EXECUTIVE SUMMARY

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Beyond PPML: Exploring machine learning alternatives for gravity model estimation in international trade

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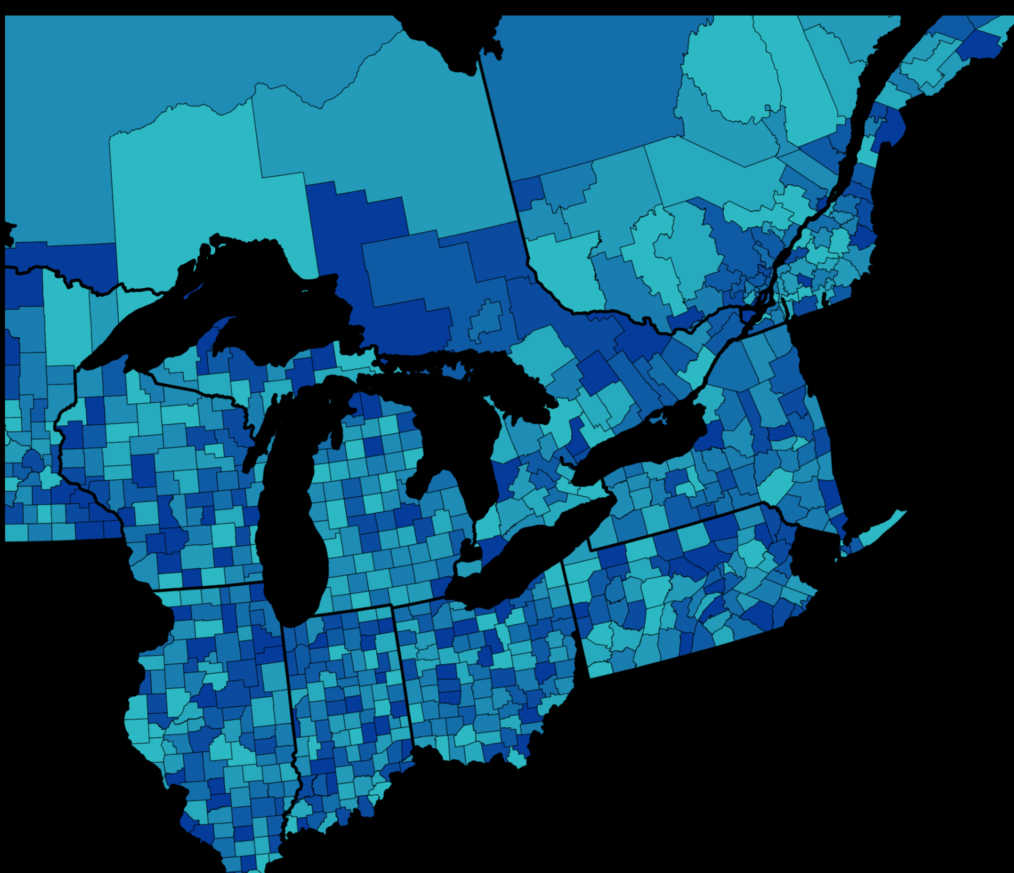

Abstract

This study investigates the potential of machine learning (ML) methods to enhance the estimation of the gravity model, a cornerstone of international trade analysis that explains trade flows based on economic size and distance. Traditionally estimated using methods such as the Poisson Pseudo Maximum Likelihood (PPML) approach, gravity models often struggle to fully capture nonlinear relationships and intricate interactions among variables. Leveraging data from Canada and the US, one of the largest bilateral trading relationships in the world, this paper conducts a comparative analysis of traditional and ML approaches. The findings reveal that ML methods can significantly outperform traditional approaches in predicting trade flows, offering a robust alternative for capturing the complexities of global trade dynamics. These results underscore the value of integrating ML techniques into trade policy analysis, providing policymakers and economists with improved tools for decision-making.

Introduction and Contribution

The gravity model has been a fundamental tool in international trade analysis, traditionally estimated using econometric methods such as Ordinary Least Squares (OLS) and Poisson Pseudo Maximum Likelihood (PPML). These conventional techniques, however, face challenges in capturing nonlinearities and handling zero trade flows effectively. This study explores the potential of machine learning (ML) techniques—Random Forest, XGBoost, and Neural Networks—to improve the predictive accuracy of gravity models and provide new insights into trade patterns.

Our research offers a significant contribution by systematically comparing traditional econometric models with ML approaches using trade data between Canadian provinces and U.S. states. This comparison highlights the strengths and weaknesses of each method, providing valuable guidance for policymakers and researchers in selecting the most appropriate estimation techniques for different trade modeling scenarios.

Methodology

The study employs a two-stage approach. First, we estimate gravity equations based on [McCallum, 1995] and [Anderson and Van Wincoop, 2003] using both traditional econometric models (OLS, PPML, Gamma PML, and Negative Binomial PML) and ML methods (Random Forest, XGBoost, and Neural Networks). Second, we compare their predictive performance using root mean square error (RMSE), mean absolute error (MAE), and R-squared metrics.

Our dataset comprises trade flows among Canada's provinces and between Canadian provinces and U.S. states. We analyze two scenarios: one that includes zero trade flows and another that excludes them, allowing us to assess how different methods handle sparse data. The ML models are trained on a portion of the dataset and tested on an independent sample to evaluate their predictive capabilities. Similarly, the traditional models are estimated using the same subset, and their performance is measured using the test dataset.

Key Findings

- **Improved Predictive Accuracy**: ML models, particularly XGBoost and Random Forest, outperform traditional econometric models in predictive accuracy when zero trade flows are excluded. These models capture complex relationships between trade determinants that standard methods may overlook.

- **Handling of Zero Trade Flows**: When zero trade flows are included, PPML and Negative Binomial PML perform better in terms of robustness and interpretability. Machine learning models experience a decline in predictive performance under these conditions.
- **Trade-off Between Interpretability and Performance**: While ML models provide superior predictive power, traditional methods retain an advantage in terms of coefficient interpretability, which is crucial for policy analysis and economic inference.
- **Log Transformations Enhance ML Performance**: Applying log transformations to trade values significantly improves the accuracy of ML models, suggesting that preprocessing plays a critical role in optimizing these techniques for trade data analysis.

Policy Implications

The findings of this study have direct implications for policymakers and trade analysts. Given the increasing complexity of global trade networks, integrating ML approaches into trade policy analysis can enhance forecasting accuracy, improve the identification of trade barriers, and facilitate data-driven decision-making. However, when zero trade flows are prevalent, traditional econometric methods remain essential for obtaining reliable policy insights. By leveraging both econometric and ML techniques, policymakers can gain a more comprehensive understanding of trade dynamics and make informed decisions regarding tariffs, trade agreements, and regional economic integration. Future research should explore hybrid modeling approaches that combine the interpretability of traditional methods with the predictive power of ML, further advancing the field of trade economics.

Conclusion

This study demonstrates that machine learning methods offer a promising alternative to conventional gravity model estimation techniques, particularly in scenarios where predictive accuracy is the primary objective. However, traditional methods continue to play a crucial role in addressing issues related to zero trade flows and ensuring model interpretability. The integration of ML into trade analysis represents an important methodological advancement, providing new opportunities for enhancing the robustness and reliability of trade flow predictions.

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