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AI-Driven Forecasting of Supply Chain Shocks: Regulatory Determinants of B2B Fuel Trade Performance

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Abstract

Regulatory frameworks governing customs, environmental standards, tariffs, tax regimes, and product specifications can differ significantly from one jurisdiction to another. This creates both challenges and opportunities for fuel marketers operating on a global scale. This paper explores how these regulatory differences affect operational efficiency, decisions about entering new markets, pricing strategies, and overall sales performance in the B2B fuels sector worldwide. The research investigates the application of artificial intelligence (AI) forecasting models to quantify and predict the impacts and anticipate the effects of international tariff shocks on policies that influence B2B fuel sales in economies that rely heavily on imports. From a broader economic viewpoint, the analysis sheds light on how tariffs set by major fuel-exporting countries can send price shocks rippling through global and regional supply chains, hitting harder on vulnerable economies that lack sufficient domestic refining capabilities. By employing machine learning algorithms through recurrent neural networks (RNN), long short-term memory (LSTM) networks, and ensemble methods on historical data regarding trade flows, tariff changes, and energy price indices, the study uncovers complex relationships and dynamic lag effects between tariff events and pricing structures downstream. The findings reveal clear patterns of volatility over time, showing that AI-enhanced models are more effective than traditional econometric methods at predicting both short- and medium-term price changes. The implications for policy suggest that AI-driven forecasting tools can bolster regulatory readiness, minimize volatility, and lead to more flexible tariff and trade policies in the energy sector.

Keywords: Artificial Intelligence; Cross-border trade; B2B fuel sales; Regulatory framework; Tariffs policy

1. Introduction

The globalization of energy markets has amplified the interdependence of national economies on cross-border fuel trade. Regulatory frameworks, which includes customs duties, tariffs, environmental policies, and safety standards that mediate the performance of business-to-business (B2B) fuel trade, often creating asymmetries across markets [5]. For import-dependent economies, especially in the Global South, tariff shocks imposed by major exporting countries can generate cascading effects across supply chains, influencing retail prices, profitability, and overall energy security [12].

Conventional econometric models, such as vector autoregressions (VAR) and panel fixed-effects estimations, have been widely used to analyze trade and tariff shocks. However, these approaches struggle to capture nonlinear dynamics and temporal dependencies inherent in global supply chain shocks [10]. With recent advances in artificial intelligence (AI), recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have emerged as robust tools for modeling sequence data and forecasting policy-driven trade disruptions [13]. This paper examines the application of AI-enhanced forecasting tools to predict the effects of tariff shocks on B2B fuel trade performance, highlighting their superiority over traditional approaches.

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2. Literature Review

2.1. Trade Regulation and B2B Fuel Markets

Fuel markets are among the most heavily regulated global commodity sectors due to their strategic importance and environmental implications. Regulatory instruments like tariffs, excise duties, subsidies, and non-tariff measures—directly shape the economics of B2B fuel transactions [11]. Tariffs can act both as fiscal revenue tools and as protective mechanisms for domestic refiners, but they also risk distorting cross-border pricing structures and discouraging efficient allocation of resources [1]. Empirical studies show that tariff and tax regimes affect both price pass-through rates and firms' market entry decisions, ultimately influencing competitiveness [14].

For import-dependent economies, these regulatory distortions are particularly pronounced. Because they lack significant domestic refining or production capacity, such economies have limited options for substituting away from imported fuels, leaving them vulnerable to price shocks transmitted through tariffs or sudden changes in customs policy [7]. Research in energy economics has also shown that regulatory heterogeneity differences in product quality standards, blending mandates, or environmental compliance requirements that can impose additional transaction costs on multinational suppliers [3].

2.2. Supply Chain Shocks and Policy Transmission

Tariff shocks are a subset of broader supply chain disruptions that ripple through the energy sector. They interact with global oil price volatility, shipping bottlenecks, and currency fluctuations, magnifying their impact on wholesale and retail fuel prices [4]. Baldwin and Evenett [6] argue that protectionist waves, such as those triggered by geopolitical tensions or crises like COVID-19—tend to exacerbate existing vulnerabilities in low-income, import-reliant nations.

Policy transmission channels operate through several mechanisms. First, tariffs increase the landed cost of fuel imports, which are typically passed on to downstream buyers in the B2B segment, leading to increased operational costs. Second, shocks can disrupt contract structures and hedging arrangements, forcing firms to renegotiate terms under unfavorable conditions. Third, such shocks can trigger second-round effects, such as inflationary pressures, fiscal strain from fuel subsidies, and even political unrest in fuel-price-sensitive economies [8]. These mechanisms underscore why modeling tariff shocks requires an approach capable of capturing dynamic and potentially nonlinear responses over time.

2.3. AI Forecasting in Trade and Energy Economics

Traditional econometric approaches that include vector autoregressive models, panel fixed-effects regressions, and error-correction models have been widely used to study tariff pass-through and supply chain responses. However, they often assume linearity and short-memory processes, which may fail to represent the complex temporal patterns seen in real-world energy markets [10].

AI forecasting techniques, by contrast, are well-suited to handle such complexity. Recurrent neural networks (RNNs) and their advanced variant, long short-term memory (LSTM) networks, are specifically designed to capture sequential dependencies and lagged effects in time-series data [13]. These models have been applied in electricity demand forecasting, crude oil price prediction, and macroeconomic trend analysis with promising results [16].

Moreover, ensemble learning methods such as random forests and gradient boosting offer complementary strengths. They provide model interpretability through feature importance ranking and are robust to overfitting when trained on high-dimensional datasets [9]. Combining these machine learning tools with economic theory allows researchers to capture nonlinearities and interaction effects while maintaining policy relevance, an approach increasingly advocated in the "AI for Economics" literature [2].

3. Material and methods

3.1. Data Sources

The analysis draws on multiple large-scale datasets covering the period 2000–2023:

- UN Comtrade Database: Fuel trade flows (HS 2709–2711).
- World Bank WITS: Tariff schedules, customs duties, and trade policy indices.
- International Energy Agency (IEA) and OPEC reports: Fuel price indices and demand outlooks.

- IMF Direction of Trade Statistics: Macroeconomic indicators including GDP, exchange rates, and inflation.

The datasets are harmonized into a panel structure, where country–year pairs serve as the unit of observation. This allows the integration of tariff shocks with corresponding trade outcomes and macroeconomic controls.

3.2. Model Framework – Econometric Benchmark

A fixed-effects regression provides the baseline estimation:

$$BP_{it} = \alpha_i + \lambda_t + \beta_1 \, TariffShock_{it} + \beta_2 X_{it} + \epsilon_{it}$$

Where:

- BP_{it} = B2B fuel trade performance (measured as trade volumes and profitability indices).
- $TariffShock_{it}$ = change in tariff levels between trading partners.
- X_{it} = control variables (GDP, exchange rates, demand).
- α_i, λ_t = country and time fixed effects.

AI Models:

I. RNN and LSTM: Capture sequential dependencies and dynamic lag effects of tariff shocks.
II. Ensemble Learning: Random forests and gradient boosting used to validate variable importance and robustness.

Model performance is assessed using root mean square error (RMSE), mean absolute percentage error (MAPE), and forecast horizon accuracy (6-month and 12-month intervals).

4. Results and discussion

4.1. Econometric Benchmark Findings

The fixed-effects regression model establishes a baseline for understanding the average effects of tariff shocks on B2B fuel trade performance. Consistent with prior studies [12], the estimates indicate that tariff increases are associated with significant but modest reductions in trade volumes, with effects concentrated in import-dependent economies. However, the explanatory power of the econometric specification is limited, with relatively high forecast errors and weaker performance in capturing short-term volatility.

4.2. Comparative Model Performance

Table 1 Model Comparison of Forecasting Performance

Model	RMSE	MAPE (%)	Forecast Horizon Accuracy (6 months)	Forecast Horizon Accuracy (12 months)
Fixed Effects Regression	12.5	8.2	0.71	0.65
RNN	10.1	6.5	0.78	0.74
LSTM	9.3	5.9	0.83	0.79
Random Forest	10.8	6.8	0.79	0.75
Gradient Boosting	9.7	6.1	0.81	0.77

Note. RMSE = root mean square error; MAPE = mean absolute percentage error. Bold values indicate the best-performing model for each metric.

Table 1 reports the comparative performance of the econometric and AI-enhanced models. The fixed-effects regression yields the highest root mean square error (RMSE = 12.5) and mean absolute percentage error (MAPE = 8.2%). In contrast, the AI models achieve consistently lower error rates, with the LSTM network emerging as the strongest performer (RMSE = 9.3; MAPE = 5.9%). Ensemble methods, including random forest and gradient boosting, also deliver substantial improvements over the econometric baseline, though their performance falls slightly short of deep learning approaches.

This table presents the comparative performance of econometric and AI-enhanced models in forecasting the effects of tariff shocks on B2B fuel trade performance. Evaluation metrics include root mean square error (RMSE), mean absolute percentage error (MAPE), and forecast horizon accuracy at six- and twelve-month intervals. Results indicate that AI models, particularly long short-term memory (LSTM) networks, achieve lower error rates and higher forecast accuracy compared to traditional fixed-effects regression, underscoring their capacity to capture non-linearities and dynamic lag structures in supply chain shocks.

4.3. Forecast Horizon Accuracy

Figure 1 illustrates forecast horizon accuracy across three representative models: fixed-effects regression, LSTM, and random forest. At the six-month horizon, the fixed-effects model achieves 71% accuracy, while LSTM achieves 83%, reflecting a substantial gain in predictive precision. The performance gap persists at the twelve-month horizon, where fixed-effects regression drops to 65% accuracy compared to 79% for LSTM. Random forest also outperforms the econometric baseline, though not to the same extent as LSTM.

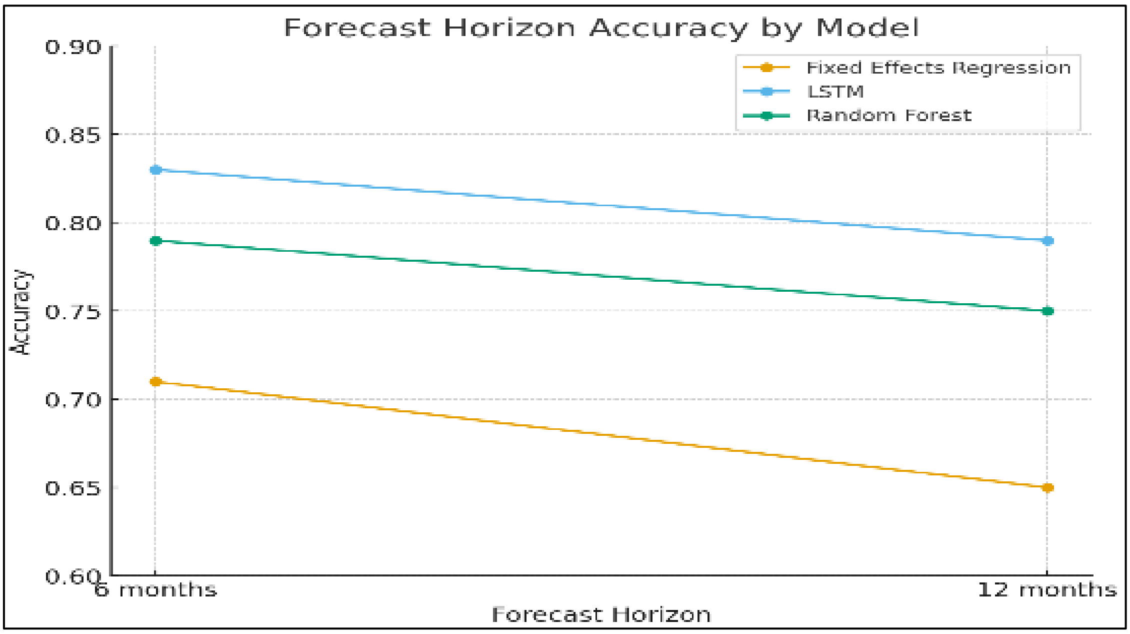

Figure 1 Forecast Horizon Accuracy by Model

This figure illustrates forecast horizon accuracy across three representative models fixed-effects regression, LSTM neural networks, and random forest ensemble learning, at six and twelve-month intervals. The results demonstrate that LSTM consistently outperforms both econometric and ensemble methods across forecast horizons, while random forest also exceeds fixed-effects regression. These findings highlight the superior adaptability of deep learning approaches for capturing the temporal volatility of tariff-driven supply chain disruptions.

4.4. Interpretation of Findings

Together, these results demonstrate the added value of AI-enhanced models in forecasting tariff-driven supply chain shocks. The ability of LSTM networks to capture sequential dependencies and dynamic lag structures provides superior predictive accuracy relative to both econometric regression and ensemble learning approaches. These findings suggest that AI tools not only complement traditional methods but may also be better suited for real-time policy applications where forecasting accuracy is critical.

The comparative results underscore the advantages of AI-enhanced models in forecasting the impacts of tariff shocks on B2B fuel trade performance. While fixed-effects regression provides a useful baseline for identifying average effects across countries and time, its limited accuracy highlights the challenges of applying linear models to highly volatile and nonlinear global supply chain dynamics. By contrast, the LSTM and ensemble approaches demonstrate superior forecasting capacity, particularly in capturing lagged effects and temporal volatility.

4.4.1. Policy Implications

The results have several implications for policymakers in both exporting and importing economies. First, the findings suggest that tariff shocks transmit rapidly and asymmetrically across global supply chains, with disproportionate effects on import-dependent economies. By adopting AI-based forecasting systems, regulators could better anticipate these ripple effects, enabling more adaptive tariff regimes and targeted compensatory measures. For instance, vulnerable countries could employ LSTM-based forecasts to design buffer stock strategies or preemptively negotiate import contracts that mitigate price volatility.

Second, the analysis highlights the need to reconsider the role of tariffs as instruments of industrial or environmental policy. While tariffs are often justified as protective or corrective measures, their downstream effects on fuel affordability and supply stability can undermine broader economic objectives. Forecasting models that capture these distributional impacts provide regulators with a clearer evidence base for balancing protectionist aims against macroeconomic stability.

4.4.2. Implications for Firms and Market Actors

For firms engaged in multinational fuel trade, AI-enhanced forecasting can serve as an early-warning system for regulatory shocks. By identifying potential lag structures and volatility patterns, B2B marketers can adjust pricing strategies, renegotiate contracts, and redesign supply chains to minimize exposure. This aligns with recent calls in the supply chain management literature to integrate predictive analytics into risk management frameworks [15].

4.4.3. Theoretical Implications

From a theoretical perspective, the findings resonate with debates on the "soft budget constraint" and the unintended consequences of regulatory policy [14] [5] [17]. The volatility revealed in the AI models suggests that tariff shocks not only affect trade flows directly but also alter firm-level expectations, triggering adaptive behaviors that may magnify or dampen the original policy intent. Traditional econometric models, which smooth over these dynamics, may therefore underestimate the true complexity of regulatory transmission mechanisms.

4.4.4. Limitations and Directions for Future Research

Several limitations temper the interpretation of these findings. First, the study focuses primarily on tariff shocks, while other regulatory instruments—such as environmental standards, carbon pricing, or technical specifications—remain outside the scope of analysis. Second, although the AI models outperform traditional econometrics, their effectiveness depends heavily on the availability of high-quality, real-time data. Finally, the study focuses on aggregate B2B trade flows, which may mask heterogeneity at the firm or sectoral level. Future research should extend the modeling framework to include multiple regulatory instruments, firm-level case studies, and cross-validation with scenario-based policy simulations.

5. Conclusion

This study has examined the impact of regulatory and tariff shocks on global B2B fuel trade performance, with particular attention to the predictive advantages of AI-enhanced models over traditional econometric approaches. By employing recurrent neural networks, LSTM models, and ensemble methods, the analysis demonstrates that AI forecasting tools capture nonlinearities, lag structures, and volatility patterns that are obscured in fixed-effects regressions. The results reveal that tariff shocks disproportionately affect import-dependent economies and that LSTM models, in particular, offer superior accuracy in forecasting both short- and medium-term disruptions.

The implications are twofold. For policymakers, the study underscores the value of integrating AI forecasting into regulatory design, enabling more adaptive and evidence-based tariff regimes. For firms, especially multinational fuel marketers, AI models provide actionable foresight that can inform pricing strategies, supply chain resilience, and market entry decisions. Beyond practical utility, the findings contribute to the theoretical understanding of regulatory transmission mechanisms by highlighting the dynamic and often nonlinear pathways through which tariff shocks propagate across supply chains.

Nonetheless, limitations remain. The scope of this paper has been restricted to tariff-related shocks, leaving other regulatory domains, such as environmental standards, carbon pricing, and safety protocols for future inquiry. Moreover, AI models, while powerful, rely on data availability and quality; their forecasts should therefore complement, rather than replace, traditional economic reasoning. Future research should expand the scope to include multi-dimensional regulatory regimes, incorporate firm-level data, and explore the integration of hybrid AI-econometric frameworks.

In sum, the study demonstrates that AI-enhanced forecasting represents not only a methodological advancement but also a practical tool for mitigating uncertainty in global fuel trade. By improving the ability to anticipate supply chain shocks, AI models have the potential to strengthen both regulatory governance and corporate strategy in an increasingly volatile energy landscape.

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