Tariff Goods Pricing Increase

Andy Zheng and Si Qin

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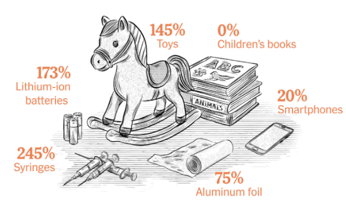
1 Introduction

With new trade policies rolling out so rapidly, we're curious how they'll affect our daily lives. In 2024 and early 2025, the U.S. announced new rounds of tariffs on Chinese imports under Section 301. These included proposed tariff increases on electric vehicles, batteries, critical minerals, and solar equipment. During the most recent US — China "tariff war" in March, some rates have been pushed as high as 145%. After negotiations in May, both countries agreed to temporarily reduce these tariffs for a 90-day public comment and review period, most Chinese products are now subject to additional 30% tariff in the United States.

List	Effective Date	Tariff Rate	Coverage
List 1	July 6, 2018	25%	~$34B worth of goods
List 2	August 23, 2018	25%	~$16B
List 3	September 24, 2018	Initially 10%, raised to 25% in May 2019	~$200B
List 4	List 4A imposed Sept 2019	15% (later reduced to 7.5%)	~$120B



As current tariffs on lithium-ion batteries from China have risen to as high as 80–100%, this has placed considerable strain on manufacturers and industries that heavily rely on battery technologies. These include electric vehicles, renewable energy storage systems, consumer electronics, and medical devices—sectors where lithium-ion batteries are essential components. "US manufacturers and importers have faced significant challenges due to the tariff. The increased cost of importing lithium-ion batteries has strained profit margins, particularly for small and medium-sized businesses. Many manufacturers have struggled to compete with foreign companies that do not face similar tariffs. This has created an uneven playing field, reducing competition in the global market."[1]

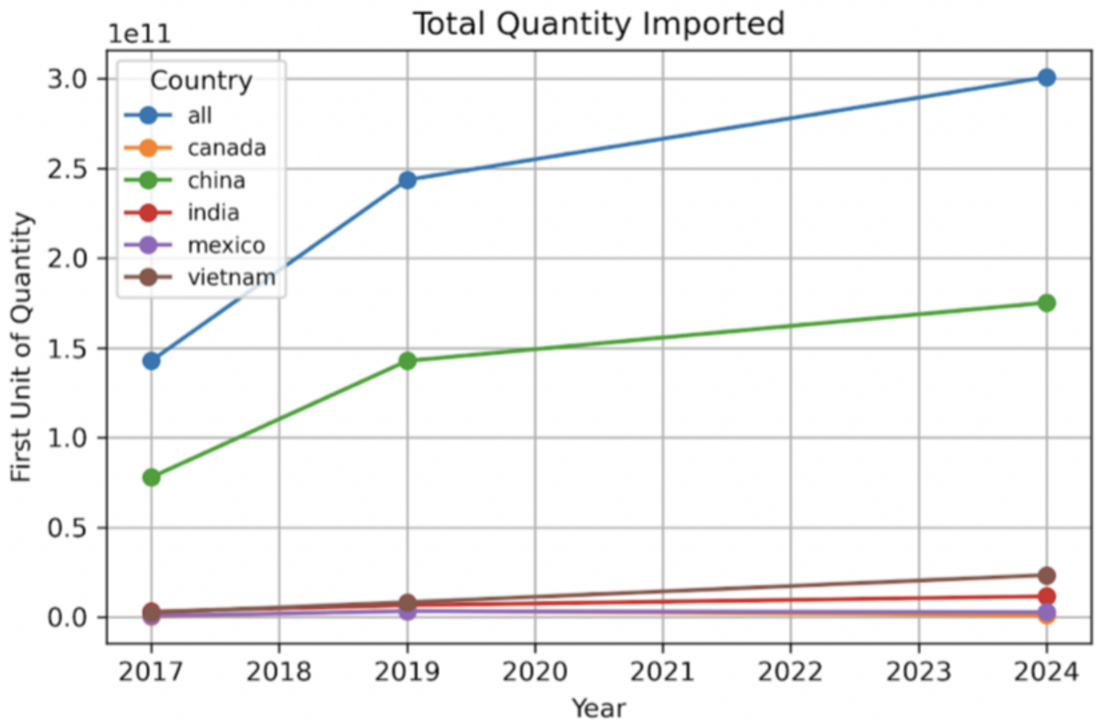
Tariffs of this magnitude risk slowing clean energy adoption, raising consumer prices, and weakening the global competitiveness of U.S. firms. Identifying goods most vulnerable to these pressures is critical for assessing supply chain risks and anticipating broader economic impacts. Our objective is to identify which goods are most likely to experience price increases due to these trade measures, in order to evaluate supply chain vulnerabilities and anticipate downstream effects on consumers and businesses.

2 Data

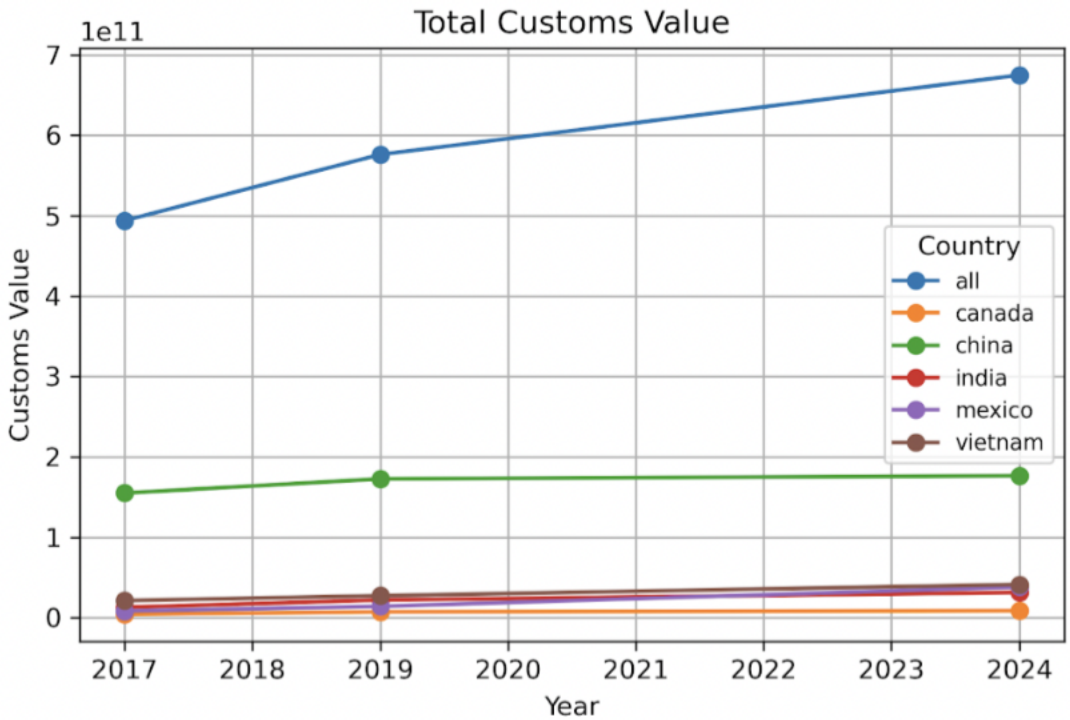
To assess the impact of tariffs and trade patterns, we collected data from several key sources. Consumer Price Index (CPI) data was obtained from the U.S. Bureau of Labor Statistics (BLS) for the years 2017 through 2024[2], offering a comprehensive view of inflation trends across consumer goods. Import data was sourced from the U.S. International Trade Commission (USITC)[3], including import quantities, customs values, and CIF (Cost, Insurance, and Freight) import values. We focused on three benchmark years: 2017 (pre-tariff baseline), 2019 (period of tariff escalation), and 2024 (new post-policy baseline). This data spans key trading partners such as China, Canada, Mexico, Vietnam, India, and all countries collectively. Additionally, we integrated tariff data from the USITC, including Most Favored Nation (MFN) rates for 2017, 2019, and 2024,along with additional tariffs imposed under Section 301 between 2018 and 2019.[4] Together, these datasets support a detailed analysis of price shifts and trade flow changes over time.

2.1 Data Visualization

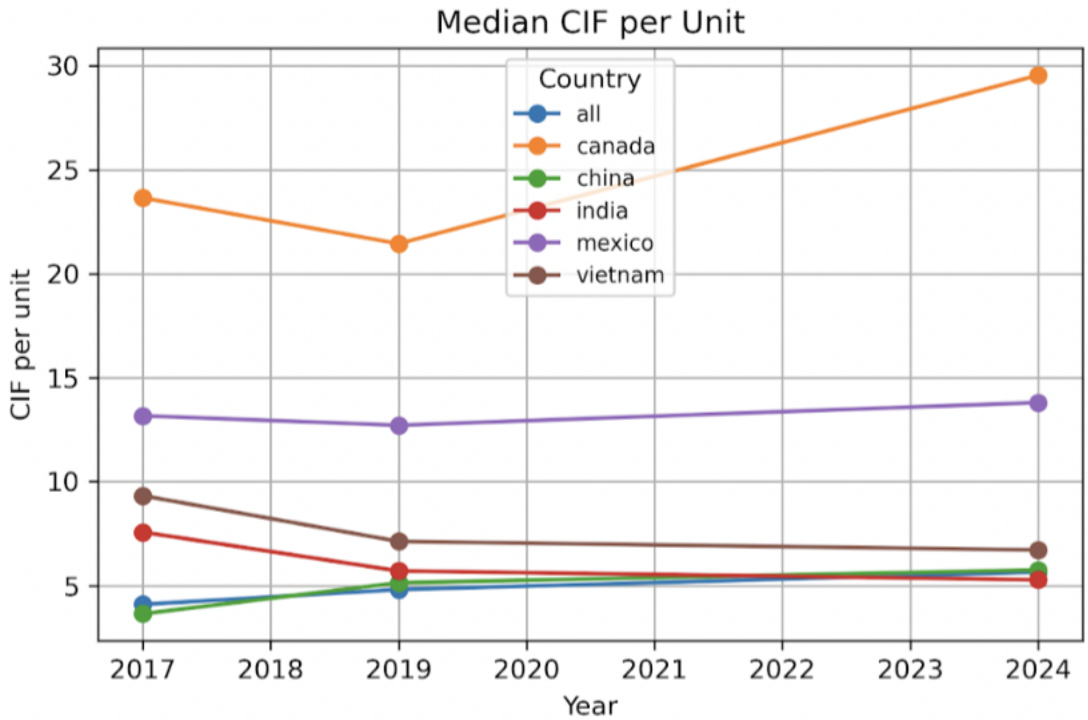
To visualize these dynamics and uncover patterns across countries and time, we generated a series of comparative charts that highlight changes in import behavior and tariff exposure. These visualizations provide a clearer picture of how trade volumes, customs values, per-unit costs, and applied tariffs have evolved from 2017 to 2024, offering critical insights into the economic effects of shifting trade policies.



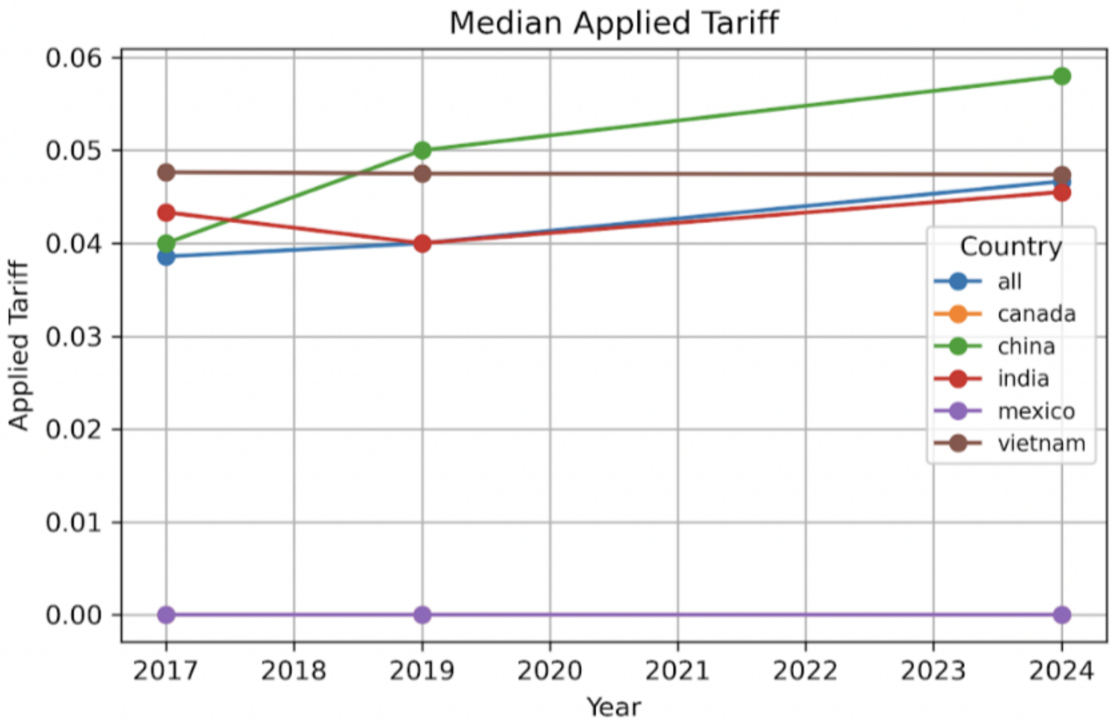
This ”Total Quantity Imported” chart illustrates the growth in U.S. import volumes from 2017 to 2024 across major trading partners, including China, Canada, Mexico, Vietnam, and India, as well as the overall aggregate. Total imports increased steadily over this period, with China and the combined “All Countries” group showing the largest volumes. China’s import quantity grew significantly from 2017 to 2019, then stabilized, suggesting a potential impact from rising tariffs, though not a sharp decline. Canada also maintained high and stable import levels, likely supported by tariff exemptions under agreements like USMCA. Notably, Vietnam and India experienced consistent growth, indicating a gradual shift in sourcing as companies diversify beyond China. Mexico’s import levels remained relatively flat, showing less volatility.



The "Total Customs Value" chart shows the cumulative value of imported goods into the U.S. from 2017 to 2024, reflecting trends across key trading partners. Overall, customs values rose significantly, with the aggregate ("All Countries") increasing from approximately $5 trillion to over $6.5 trillion. China consistently accounted for the largest share among individual countries, despite escalating tariffs. Vietnam and India exhibited steady growth in customs value, indicating their increasing role in U.S. trade. Canada and Mexico remained relatively stable throughout the period. These trends suggest that rising import costs did not significantly deter trade but may reflect inflation or value-added shifts.



The "Median CIF per Unit" chart illustrates the median cost, insurance, and freight (CIF) value per unit of imported goods from 2017 to 2024 for key U.S. trading partners. Canada consistently reported the highest CIF per unit, with a gradual increase over the period, suggesting higher shipping costs or a concentration of higher-value goods. In contrast, India and Vietnam both showed relatively low or declining CIF values. This may reflect growing cost-efficiency from mature export operations and streamlined supply chains, especially in sectors like textiles, electronics, or machinery. Such patterns align with these countries' expanding roles in global manufacturing and trade rebalancing. These trends highlight substantial variation in per-unit import costs across countries, influenced by differences in logistics, product categories, and trade relationships, especially under evolving tariff conditions.



The "Median Applied Tariff" chart displays the average tariff rates applied to imports from major U.S. trading partners between 2017 and 2024. The data reveals significant divergence in tariff exposure across countries. China experienced the most dramatic increase, with median tariffs rising sharply after 2018 due to the implementation of Section 301 tariffs, peaking near 5.8% by 2024. This reflects ongoing trade tensions and policy measures targeting Chinese goods. Vietnam and India also saw noticeable increases beginning in 2019, though their rates remained below those imposed on China. In contrast, imports from Mexico and Canada consistently faced minimal or zero tariffs, a result of preferential treatment under NAFTA and USMCA agreements. The "All Countries" aggregate line showed a moderate upward trend, indicating broader increases in average tariff burdens.

3 Model

$$\hat{y} = f(x) = f(x_1, x_2, x_3, x_4, x_5)$$

- $\hat{y}$: Goods that are likely to increase in price
- x_1: Normalized quantity of units purchased
- x_2: Normalized CIF (Cost, Insurance, and Freight) value

- x_3: Normalized customs value
- x_4: Applied tariff
- x_5: Country of origin (one-hot encoded or categorical)

4 Empirical Analysis

To empirically evaluate the relationship between trade policies and consumer price changes, we constructed a supervised classification framework using publicly available data on prices and imports. The target variable was defined as a binary indicator of a significant consumer price increase (specifically,$y = 1$ if the CPI for a good's category rose by 5% or more from 2017 to 2020, and $y = 0$ otherwise). We trained our model on 2017 data as a pre-tariff baseline and then applied the trained model to 2024 import data to predict which goods were likely to experience price increases under the current trade environment. The feature set included five input variables derived from the trade datasets: normalized import quantity, import values (both cost-insurance-freight and customs value), the applied tariff rate, and the country of origin for each good. These features capture the initial volume, cost, and tariff conditions of goods entering the U.S., providing the model with a snapshot of trade and price-related factors prior to the tariff changes.

4.1 Selection of Model

To identify the most informative predictors, we first performed feature selection using the SelectKBest method from scikit-learn. This analysis confirmed that the applied tariff rate was the single most predictive feature for classifying price increases. After establishing the feature importance, we trained and evaluated several candidate classification models (including logistic regression, decision trees, random forests, gradient boosting, and K-Nearest Neighbors) to determine which algorithm yielded the best performance. In initial cross-validation experiments, tree-based models and a KNN classifier achieved the highest accuracy, F1-scores, and ROC-AUC values among the models tested. However, their F1-scores were still relatively low, a result of the severe class imbalance in our data – only about 11.3% of training samples were labeled as positive (price increase). This imbalance meant that even well-performing models tended to miss many of the minority-class instances, underscoring the need for techniques to boost sensitivity to price increases.

To improve the model's predictive power under these conditions, we employed a rigorous tuning and resampling strategy. We used repeated stratified k-fold cross-validation (RepeatedStratifiedKFold) combined with GridSearchCV to optimize hyperparameters for each classifier in a way that preserved the class distribution in each fold. Within each training fold, we applied SMOTE (Synthetic Minority Oversampling Technique) to generate synthetic examples of the minority class, thereby balancing the class distribution and alleviating the bias toward the majority class. Additionally, we optimized the classification threshold probability for positive predictions, rather than relying on the default 0.5 cutoff. Specifically, we selected the threshold that maximized the F1-score on validation data, using precision–recall curves to identify the point at which the trade-off between precision and recall was optimal. This threshold optimization further improved the model's ability to capture true positives while controlling false positives, a crucial step for improving F1 given our imbalanced labels.

After incorporating these enhancements (hyperparameter tuning, SMOTE re-balancing, and threshold adjustment), we compared the refined models and also explored ensemble approaches. We experimented with an ensemble via soft voting (averaging the predicted probabilities of multiple classifiers) and a stacking model (training a meta-classifier on the outputs of base models) to see if a combined model could outperform the individual classifiers. In our results, however, the highest performance was achieved by a single tree-based model rather than any ensemble. Specifically, an Extreme Gradient Boosting classifier (XGBoost) emerged as the top performer. The optimized XGBoost model (with its custom probability threshold) attained an F1-score of 0.513, which was the highest among all models and ensemble variants evaluated. This F1 was a notable improvement over other algorithms and remained our primary metric for model selection due to its balance of precision and recall. Consequently, we selected XGBoost as the final model for forecasting price increase risks. In addition to its leading F1-score, this final model also achieved a precision of approximately 0.543 and a ROC AUC of about 0.793 after the SMOTE and threshold optimization steps, indicating that it not only catches a higher proportion of at-risk goods but also maintains relatively strong overall accuracy and class discrimination. The XGBoost model's superior performance across these metrics, even compared to more complex ensemble methods, made it the most robust choice for our predictive task.

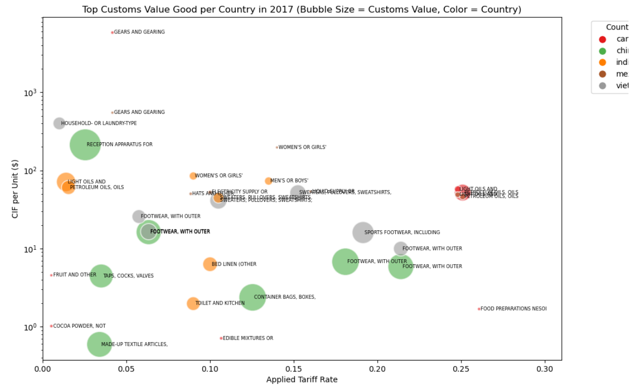
4.1.1 Constraints

While the modeling approach proved useful, there are several important constraints and limitations to acknowledge: First, the feature set available for our analysis was limited in scope. Many factors known to influence consumer prices—such as supply chain disruptions, changes in consumer demand, competitive market dynamics, and retail pricing strategies—were not captured in our dataset. The exclusion of these contextual variables means the model cannot account for a wide range of real-world effects that may drive price changes, potentially leaving out key predictors.

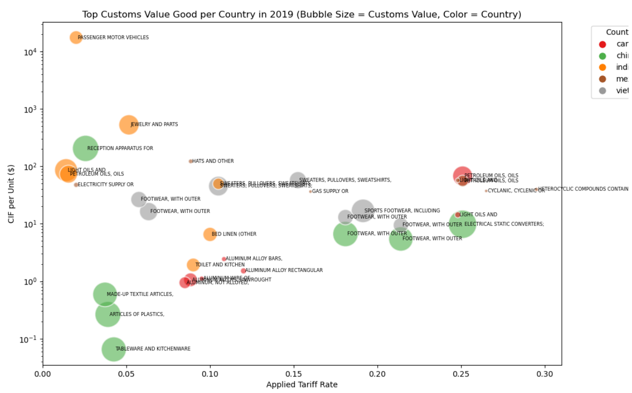
Second, there was a mismatch in data granularity between the price data and the trade data we used. The CPI-based price inflation labels were defined at a broad consumer category level, whereas the import features (quantity, value, tariff) were measured for specific products at the detailed HTS6 code level. This disparity likely introduced noise and labeling errors: a particular product could be tagged as having a price increase due to its category's CPI rising, even if that specific item did not truly experience a price hike. Such misalignment between data sources could cause the model to learn some spurious associations.

Third, the relationship between tariffs and consumer prices is complex and not strictly linear. Tariff effects can be delayed or dampened by various economic adjustments – for example, importers and retailers might absorb added costs, or supply chains may shift to alternative suppliers to avoid tariffs. Our model, by design, assumes a more direct linkage based on the training data patterns. These complexities and omissions in the modeling scope likely reduced the model's predictive accuracy and robustness, as the classifier was unable to learn or represent many real-world mechanisms behind price changes.

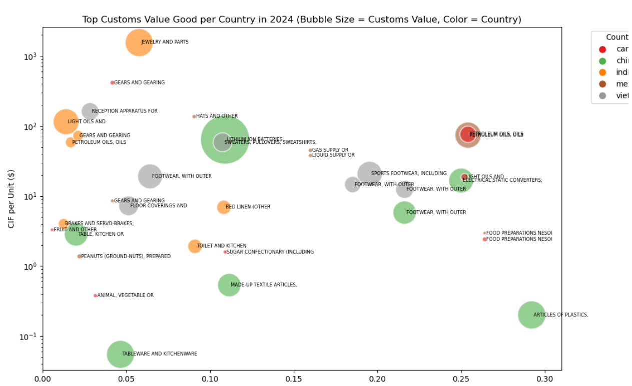
Another critical limitation is the emergence of new high-value goods and shifting trade patterns in the period beyond our training data. The model was trained on historical data (primarily from 2017, with CPI outcomes through 2020), which means it learned relationships based on the goods and tariff structures prevalent at that time. However, by 2024 the trade environment introduced product categories and tariff events that were not present in the training period. A notable example is lithium-ion batteries. This category was essentially absent or insignificant in the 2017–2019 data used for training, yet it became highly prominent in the 2024 import dataset. In 2024, the United States imposed steep tariffs on Chinese lithium-ion batteries – the rate jumped from 7.5% to 25%, eventually combining to an effective 58% tariff by 2025 – dramatically increasing their cost. Such a development represents a form of distribution shift that our model was not exposed to during training. Because lithium-ion batteries (and similar newly emergent goods) did not appear as significant items in the historical data, the model has no basis to recognize them as high-risk goods, even though they are now subject to substantial tariffs and likely price surges. This creates a forecasting blind spot: the model may under-predict or entirely miss the risk of price increases for these new products. In general, when the trade dynamics evolve beyond the scope of the training set – introducing new product categories, technologies, or policy changes – a static model's predictive power diminishes. The case of lithium-ion batteries exemplifies how our model's performance is constrained by the representativeness of its training data. Going forward, this limitation suggests that the model would need periodic retraining or adaptation with updated data (e.g. incorporating 2024 and beyond) to reliably reflect shifting trade patterns and the introduction of high-value goods not previously seen.



(a) 2017



(b) 2019



(c) 2024

Figure 1: Top Import Goods by Customs Value for 2017, 2019, and 2024

5 Conclusion

The analysis indicated that imported goods most likely to face increased customs prices are concentrated in categories related to textiles, raw materials, and industrial inputs. Items such as cotton, thread, yarn, fabric, and various woven or knitted materials appear frequently among the predicted high-risk goods, suggesting that the textile and apparel sector may be particularly vulnerable to rising import costs. In addition, materials like rubber, aluminum, plastic, and certain metals are also prevalent, pointing to potential cost pressures on manufacturing and intermediate goods. A significant portion of these items are sourced from China, aligning with earlier findings that elevated tariffs under Section 301 continue to affect Chinese-origin goods more heavily. This pattern highlights the ongoing impact of trade policy on critical supply chains and raises concerns about potential downstream price effects on both producers and consumers in the U.S. market.

Imported Goods Likely to Become More Expensive (Chinese -- more in Red)

6 Recommendations

Based on the analysis and model predictions, several recommendations emerge for policymakers, analysts, and supply chain stakeholders. First, the results suggest that goods related to textiles, raw materials, and industrial inputs—particularly those imported from

China—are most vulnerable to price increases under current tariff conditions. Policymakers should closely monitor these categories for inflationary pressures and consider targeted trade adjustments or exemptions to mitigate downstream impacts on manufacturers and consumers. Second, the consistent presence of high-cost goods from low-tariff countries like Canada indicates that tariffs are not the sole driver of price increases; therefore, broader economic conditions and cost structures should be factored into future trade assessments. Third, importers and retailers may benefit from diversifying sourcing strategies toward countries less affected by tariffs, such as Vietnam or India, to reduce long-term exposure. Finally, the analysis highlights the need for improved data integration and more granular tracking of import categories to enable more accurate, real-time policy responses.

References

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