selected this approach because it offers several advantages over traditional econometric models, particularly in capturing time-varying sensitivities to geopolitical events and accounting for the inherent uncertainty in financial market dynamics. For each renewable energy market the response variable $y_{c,t}$ at time t is modeled as:

$$y_{c,t} \sim p_c(y_{c,t}|y_{c,t-1}, x_{c,t}, \theta), \quad (1)$$

where:

- $y_{c,t}$: Observed value of the renewable energy index for market c at time t ,
- $y_{c,t-1}$: Lagged value of the renewable energy index for market c ,
- $x_{c,t}$: Measure of US-China tensions at time t ,
- θ : Set of all model parameters.

The conditional distribution p_c depends on a linear predictor $\eta_{c,t}$ structured as follows:

$$\eta_{c,t} = \alpha_{c,t} + X_{\beta,c}\beta_c + X_{\delta,c,t}\delta_{c,t} + \lambda_c\psi_{c,t}, \quad (2)$$

where:

- $\alpha_{c,t}$: Time-varying intercept capturing the baseline level of the renewable energy index,
- β_c : Vector of time-invariant coefficients for exogenous predictors,
- $\delta_{c,t}$: Vector of time-varying coefficients for exogenous predictors, including sensitivity to US-China tensions,
- $\psi_{c,t}$: Latent dynamic factor capturing unobserved market dynamics,

- λ_c : Factor loading for the latent factor.

In our model, $\alpha_{c,t}$ represents the baseline trajectory of each renewable energy market, independent of geopolitical factors. The time-varying coefficient $\delta_{c,t}$ specifically measures the sensitivity of each market to US-China tensions, with positive values indicating market growth in response to increased tensions and negative values suggesting market decline. The persistence parameter τ (derived from the temporal evolution of $\delta_{c,t}$) quantifies how long the effects of tensions persist in each market, while the volatility parameter σ measures the inherent variability of market responses.

Predictions are based on the posterior predictive distribution with uncertainty quantified via prediction intervals:

$$\hat{y}_{c,t} = \mathbb{E}[y_{c,t} | y_{c,t-1}, x_{c,t}, \theta] \quad (3)$$

3. Empirical Results

This section presents our findings on the impact of US-China tensions on renewable energy markets. We begin by examining the time-varying parameter estimates across the four markets (Table 1), followed by an analysis of model performance and validation metrics. Figure 2 illustrates the evolution of market sensitivities to geopolitical tensions over a 14-year period.

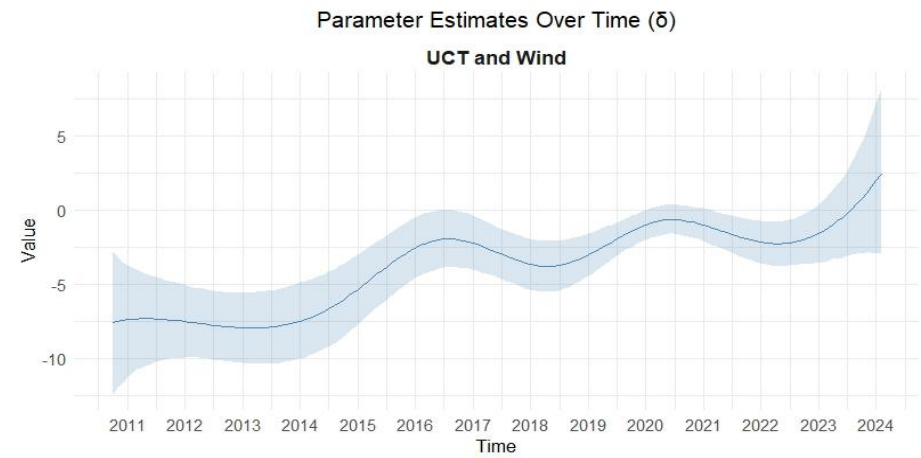
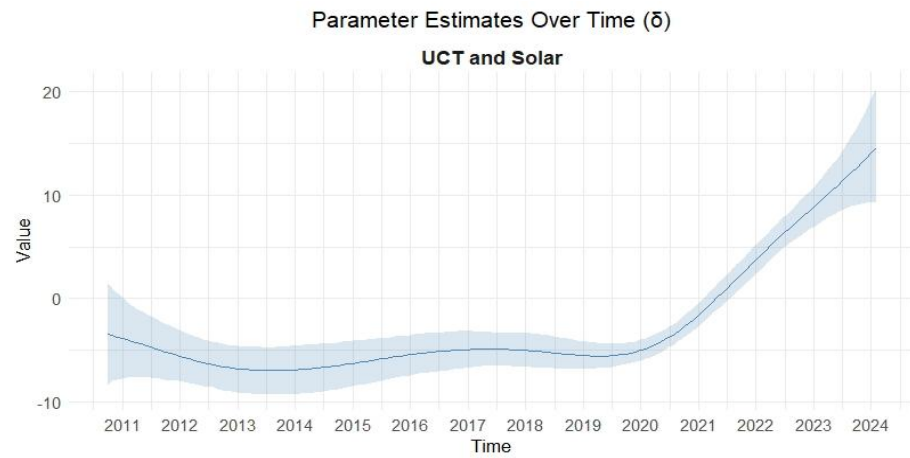
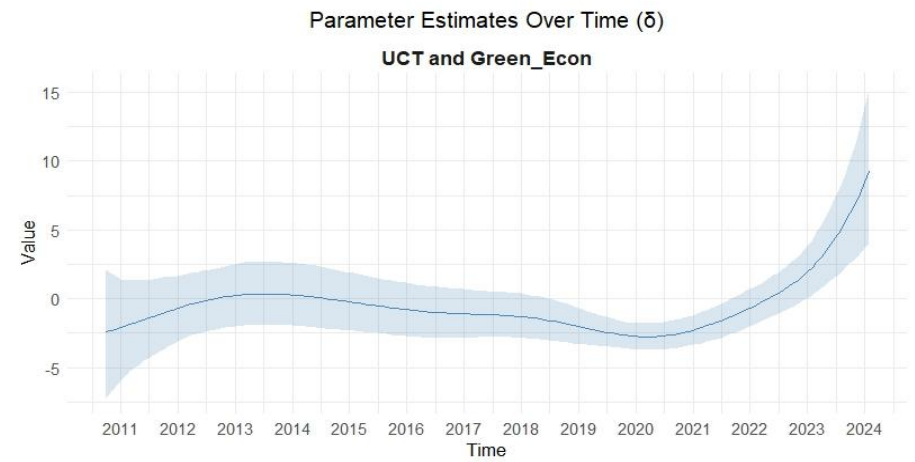
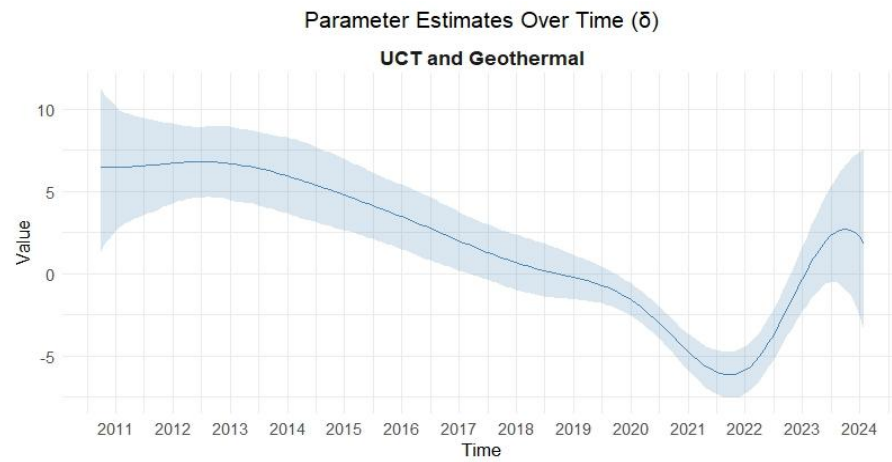


Figure 2. Time-varying parameter estimates for sensitivity to US-China tensions.

Solar energy demonstrates the most dramatic transformation, transitioning from initial negative sensitivity (-3.47) to the strongest positive response (14.54) by the study's end, with narrow confidence intervals supporting statistical significance. This suggests increasing resilience and potential benefits from trade tensions, possibly through domestic capacity development and policy support. Green Economy investments show similar directional shift, evolving from early negative effects (-2.42) to substantial positive impact (9.29) in recent periods with narrowing confidence intervals. Geothermal sector exhibits declining sensitivity, moving from strong initial positive response (6.47) to moderate effect (1.82), with widening confidence intervals indicating increased uncertainty. This suggests diminishing the influence of geopolitical factors on this established technology. Wind energy shows progressive improvement from initial negative impact (-7.56) to modest positive effect (2.40), though wider final confidence intervals suggest heterogeneous market responses. This indicates gradual development of market resilience to international tensions.

Table 2: Impact of US-China Tensions on renewable energy market

Parameter	Geothermal	Green_Econ	Solar	Wind
Model Parameters				
δ (US-China tensions effect)	-809.596*** [342.824]	145.106*** [339.773]	204.416*** [342.557]	504.1441*** [342.442]
τ (Persistence)	8.365*** [2.625]	4.389*** [1.7813]	6.365*** [2.0124]	6.411*** [2.4144]
σ (Volatility)	121.866*** [6.9396]	114.322*** [6.90]	251.174*** [14.960]	222.388*** [13.402]
Time-Varying Intercepts (α):				
Initial (Oct 2010)	1079.585*** [147.360]	1346.568*** [443.377]	1367.85*** [428.112]	1245.492*** [546.815]
Mid-Period (Jun 2017)	1072.062*** [89.090]	1636.734*** [137.966]	1404.23*** [194.596]	1982.319*** [214.736]
Final (Feb 2024)	1206.15*** [148.258]	970.7908*** [673.740]	3677.368*** [634.214]	1674.993*** [904.828]

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The findings (Table 2) demonstrate heterogeneity in market responses. The geothermal sector exhibits the highest persistence ($\tau = 8.365$) and lowest volatility ($\sigma = 121.866$) among all renewable segments. However, its negative sensitivity coefficient ($\delta = -809.596$) suggests vulnerability to escalating geopolitical tensions. Despite this, the sector maintained relatively stable valuations, progressing modestly from 1079.585 to 1206.15 over the study period. Solar energy is the most dynamic segment, demonstrating growth trajectory (α : 1367.85 to 3677.368) despite elevated volatility ($\sigma = 251.174$). This, coupled with moderate geopolitical sensitivity ($\delta = 204.416$), indicates the sector's capacity to leverage international tensions for market expansion. The wind energy sector presents the strongest positive response to geopolitical tensions ($\delta = 504.144$). Its mid-period peak ($\alpha = 1982.319$) suggests adaptation to international dynamics, though relatively high volatility ($\sigma = 222.388$) indicates ongoing market adjustment processes. Green economy demonstrates cyclical behavior, with a mid-period peak ($\alpha = 1636.734$) followed by a significant correction. This pattern, combined with moderate

sensitivity ($\delta = 145.106$) and lowest volatility ($\sigma = 114.322$), suggests a maturing market segment.

Figure 3 compares actual values (dashed lines) against model predictions (solid lines) with 95% prediction intervals (shaded areas).

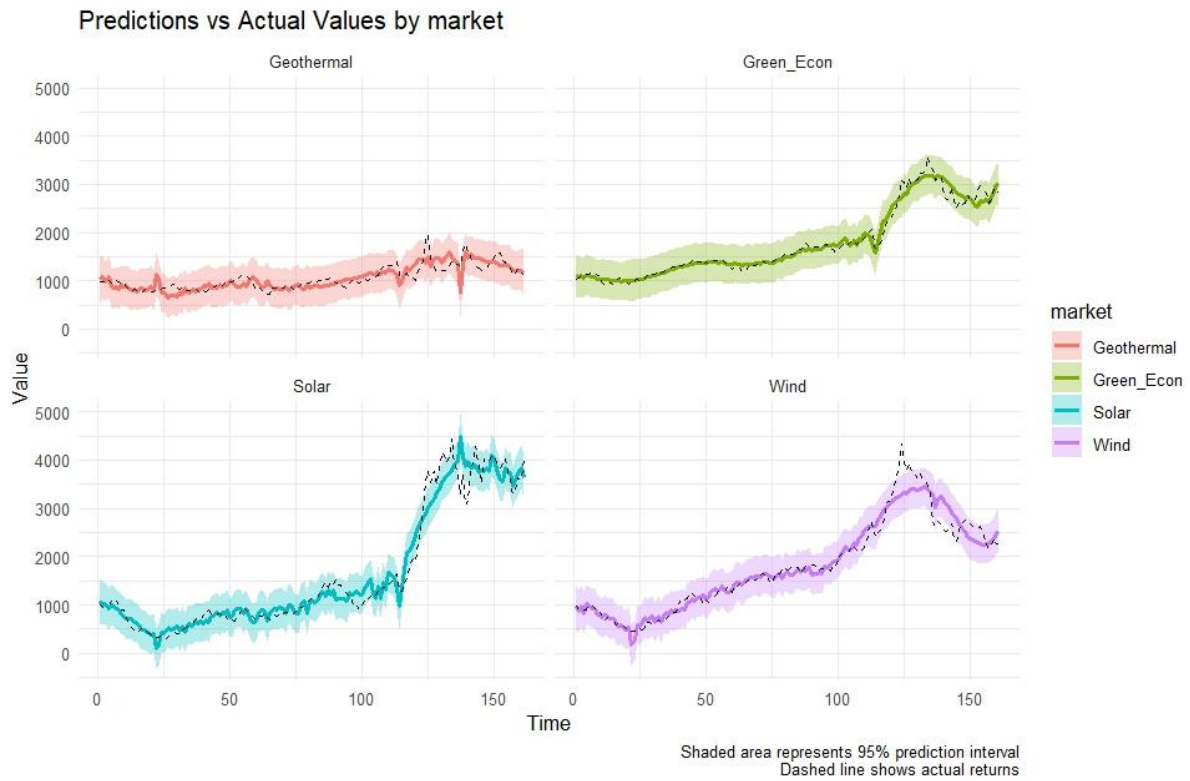


Figure 3. Predictive performance of Bayesian models.

Geothermal shows stability, with tight prediction intervals indicating high model reliability and market predictability. Green Economy displays upward trajectory with widening prediction intervals post-2020, suggesting increasing market uncertainty despite. Solar exhibits growth pattern, with model accurately capturing the steep acceleration post-2020. Wind demonstrates cyclical behavior with a pronounced peak followed by decline. Overall prediction quality is strong across all markets, with actual values consistently falling within 95% prediction intervals.

Table 3: Performance Prediction by market

Market	Mean Pred.	SD Pred.	Mean Actual	RMSE	MAE
Geothermal	1049.346	318.677	1049.476	255.041	202.399
Green_Econ	1786.405	734.813	1785.986	236.688	187.559
Solar	1628.433	1251.716	1627.847	330.484	251.960
Wind	1790.801	913.054	1791.692	307.002	235.859

The model demonstrates strong overall accuracy (Table 3), with mean predicted values closely matching actual means across all sectors (within 1% deviation). Geothermal exhibits the lowest standard deviation (318.677) and competitive error metrics (RMSE: 255.041, MAE: 202.399), reflecting its stable market characteristics. Green Economy shows the best predictive accuracy (lowest RMSE: 236.688, MAE: 187.559) despite substantial volatility (SD: 734.813). Solar presents the highest prediction variability (SD: 1251.716) and largest errors (RMSE: 330.484), consistent with its dynamic growth phase. Wind energy demonstrates intermediate performance metrics (RMSE: 307.002), balancing prediction accuracy with market volatility (SD: 913.054). Figure 4 tracks prediction accuracy across market segments.

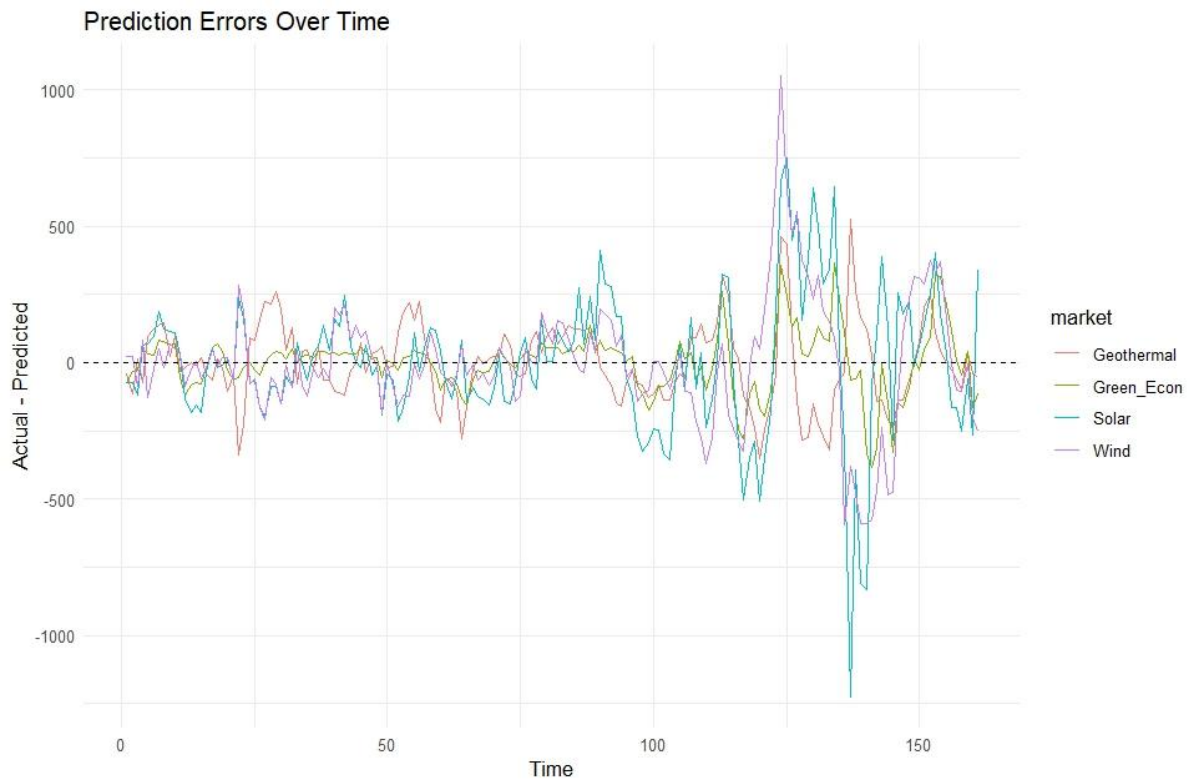


Figure 4. Prediction errors over time.

The initial study period demonstrates consistency, with prediction deviations contained within ± 200 points. However, the latter period exhibits increased error volatility. Solar energy presents the most challenging predictions, with errors ranging from -1000 to +800 points. Wind energy shows oscillations in prediction accuracy, while Green Economy maintains relatively controlled error margins. Notably, Geothermal consistently demonstrates the smallest prediction errors.

To ensure robust model evaluation, we implemented leave-one-out cross-validation (LOO-CV) using Pareto-smoothed importance sampling (Table 4).

Table 4: Leave-One-Out Cross-Validation Results

Model	ELPD_LOO	ELPD_SE	P_LOO	P_LOO_SE	LOOIC	LOOIC_SE
Geothermal	-1007.9	17.8	12.4	3.4	2015.7	35.6
Green_Econ	-1003.7	14.8	21.6	4.7	2007.5	29.7
Solar	-1128.3	16.8	18.2	5.3	2256.6	33.5
Wind	-1108.0	14.4	16.6	3.3	2215.9	28.9

Note: ELPD-LOO = expected log pointwise predictive density; p-LOO = effective number of parameters; LOOIC = leave-one-out information criterion; SE = standard error.

The Green Economy model shows optimal predictive performance (ELPD-LOO: -1003.7) with moderate parameter complexity (p-LOO: 21.6), while Solar exhibits lower predictive density (ELPD-LOO: -1128.3), reflecting its higher market volatility. The Geothermal model achieves strong predictive performance (ELPD-LOO: -1007.9) with the lowest parameter complexity (p-LOO: 12.4), indicating efficient market dynamics capture. Wind maintains balanced performance metrics (ELPD-LOO: -1108.0, p-LOO: 16.6). All models show good Pareto k estimates ($k < 0.7$), confirming reliable cross-validation results. The relatively small standard errors across metrics suggest stable model performance, with LOOIC values reinforcing the comparative model rankings.

4. Conclusion

This study shed light on the interplay between US-China trade tensions and renewable energy markets, using Dynamic Bayesian Inference. Solar energy showed resilience, while Green Economy investments showed cyclical yet increasingly positive trends. Geothermal's sensitivity waned, and Wind energy demonstrated gradual improvement despite volatility. This diverse response suggests that each sector is developing unique mechanisms facing geopolitical risks. The study's innovative methodology offered deeper insights than traditional approaches, providing valuable guidance for policymakers crafting energy security strategies and investors navigating geopolitical risks in their portfolio decisions.

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