

Machine Learning Counterfactual Analysis of Section 301 Tariffs

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1 Introduction

This memo presents a machine learning counterfactual analysis of U.S. vehicle production and sales in the context of the Section 301 tariffs. The objective is to construct a data-driven benchmark for how production and sales would have evolved in the absence of policy-induced disruptions, using only observable macroeconomic and industry fundamentals.

The analysis focuses on four key outcomes: commercial vehicle production, light vehicle production, commercial vehicle sales, and light vehicle sales. For each outcome, a walk-forward machine learning model is used to generate real-time forecasts that serve as counterfactual predictions. The difference between observed values and these predictions provides a transparent measure of deviations from expected economic dynamics.

2 Data

The underlying dataset is derived from the monthly HS6-level panel constructed in Sosa (2026). The original panel is collapsed to a national monthly time series for each outcome by aggregating across product categories. This transformation produces a unified macro-level dataset that is consistent with both the econometric analysis and the forecasting framework.

Each outcome variable, denoted generically as (Y_t) , corresponds to one of the four series of interest. The feature set includes macroeconomic controls such as unemployment, inflation, interest rates, and time trends, along with indicators for major structural periods such as the COVID-19 shock.

The feature vector is defined as:

$$X_t = \left(Z_t, Y_{t-1}, Y_{t-2}, Y_{t-3}, Y_{t-6}, Y_{t-12}, \bar{Y}_t^{(3)}, \bar{Y}_t^{(6)}, \bar{Y}_t^{(12)}, S_t \right)$$

where (Z_t) represents macroeconomic controls, lagged values of the outcome capture persistence, rolling averages summarize recent dynamics, and (S_t) denotes seasonal

indicators constructed from monthly dummies.

This structure allows the model to capture both short-run dynamics and longer-term trends in production and sales.

3 Methodology

The analysis implements a walk-forward forecasting framework designed to mimic real-time prediction. At each point in time, the model is estimated using only information available up to the previous period, and a forecast is generated for the current period. Formally, the prediction is given by:

$$\hat{Y}_t = f_t(X_t), \quad \text{where } f_t \text{ is estimated using data up to } t - 1$$

The function ($f_t(\cdot)$) is approximated using a Random Forest model, which captures nonlinear relationships and interactions among predictors. The estimation is repeated recursively for each period, producing a sequence of out-of-sample forecasts.

The key object of interest is the counterfactual gap:

$$\text{Gap}_t = Y_t - \hat{Y}_t$$

This gap measures the deviation between observed outcomes and the level predicted by macroeconomic fundamentals. A negative gap indicates underperformance relative to expected dynamics, while a positive gap indicates stronger-than-expected outcomes.

The analysis explicitly distinguishes between several periods, including the pre-policy phase, the post-policy period following the introduction of Section 301 tariffs in July 2018, the COVID-19 disruption window, and the subsequent recovery period. This structure allows for a nuanced interpretation of forecast deviations across different economic environments.

4 Results

The results indicate that the machine learning models track pre-policy dynamics closely, suggesting that the selected features provide a strong representation of underlying economic conditions. After the introduction of the tariffs, however, systematic deviations between observed and predicted values emerge across multiple outcomes.

In the post-policy period, observed production and sales frequently fall below their predicted levels, generating negative gaps that are consistent with disruptions to supply chains and increases in input costs. These deviations are particularly informative when examined outside the COVID-19 window, where confounding macroeconomic shocks are less pronounced.

The walk-forward framework ensures that these results are not driven by look-ahead bias, as each prediction is based solely on information available at the time. As a result, the estimated gaps can be interpreted as real-time deviations from expected economic trajectories.

5 Contributions

This analysis extends the empirical framework of Sosa (2026) by introducing a machine learning-based counterfactual approach. While the main paper relies on causal inference methods such as difference-in-differences and event-study designs, the present framework provides a complementary predictive perspective.

The counterfactual gaps generated by the model offer an intuitive and transparent way to visualize the aggregate impact of policy interventions. By comparing observed outcomes to a benchmark driven purely by macroeconomic fundamentals, the analysis isolates periods in which production and sales deviate from expected patterns.

In addition, the project demonstrates the integration of high-dimensional administrative data, machine learning forecasting, and automated data pipelines. This end-to-end workflow highlights the practical applicability of modern data science methods in applied economic research.

6 Interactive Dashboard

An interactive Tableau dashboard accompanies this analysis and presents the counterfactual predictions and gaps for all four outcomes. The dashboard allows users to compare observed and predicted series over time, visualize deviations across policy periods, and explore differences between production and sales dynamics.

The dashboard is available at:

https://public.tableau.com/app/profile/alfredo.sosa/viz/dashboard_ml_counterfactual/ML-Counterfactual

This interactive tool complements the statistical analysis by translating model outputs into an accessible visual format. It also reinforces the connection between the forecasting framework and the broader policy analysis by highlighting periods of divergence associated with trade interventions.

7 Conclusion

The machine learning counterfactual framework provides a flexible and informative approach to analyzing production and sales dynamics in the presence of trade policy shocks. By generating real-time predictions based on macroeconomic fundamentals, the model establishes a credible benchmark against which observed outcomes can be evaluated.

The resulting gaps offer a clear and intuitive measure of deviations from expected trends, complementing the causal estimates in Sosa (2026). Together, these approaches provide a more comprehensive understanding of the economic effects of Section 301 tariffs on the U.S. automotive sector.