AI Driven Analysis of Trade Tariff Impacts on Consumer Prices in the U.S.

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Abstract

The public thinks that higher U.S. tariffs directly cause higher consumer prices. Tariffs can raise import costs, but inflation is also affected by other factors such as past inflation, demand, wages, and energy prices. This project studies the link between tariffs and U.S. CPI changes from 2023 to 2025 using federal data from USITC and BLS. I cleaned and merged tariff and CPI data by category and month, then built two model groups. The first group used only tariff features. The second group added CPI lag features and seasonality. Tariff only models performed weakly ((R$\hat{2}$) around 0.06 to 0.10). Enhanced models performed much better ((R$\hat{2}$) around 0.67 to 0.84). The main finding is simple: tariffs matter, but they are not strong enough by themselves to predict the CPI well. The CPI momentum (recent CPI behavior) is a much stronger predictor. This gives a more balanced policy message: trade policy is one part of inflation but not the full story.

I. Introduction

Tariffs are often blamed for higher prices, but inflation is usually caused by many things at the same time. Tariffs can increase import costs, but wages, energy prices, supply problems, demand, and inflation expectations also matter. Because of this, one policy variable alone usually cannot explain all CPI changes.

This project studies U.S. data from 2023 to 2025 to answer a practical question: are CPI changes better explained by tariff variables or by the CPI's own recent history? To answer this, I build two models. The first group uses only tariff features. The second group adds lagged CPI and seasonality features. The goal is to compare their prediction performance and see which signal is stronger in short run CPI forecasting.

This is a predictive study, not a causal study. The results show which variables help the prediction, but do not prove the direct cause and effect.

II. Background

Tariffs are taxes on imports. Their goal may be to protect domestic industries or respond to trade disputes. However, tariffs can also increase production costs, especially in sectors that rely on imported inputs. Previous studies show that tariffs pass through, but vary by product, retailer behavior, and market structure [1]–[3]. Inflation research also shows that current inflation depends on recent inflation, expectations, and macro shocks [4]–[6]. So, the key issue is not whether tariffs matter at all, but how large their role is compared to broader inflation dynamics.

III. Problem Statement

Public debate often overstates or oversimplifies the effects of tariffs on inflation. There is limited recent category level evidence for 2023-2025 that directly compares tariff variables and the history of CPI in one modeling pipeline. This study addresses the following question: *How much do tariff related variables explain CPI changes compared to lagged CPI variables?*

IV. Research Objectives

1) Build category level tariff exposure features aligned with CPI categories and month-year timing.
2) Measure year over year CPI change in main categories.
3) Compare baseline models (tariff only features) vs enhanced models (tariff + lagged CPI + seasonality + interactions).
4) Evaluate whether tariff features materially improve prediction performance.

V. Related Work

Many studies examine how tariffs affect consumer prices. Cavallo et al. [1] show that when tariffs increase, import prices at the border increase rapidly, but retail prices adjust more slowly. Jaravel and Sager [2] find that trade exposure changes prices differently between products and households. Flaaen et al. [3] show that firms respond to trade policy by changing where they produce and how they set prices.

Amiti, Redding, and Weinstein [7] find that recent U.S. tariffs were paid mainly by domestic consumers and firms, not foreign exporters. Fajgelbaum et al. [8] estimate that tariff increases led to measurable welfare losses for U.S. consumers.

Although these studies show that tariffs can raise prices, other research shows that inflation is persistent. Stock and Watson [4] find that lagged inflation plays a strong role in predicting future inflation. Coibion et al. [5] emphasize that expectations help sustain inflation over time. Bernanke and Blanchard [6] argue that recent U.S. inflation was caused by several interacting forces, not one single policy.

In general, past research suggests that tariffs affect prices, but inflation is also driven by its own past behavior and broader economic forces. This study compares these effects directly using recent U.S. data.

VI. Data Collection

This project uses public federal data from:

- U.S. International Trade Commission (USITC) tariff data [9]
- U.S. Bureau of Labor Statistics (BLS) CPI data [10]

USITC files provide product level tariff information by HTS related fields. BLS files provide monthly CPI values by category and series. All data were downloaded from official government sources.

VII. Data Description

The final analysis focused on six CPI categories with tariff coverage: Food, Apparel, Housing, Transportation, Medical, and All Other Services Goods. Main target variable: year over year CPI change (Main tariff feature: normalized mean tariff (0–100 scale), plus lagged versions (3, 6, and 12 months). After cleaning and filtering, the data set used for core modeling contained about 18,948 observations. Enhanced modeling (which adds CPI lag features) used a smaller complete case sample (about 11,528) due to lag requirements.

VIII. Methodology

A. Data Preparation

I used public data from USITC (tariffs) and BLS (CPI). First, I cleaned both datasets and aligned them by category, year, and month. Next, I mapped the description of the tariff products into CPI categories using keyword rules. Then I merged the two datasets and forward filled tariff snapshots within each category to allow the monthly CPI records to match. After merging, I created useful features:

- Normalized mean tariff (0–100 scale)
- Tariff lags (3, 6, 12 months)
- CPI lag features (1, 3, 6, 12 months)
- Month seasonality indicators
- Tariff by category interaction terms

I also capped extreme CPI values at the 1st and 99th percentiles to improve model stability.

B. Modeling and Validation

Six models were trained: Linear Regression, Ridge, lasaso, Elastic Net, Random Forest, and Gradient Boosting.

I tested two sets of controls:

1) **Baseline:** tariff features only.
2) **Enhanced:** tariff features + CPI lag features + month seasonality indicators + tariff by category interaction terms.

For model evaluation, I used R^2, RMSE, and MAE on both training and test data. Since the data are ordered by time, I used a chronological split: earlier months for training and later months for testing. This avoids look ahead bias. As an extra check, rolling origin (walk forward) validation can also be used to confirm that model performance is stable over time.

CPI is a time based series, so past inflation often affects current inflation. For this reason, I added lagged CPI features. These lag features help the models capture inflation momentum. Without them, the models miss an important part of CPI behavior.

Ridge, Lasso, and Elastic Net are regularized linear models, so they help reduce overfitting when features are correlated. Random Forest and Gradient Boosting are Tree-based models, so they can learn nonlinear relationships between tariffs, CPI history, and seasonal patterns. Using a chronological train test split helps make the evaluation closer to real forecasting conditions.

In addition to the modeling pipeline, I developed an interactive web simulation app to explore tariff scenarios and predicted CPI effects. Users can change tariff levels and compare baseline and enhanced model outputs. The full app code is available on GitHub for transparency and reproducibility [11].

IX. Results

This section summarizes (i) the overall CPI data patterns and (ii) baseline vs. enhanced model performance.

A. Data Pattern

Before evaluating model performance, we briefly examine the overall data behavior across the CPI categories. In descriptive summaries, the changes in the CPI varied significantly by category and time period, reflecting both the general inflation momentum and the category specific dynamics.

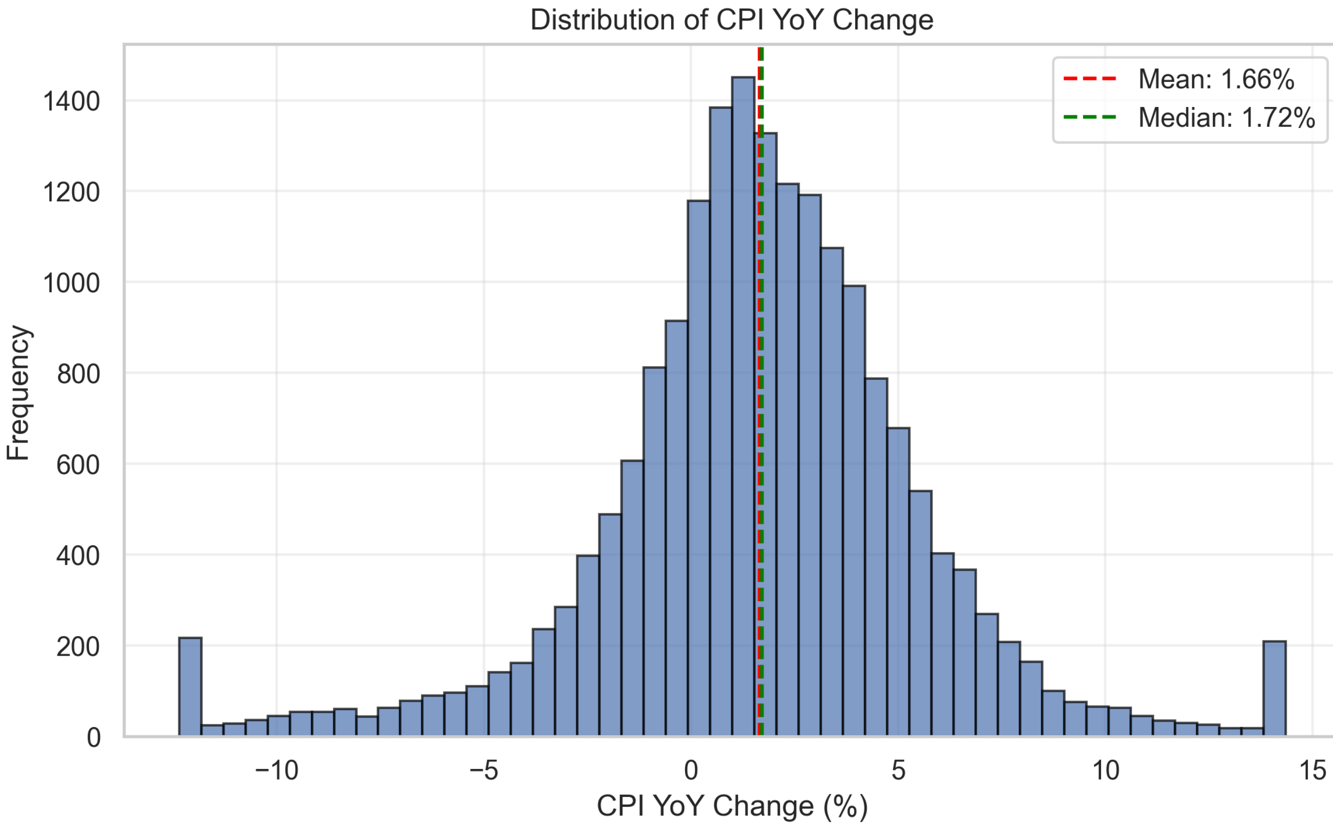

Fig. 1. Distribution of CPI year-over-year change across categories (summary view).

Distribution of year over year CPI changes, centered on low positive values (mean 1.66%, median 1.72%), with most observations between 0% and 4% and relatively rare extreme movements (approximately − 12,6]

B. Baseline vs. Enhanced Performance

We compare baseline models (tariff features only) against enhanced models (tariff features plus lagged CPI and seasonality features).

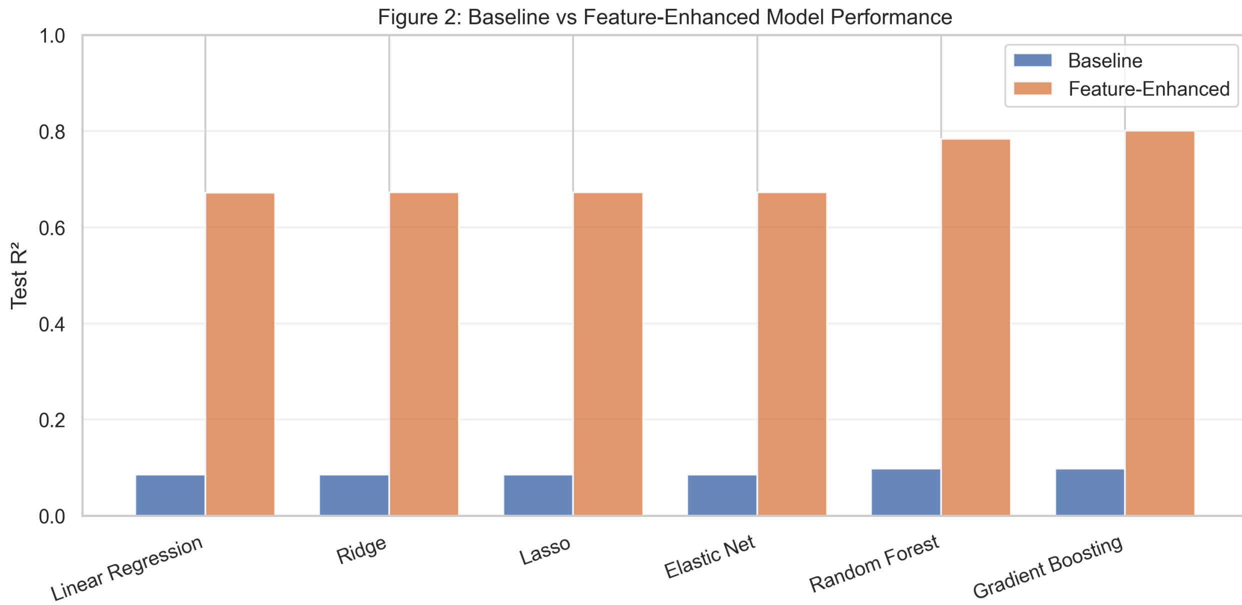

Fig. 2. Baseline vs. enhanced model performance (test R^2).

Figure 2 shows a consistent performance gap between the baseline and Feature enhanced models in all six algorithms. Baseline models cluster at low explanatory power (test R^2 around 0.08 to 0.10), while Feature enhanced models increase substantially (about 0.67 to 0.80). This uniform improvement indicates that adding CPI lags, seasonality, and interaction features captures an important structure in inflation dynamics that tariff only inputs miss. The strongest performance is observed in Tree-based models, especially Gradient Boosting, while linear and regularized models also improve to a similar mid range level. Overall, the pattern suggests that historical inflation information is a dominant predictor of CPI movements, with tariffs contributing as part of a broader set of characteristics.

TABLE I
BASELINE AND ENHANCED MODEL PERFORMANCE

Model	Baseline R^2	Baseline RMSE	Baseline MAE	Enhanced R^2	Enhanced RMSE	Enhanced MAE
Linear Regression	0.0860	3.8291	2.7444	0.6721	2.1710	1.4112
Ridge	0.0860	3.8291	2.7445	0.6726	2.1691	1.4108
Lasso	0.0859	3.8294	2.7447	0.6723	2.1704	1.4070
Elastic Net	0.0859	3.8295	2.7454	0.6724	2.1698	1.4088
Random Forest	0.0983	3.8034	2.7189	0.7838	1.7627	1.1348
Gradient Boosting	0.0982	3.8035	2.7200	0.8005	1.6935	1.1216

The improvement from baseline to enhanced models is large. The R^2 increases from about 0.09 to greater than 0.70. This suggests that the most predictable CPI movement during this period comes from inflation's own past behavior rather than tariff variables alone. This result is consistent with previous research showing that lagged inflation is often a strong short term predictor [4].

This does not mean that tariffs have no effect. Instead, it shows that tariffs alone cannot explain most month to month CPI changes.

C. Main Finding

Across the model families, the baseline performance (tariff only) was poor (test $R^2 \approx 0.09$). After adding lagged CPI and seasonality features, performance improved substantially (test R^2 up to about 0.80). The greatest improvement came from including lagged CPI terms, which capture inflation momentum.

D. Model Comparison

Six models were used to test the same problem in different ways. Some models are simple and easy to explain. Some models are more flexible and can find complex patterns.

- **Linear Regression:** the simplest model. It draws a straight-line relationship.
- **Ridge:** similar to Linear Regression, but adds a penalty to keep coefficients smaller and more stable.
- **Lasso:** also adds a penalty and can remove less useful features by setting some coefficients to zero.
- **Elastic Net:** combines Ridge and Lasso, so it can both stabilize and select features.
- **Random Forest:** uses many decision trees and averages them. Good for nonlinear relationships.
- **Gradient Boosting:** builds trees step by step to fix earlier errors. Often gives high prediction accuracy.

E. Category Notes

The behavior of the categories was not uniform. In some slices, Transportation showed negative average YoY CPI values, while still being highly relevant in model based diagnostics. This is expected: simple correlation summarizes pairwise linear association, whereas model based importance reflects contribution within a multivariate predictive system.

X. Comparison with Real World Evidence

The model results are consistent with the research patterns in real life.

First, previous studies show that the pass through of tariffs exists, but is incomplete and uneven between products and sectors [1]–[3]. Our baseline results match this pattern: tariff only features explain only a small part of CPI changes ($R^2 \approx 0.09$).

Second, inflation studies show that persistence (inflation momentum) is a strong short term driver [4], [5]. Our enhanced models show the same pattern: When the lagged CPI and seasonality are added, the performance increases strongly (up to $R^2 = 0.8005$).

Overall, this supports a balanced interpretation: tariffs can add price pressure, but CPI history and broader macro dynamics provide more predictive power in the short run.

XI. Project Timeline (8 Weeks)

1) Review relevant literature and finalize project design.
2) Collect data from USITC and BLS.
3) Clean and preprocess the collected data.
4) Conduct feature analysis and exploratory data analysis.
5) Develop baseline models.
6) Build and compare enhanced models.
7) Interpret results and create visualizations.
8) Prepare the final report and presentation.

XII. Conclusion

This study asked a simple question: are U.S. CPI changes better predicted by tariff variables alone, or by tariff variables plus CPI history?

The results are clear. Tariff only models had low predictive power (test $R^2 \approx 0.086$–0.098). After adding lagged CPI and seasonality features, model performance improved strongly (test $R^2 \approx 0.672$–0.801).

This means that tariffs are part of the inflation story, but they are not enough by themselves to explain short run CPI movements. Recent CPI behavior (inflation momentum) is a much stronger predictor.

These findings match real world evidence: there is a tariff pass through, but inflation is also driven by persistence and broader macroeconomic forces. Because this is a predictive study, the results should be read as forecasting evidence, not as proof of causality.

In future work, this study can be improved in a few practical ways. First, I can use stronger time based testing, such as rolling or walk forward validation, to check whether model performance stays stable across different periods. Second, I can report uncertainty ranges, not only single prediction scores, so the results are easier to interpret in real decision settings. Third, I can improve the category mapping from tariff to CPI and add more economic variables, such as energy prices, wages, and exchange rates, to better represent real inflation drivers. I can also extend the data set to a longer time period and directly test the major tariff policy events. These steps would make the results more robust, more realistic, and more useful for policy analysis.

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