Forecasting the Economic Implications of the 2025 Tariffs: A Time-Series Polynomial Regression Approach

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1 Background Information and Introduction

1.1 What are Tariffs?

Tariffs have been historically used by U.S. foreign policy to protect domestic industries from numerous factors such as foreign competition and trade imbalances, and they can also help generate more government revenue (YouTube). Despite these benefits however, the effectiveness and consequences of tariffs remain widely debated, with opponents of such policies emphasizing that reliance on tariffs often lead to higher costs for domestic businesses and consumers, disrupt global supply chains, and trigger retaliatory measures from trading partners (Krugman & Obstfeld, 2021). While tariffs can be an effective tool for protecting domestic production, they also "increase the cost of imports, which can lead to higher prices for consumers" (Hersh & Bivens 2025) and create additional economic challenges for businesses reliant on foreign supply chains.

1.2 President Donald Trump's Current Tariff Plans

As President Trump retakes office for his second term, the topic of tariffs has been rejuvenated, as he has vowed to impose heavy taxes on many foreign nations, including a 60% tariff on Chinese imports and a 200% tariff on some foreign automobiles (Chu 2025). While the Trump administration claims that these tariffs are intended to enrich American citizens (The United States Government 2025) by increasing domestic production and address trade imbalances, the EPI highlights that tariffs can have counterintuitive effects, noting that "large, broad-based tariffs can put upward pressure on the value of the U.S. dollar, making American goods more expensive to foreign buyers" (Hersh & Bivens 2025). This would ultimately negate the intended economic benefits, placing the burden on domestic businesses and consumers.

1.3 Problem Statement

The objective of this study is to evaluate how tariffs affect trade, production costs, consumer prices, and overall economic stability by drawing insights from past tariffs and simulating potential outcomes of current tariff proposals. By analyzing historical data and simulating potential outcomes of current tariff proposals, we aim to provide a comprehensive assessment of tariff policies and their consequences.

Our study is centered around two primary questions:

1. Do the tariffs proposed by the Trump Administration align with their intended economic objectives or risk harming the very industries and consumers they aim to protect?
2. What consequences, if any, may result from these tariffs — from American households to global supply networks?

2 Data Preparation

2.1 Web Scraping

The code snippet shown below is responsible for retrieving and organizing annual U.S. trade data (imports and exports) from the World Bank's WITS portal for the years 2000–2022. The script iterates through each year in the specified range and constructs a dataframe/CSV file containing trade data between the United States and every one of its trade partners (around 220 countries).

[119]:
```python
for year in range(2000, 2023):

    # Get the HTML response from the webpage
    response = requests.get(f"https://wits.worldbank.org/CountryProfile/en/
↪Country/USA/Year/{year}/TradeFlow/EXPIMP/Partner/by-country#")

    # Extract the JavaScript table data
    soup = BeautifulSoup(response.text, "html.parser")
    script_tags = soup.find_all("script", string=re.compile(r'var col\d+ ='))

    # Get the script content
    data, columns = {}, []; script_content = script_tags[0].string
    for col_match in re.finditer(r"var (col\d+) =\s+\[([^\]]+)\];",␣
↪script_content):
        col_name = col_match.group(1)  # e.g., col0, col1
        col_data = eval(col_match.group(2))  # Convert array string to Python␣
↪list
        data[col_name] = col_data; columns.append(col_name)

    # Extract column headers
    headers_match = re.search(r"columns: \[\{ text:'([^']+)", script_content);␣
↪headers = []
    if headers_match: headers = [header.group(1) for header in re.
↪finditer(r"text:'([^']+)", script_content)]
    if not headers: headers = [f"Column {i}" for i in range(len(columns))]

    # Convert to DataFrame and save to dictionary and file storage
    df = pd.DataFrame(data).rename(columns={f"col{i}": headers[i] for i in␣
↪range(len(headers))})
    year_data[year] = df; df.to_csv(f"Data/USImpExp/{year}.csv", index = False)
```

We can better understand the features of this data by running `year_data[2022]`.

[120]:
```
year_data[2022].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 223 entries, 0 to 222
Data columns (total 35 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Partner Name                            223 non-null    object
 1   No Of exported HS6 digit Products       223 non-null    object
 2   No Of imported HS6 digit Products       223 non-null    object
 3   Export Share in Total Products (%)      223 non-null    object
 4   Import Share in Total Products (%)      223 non-null    object
 5   Trade Balance (US$ Thousand)            223 non-null    object
 6   Export (US$ Thousand)                   223 non-null    object
 7   Import (US$ Thousand)                   223 non-null    object
 8   Import Partner Share (%)                223 non-null    object
 9   Export Partner Share (%)                223 non-null    object
 10  AHS Simple Average (%)                  223 non-null    object
 11  AHS Weighted Average (%)                223 non-null    object
 12  AHS Total Tariff Lines                  223 non-null    object
 13  AHS Dutiable Tariff Lines Share (%)     223 non-null    object
 14  AHS Duty Free Tariff Lines Share (%)    223 non-null    object
 15  AHS Specific Tariff Lines Share (%)     223 non-null    object
 16  AHS AVE Tariff Lines Share (%)          223 non-null    object
 17  AHS MaxRate (%)                         223 non-null    object
 18  AHS MinRate (%)                         223 non-null    object
 19  AHS SpecificDuty Imports(US$ Thousand)  223 non-null    object
 20  AHS Dutiable Imports (US$ Thousand)     223 non-null    object
 21  AHS Duty Free Imports (US$ Thousand)    223 non-null    object
 22  MFN Simple Average (%)                  223 non-null    object
 23  MFN Weighted Average (%)                223 non-null    object
 24  MFN Total Tariff Lines                  223 non-null    object
 25  MFN Dutiable Tariff Lines Share (%)     223 non-null    object
 26  MFN Duty Free Tariff Lines Share (%)    223 non-null    object
 27  MFN Specific Tariff Lines Share (%)     223 non-null    object
 28  MFN AVE Tariff Lines Share (%)          223 non-null    object
 29  MFN MaxRate (%)                         223 non-null    object
 30  MFN MinRate (%)                         223 non-null    object
 31  MFN SpecificDuty Imports (US$ Thousand) 223 non-null    object
 32  MFN Dutiable Imports (US$ Thousand)     223 non-null    object
 33  MFN Duty Free Imports (US$ Thousand)    223 non-null    object
 34  No Of Tariff Agreement                  223 non-null    object
```

Based on the information above, we can derive information about both trade volume and tariff structure. For instance, `Partner Name`, `Export (US$ Thousand)`, and `Import (US$ Thousand)` reveal the bilateral flow of goods with each trading partner. Columns like `MFN MaxRate (%)` and `MFN MinRate (%)` detail the tariff range imposed under Most Favored Nation conditions, offering insight into potential cost barriers for certain products.

While this data does give a good overview of trade flow, it does not provide any detailed composition for each particular nation. To overcome this, we scrape more data containing the product composition for the top trade partners as shown in the code cell below.

[124]:
```
countries = {'China': 'CHN', 'Canada': 'CAN', 'Germany': 'DEU', 'Japan': 'JPN',␣
↪'Mexico': 'MEX'}
for country in list(countries.keys()):

  # Loop through the years from 1991 to 2022s
  for year in range(2000, 2023):

    # Get the response for the specific year
    time.sleep(0.05)
    response = requests.get(f"https://wits.worldbank.org/CountryProfile/en/
↪Country/USA/Year/{year}/TradeFlow/EXPIMP/Partner/{countries[country]}/Product/
↪all-groups")

    # Extract the JavaScript table data
    soup = BeautifulSoup(response.text, "html.parser");
    script_tags = soup.find_all('script', string=re.compile(r'var col\d+ ='))
    if not script_tags: continue

    # Get the script content
    data, columns = {}, [];  script_content = script_tags[0].string

    # Extract column daata
    for col_match in re.finditer(r"var (col\d+) =\s+\[([^\]]+)\];",␣
↪script_content):
        col_name = col_match.group(1)  # Column name (e.g., col0, col1)
        col_data = eval(col_match.group(2))  # Convert array string to Python␣
↪list
        data[col_name] = col_data; columns.append(col_name)

    # Extract column headers from another script variable, if available
    headers_match = re.search(r"columns: \[\{ text:'([^']+)", script_content); ␣
↪headers = []
    if headers_match:  headers = [header.group(1) for header in re.
↪finditer(r"text:'([^']+)", script_content)]
    if not headers: headers = [f"Column {i}" for i in range(len(columns))]

    # Create df for the current year and save to data structure and file storage
    df = pd.DataFrame(data).rename(columns={f"col{i}": headers[i] for i in␣
↪range(len(headers))})
    df.to_csv(f"{countries_dir}{country}/{year}.csv", index = False)
    df.to_csv(f"{years_dir}{year}/{country}.csv", index = False)
    df['Country'], df['Year'] = country, year; main_df = pd.concat([main_df,␣
↪df], ignore_index = True)
```

[125]:
```
main_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2415 entries, 0 to 2414
Data columns (total 34 columns):
 #   Column                                Non-Null Count  Dtype 
---  ------                                --------------  ----- 
 0   Product Group                         2415 non-null   object
 1   Export (US$ Thousand)                 2415 non-null   object
 2   Import (US$ Thousand)                 2415 non-null   object
 3   Export Product Share (%)              2415 non-null   object
 4   Import Product Share (%)              2415 non-null   object
 5   Revealed comparative advantage        2415 non-null   object
 6   World Growth (%)                      2415 non-null   object
 7   Country Growth (%)                    2415 non-null   object
 8   AHS Simple Average (%)                2415 non-null   object
 9   AHS Weighted Average (%)              2415 non-null   object
 10  AHS Total Tariff Lines                2415 non-null   object
 11  AHS Dutiable Tariff Lines Share (%)   2415 non-null   object
 12  AHS Duty Free Tariff Lines Share (%)  2415 non-null   object
 13  AHS Specific Tariff Lines Share (%)   2415 non-null   object
 14  AHS AVE Tariff Lines Share (%)        2415 non-null   object
 15  AHS MaxRate (%)                       2415 non-null   object
 16  AHS MinRate (%)                       2415 non-null   object
 17  AHS SpecificDuty Imports (US$ Thousand)  2415 non-null   object
 18  AHS Dutiable Imports (US$ Thousand)   2415 non-null   object
 19  AHS Duty Free Imports (US$ Thousand)  2415 non-null   object
 20  MFN Simple Average (%)                2415 non-null   object
 21  MFN Weighted Average (%)              2415 non-null   object
 22  MFN Total Tariff Lines                2415 non-null   object
 23  MFN Dutiable Tariff Lines Share (%)   2415 non-null   object
 24  MFN Duty Free Tariff Lines Share (%)  2415 non-null   object
 25  MFN Specific Tariff Lines Share (%)   2415 non-null   object
 26  MFN AVE Tariff Lines Share (%)        2415 non-null   object
 27  MFN MaxRate (%)                       2415 non-null   object
 28  MFN MinRate (%)                       2415 non-null   object
 29  MFN SpecificDuty Imports (US$ Thousand)  2415 non-null   object
 30  MFN Dutiable Imports (US$ Thousand)   2415 non-null   object
 31  MFN Duty Free Imports (US$ Thousand)  2415 non-null   object
 32  Country                               2415 non-null   object
 33  Year                                  2415 non-null   int64 
```

This dataframe contains more detailed data illustrating product-specific trade data for the top five trading partners across multiple years. Columns like `Product Group`, `Export (US$ Thousand)`, and `Import (US$ Thousand)` show the category of goods traded and the corresponding monetary values. Other columns, such as `AHS Simple Average (%)`, `MFN Weighted Average (%)`, and `Revealed comparative advantage`, highlight different tariff structures and the relative competitiveness in specific product groups. These features will be useful later during the simulation.

2.2 Preprocessing

Based on `df.info()` outputs above, we can see that a lot of these columns are stored as objects when they should be numerical. This can cause performance bottlenecks during our exploratory data analysis and simulation stages. To avoid this, we should convert each column to its appropriate data type.

[126]:
```
for col in main_df.columns:
    if col not in ["Product Group", "Country"]: main_df[col] = pd.
↪to_numeric(main_df[col], errors='coerce')

for year in range(2000, 2023):
    for col in year_data[year].columns:
        if col not in ["Partner Name"]: year_data[year][col] = pd.
↪to_numeric(year_data[year][col], errors='coerce')
```

Given that imports and exports between countries, especially the top trade partners of the United States, is usually in the billions, this could cause a numerical overflow in the simulation in case the forecasted values approach negative of positive infinity. To prevent this, we should standardize the data of the columns that contain monetary value from `US$ Thousand` to `US$ Billion`.

[127]:
```
money_cols = [col for col in main_df.columns if "(US$ Thousand)" in col]
col_names, rename_dict = list(main_df.columns), {}
for col in money_cols:
    main_df[col] = main_df[col] / 1e6
    rename_dict[col] = col.replace("(US$ Thousand)", "(US$ Billion)")
main_df.rename(columns = rename_dict, inplace = True)

for year in range(2000, 2023):
    money_cols = [col for col in year_data[year].columns if "(US$ Thousand)" in␣
↪col]
    col_names, rename_dict = list(year_data[year].columns), {}
    for col in money_cols:
        year_data[year][col] = year_data[year][col] / 1e6
        rename_dict[col] = col.replace("(US$ Thousand)", "(US$ Billion)")
    year_data[year].rename(columns = rename_dict, inplace = True)
```

[131]:
```
main_df[['Export (US$ Billion)', 'Import (US$ Billion)']].describe()
```

[131]:

	Export (US$ Billion)	Import (US$ Billion)
count	2415.000000	2415.000000
mean	17.730409	32.851346
std	36.437654	65.306280
min	0.007872	0.011533
25%	1.488912	1.081177
50%	5.870805	8.066105
75%	16.769296	33.174270
max	354.887051	575.688091

As shown in the sampled dataframe above, the values have now been standardized to reflect USD Billions. This will greatly enhance our simulation efficiency and performance since the computations will be using more regularized numbers.

3 Exploratory Data Analysis

3.1 Top 5 Trade Partners

The United States is one of the largest trade partners in the world. However, for the purpose of this project, we wanted to narrow our focus to just a several countries, particularly the top 5 trade partners of the U.S. While this definition could be subjective, our criteria for determining the top 5 partners was to find out which countries have consistently been the int top 5 importers by import value for each year over the last 23 years.

Figure 1 shows that the top 5 trade partners of the United States are Canada, Mexico, China, Germany, and Japan. These 5 countries have consistently been the top 5 importers for the United States over the last 23 years with no other country making the top 5 importers list even once, which was an interesting discovery. This also correlates with the countries with the highest GDPs which verifies the results of our data analysis.

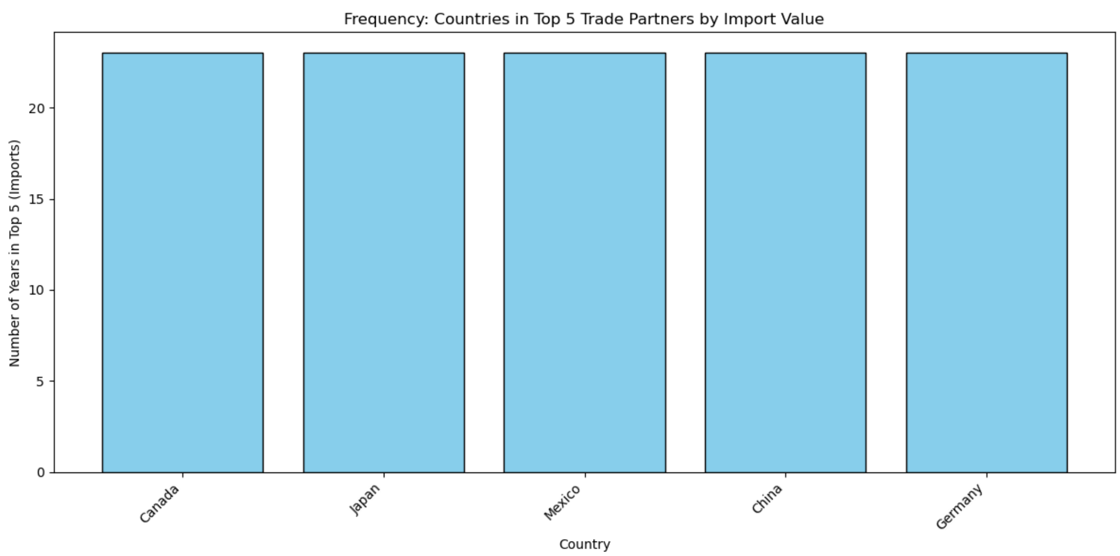

Figure 1: Top 5 Trade Partners Over the Last 23 Years

3.2 Trade Flow Analysis

With the Top 5 trade partners identified, we wanted to perform some data analysis to understand how much we were importing and exporting from each of these countries compared to the other countries in the world. The graphs in **Figure 2** and **Figure 3** helps us visualize this discrepancy.

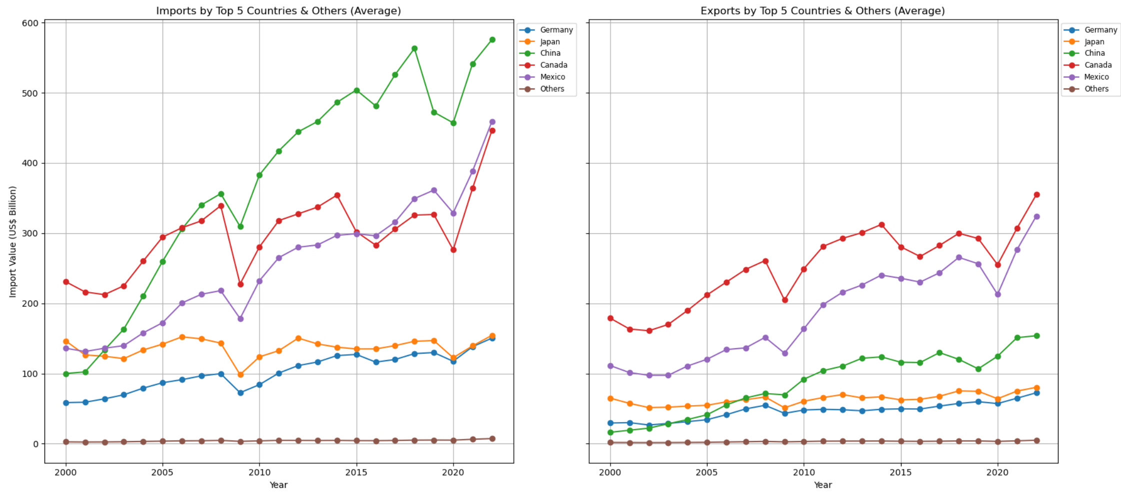

Figure 2: Imports & Exports (in US$ Billion) for Top 5 Trade Partners

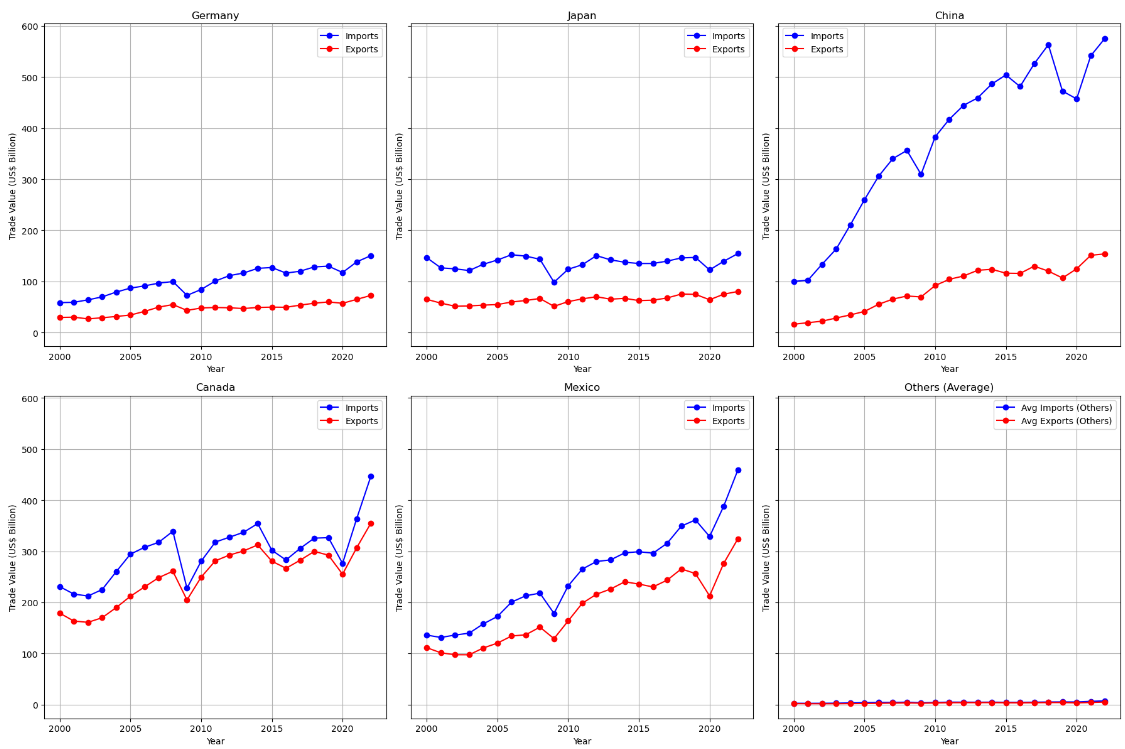

Figure 3: Imports & Exports (in US$ Billion) for Top 5 Trade Partners

Some significant spikes downwards can be seen during certain years such as between 2007-2011 symbolizing when the Great Recession took place. There was also a drop in import rates during 2020 when the world saw Covid-19 take place. We can also observe a downward spike in China's imports during 2018-19 when the trade war took place.

Figure 3 especially is able to show us that there has not been a single year in the last 23 years in which the U.S. has exported more than it has imported for any country in its top 5 trade partners, indicating a heavy dependency on foreign resources. In particular, the United States is importing from China around three times more than it is exporting to China, which shows that we are heavily reliant on foreign goods from China. This makes sense because a lot of good that American consumers use everyday are manufactured in China.

Overall, what can be derived from this is that all nations have much higher import rates compared to their exports, which suggests that the U.S. reliance on foreign resources is significant.

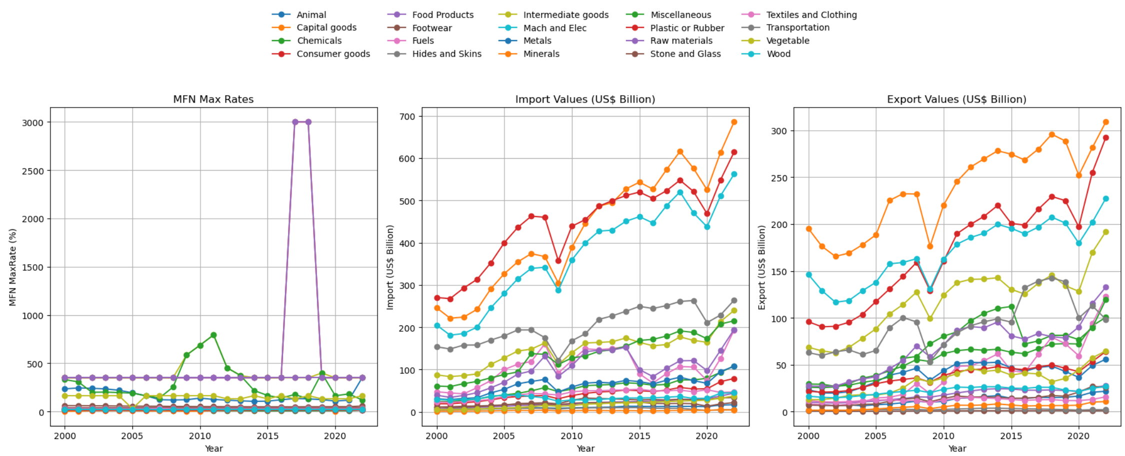

Figure 4: Imports (Center), Exports (Right) & Tariffs (Left) for Different Product Groups

Our next objective was to identify the particular industries and product groups that had the most trade flow between the United States and its trade partners as shown in **Figure 4**. This graph on the left goes over the tariff rates of each type of product or field. MFN simply stands for the "Most Favored Nations" which in this case are the 5 nations we have mentioned. The large spike reflects back to the years 2016-2018 when president Trump and his administration were in their first term and the tariffs they had implemented then.

The center graph in **Figure 4** explores all the types of products being imported. Capital and consumer goods followed by electronics & machinery are the largest importers coming in from these nations into the U.S. at incremental rates. The rest of the products are at the bottom marking that they are less important as compared to the rest of these material types.

The final graph in **Figure 4** on the right is similar to the graph on the center, but it focus on the exports. The top materials which are being exported are pretty similar to the top import materials. The main difference is that there are some more materials being exported such as miscellaneous and intermediate goods.

This means that the U.S. is importing and exporting relatively the same types of goods from these countries. This could be assumed that over time, different types of trends and expectations arise especially through social media and populations having access to a lot more on demand. People want more types of products in the modern world such as keeping up with the latest fashion trends, various cultural cuisines and high-tech items to say the least.

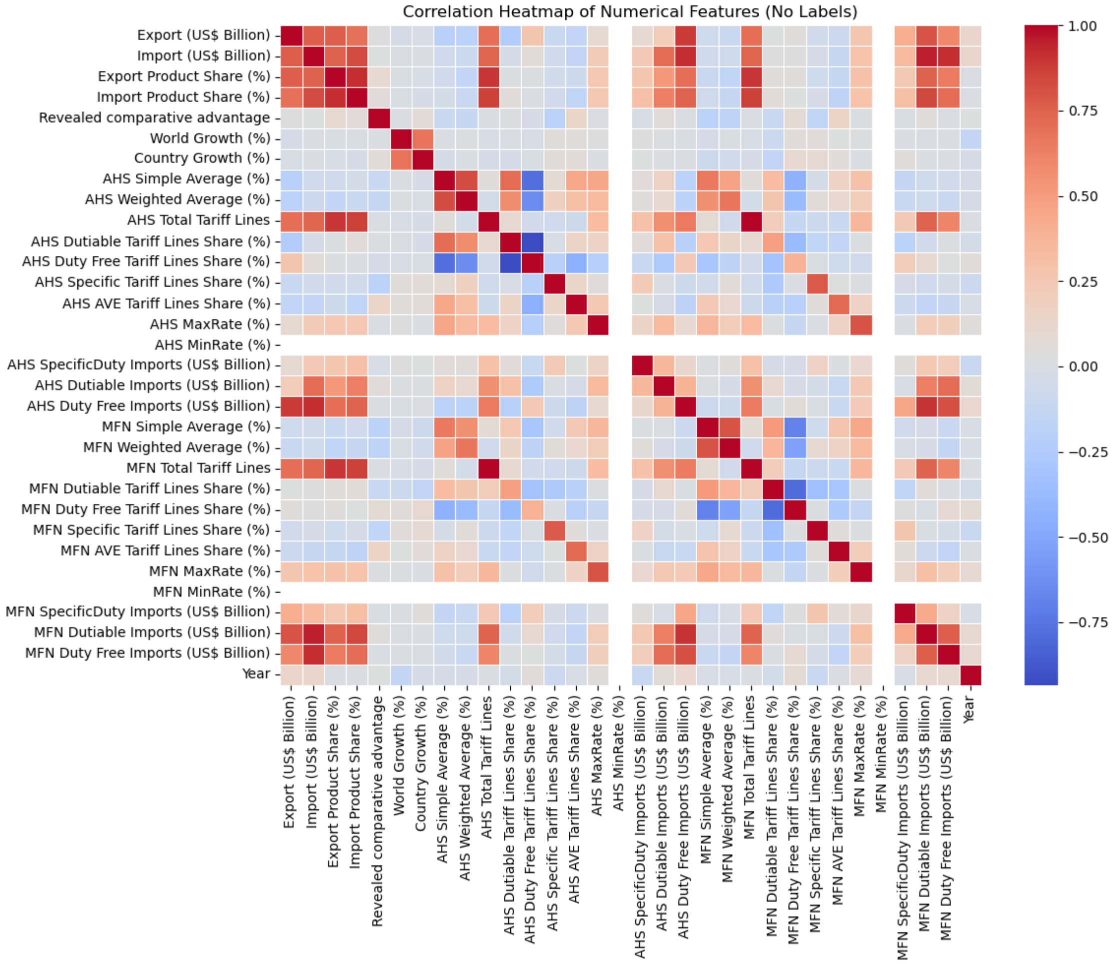

Figure 5: Feature Correlation

In preparation for creating our prediction, we explored the correlation between each of the features in the data as shown in **Figure 5**. Based on the heatmap above, It is evident that a majority of the features do not possess any correlation with the other features. However, there are a few notable exceptions that are relevant for our prediction model. Notably, `MFN Dutiable Imports (US$ Billion)` and `MFN Duty Free Imports (US$ Billion)` appear to have a pretty significant correlation with `Import (US$ Billion)`. The Imports also appears to be pretty strongly correlated with the exports itself as well as the AHS tariff rates. These findings will be important as we begin the first stage of our model selection.

4 Simulation

4.1 Ordinary Linear Regression

We explored a variety of options for creating our forecasting model. The first and simplest option that we looked into was an ordinary linear regression model. For this model, we sampled various features relating to tariff rates and economical growth to predict the Import Value. In the previous section, we created a heatmap to explore the correlation of various features. Using the results from our data analysis, we sampled those features as the predictors for our linear regression model. The results from our ordinary regression model can be observed below:

[62]:

Dep. Variable:	Import (US$ Billion)	**R-squared:**	0.136
Model:	OLS	**Adj. R-squared:**	0.135
Method:	Least Squares	**F-statistic:**	102.3
Date:	Wed, 19 Mar 2025	**Prob (F-statistic):**	6.05e-120
Time:	18:16:54	**Log-Likelihood:**	-22132.
No. Observations:	3906	**AIC:**	4.428e+04
Df Residuals:	3899	**BIC:**	4.432e+04
Df Model:	6		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
const	13.0515	16.705	0.781	0.435	-19.700	45.803
MFN Duty Free Tariff Lines Share (%)	0.3285	0.179	1.839	0.066	-0.022	0.679
MFN Dutiable Tariff Lines Share (%)	0.2320	0.168	1.385	0.166	-0.096	0.560
MFN AVE Tariff Lines Share (%)	-1.0236	0.199	-5.145	0.000	-1.414	-0.634
MFN MaxRate (%)	0.0769	0.003	23.217	0.000	0.070	0.083
World Growth (%)	-0.3095	0.172	-1.797	0.072	-0.647	0.028
Country Growth (%)	0.1888	0.131	1.444	0.149	-0.068	0.445

Omnibus:	2627.143	**Durbin-Watson:**	1.589
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	36495.791
Skew:	3.078	**Prob(JB):**	0.00
Kurtosis:	16.651	**Cond. No.**	5.60e+03

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.6e+03. This might indicate that there are
strong multicollinearity or other numerical problems.

Based on the `R-squared` value, it is evident that the selected features, while showing a high correlation on the heatmap, do not carry the same correlation when placed in a regression model. The p-values from the correlation for each coefficient further validate this with the majority of the coefficients producing a p-value greater than $\alpha = 0.05$.

4.2 Time-Series Simulation

The results from the ordinary linear regression reveal that a simple regression model is unable to capture the stochasticity of global economics and account for anomalies such as the Great Recession and COVID-19. Furthermore, the features that are being selected as predictors only contain rates regarding tariffs and global growth with no solid predictor to indicate the monetary value of the goods. Therefore, we explored a new method in time-series forecasting.

Time-Series forecasting involves using the results of the previous year to predict the next year in a recursive manner. In our model particularly, we simply created a new column in our data called `Lag Import` which holds the Import data of the previous year. We then used this as one of the predictors in our linear regression model along with other tariff-related features (e.g., `MFN MaxRate (%)`) and trained it on the historic data.

The model then simulates forward by iterating through each row in chronological order, updating the lag predictor with the model's own predicted value at every step. In other words, for each year in this range, the model uses the predicted import from the previous year to get the current year and so forth. The results of this model can be visualized in **Figure 6**.

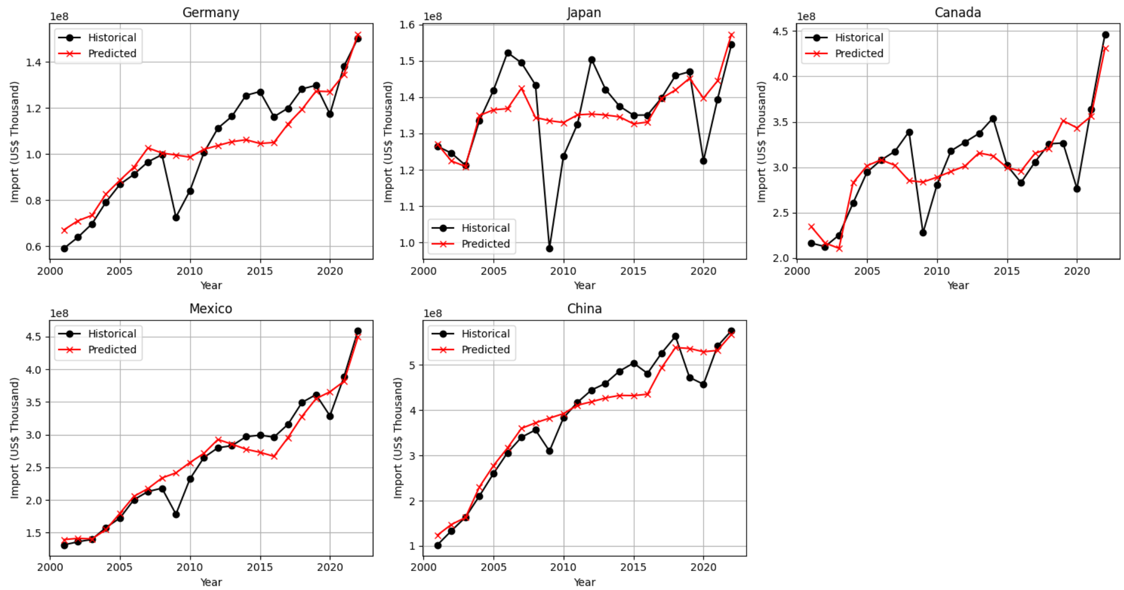

Figure 6: Time-Series Forecasting with Linear Regression on Historic Data

Figure 6 shows the predictions of the time-series forecasting on the historical data from 2000-2022, plotted against the actual historical data. As we can see from the graph, while not totally accurate, the model is able to create a generalized forecasting of the trade flow for each country. However, this model is still unable to capture the anomolies in the trade flow such as the trade war and COVID-19. To overcome this, we explored implementing time-series forecasting with polynomial regression.

4.3 Time-Series Simulation with Polynomial Regression

As mentioned earlier, linear regression is unable to capture unexpected real-world events that impact trade flow such as the Great Recession and COVID-19. We hypothesized that this was due to the non-linearity of the data that we were working with. Therefore, we created the same time-series forecasting model, except we used polynomial regression instead of a simple linear regression. We also included interaction effects to see how each of the features may be influencing each other. We allowed the model to run on several polynomial degrees and select the degree which best captured the historical data when simulated.

Figure 7 shows the predictions of the polyomial time-series simulation on historical data, plotted against the actual historical data to visualize the differences. Although some of the countries appear to contain a lot of noise in the prediction, the model is able to generalize to the historic data and capture different real life events such as the 2018 China-U.S. trade war while avoiding high variance.

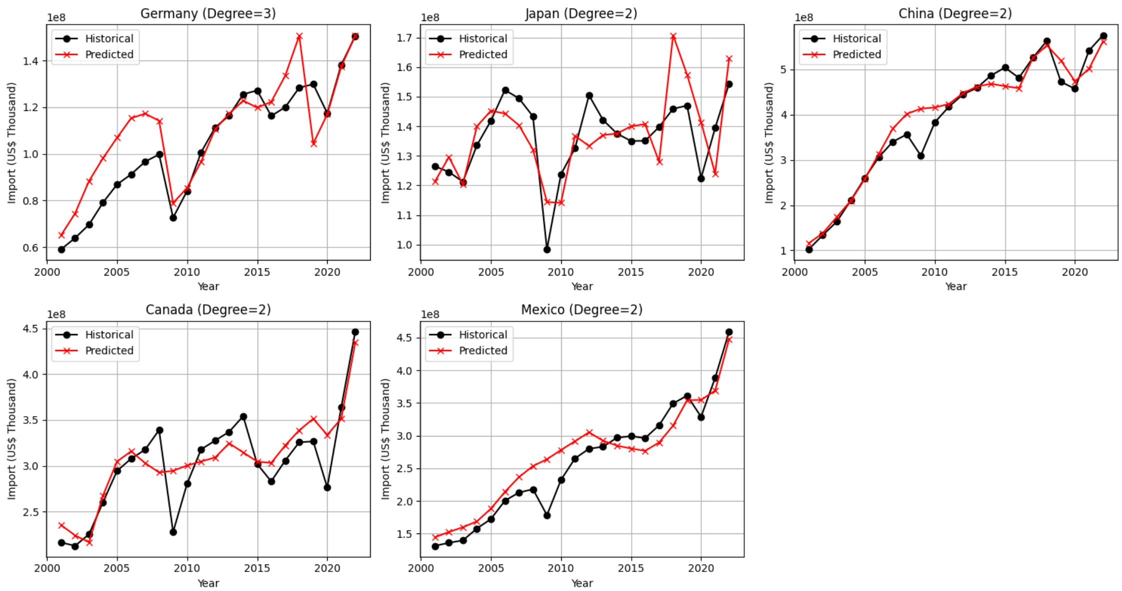

Figure 7: Time-Series Forecasting with Polynomial Regression on Historic Data

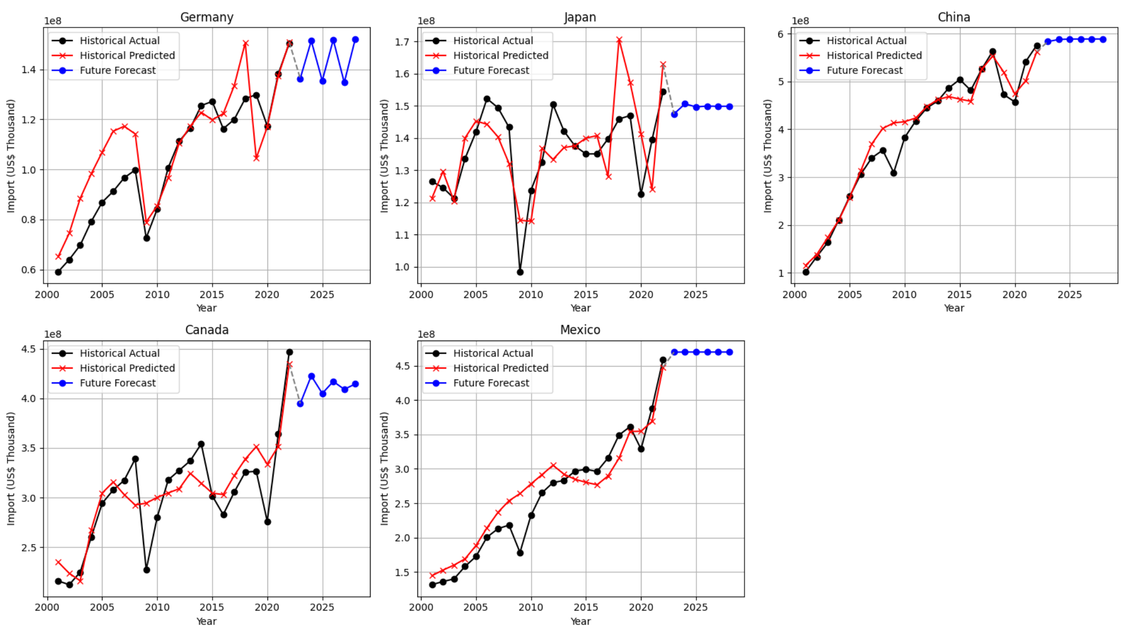

Figure 8: Time-Series Forecasting with Polynomial Regression on Proposed Tariffs

4.4 Simulation Predictions

With our model now finalized and trained on historical data, the next step was to use the trained model to generate predictions on the import values for the future. For simulation purposes, we simulated the next six years, using previous import data to generate new import data chronologically. We used the rates gathered from our background research to set the predictors for our simulation.

Figure 8 shows the results of the polynomial regression time-series model simulated over a period of 6 years into the future. The simulation yielded interesting results. Firstly, the model suggested that our imports from China would stay relatively constant. This was surprising given that China had the highest tariff rates out of all the simulated countries. However, this makes sense because as shown in our exploratory data analysis, we are heavily reliant on foreign Chinese goods that it would be near impossible to create a substitute even with high tariff rates.

Mexico yielded similar results, which also make sense given that we rely on Mexico for many agricultural goods. Germany and Canada appear to have a lot of fluctuations in the import value with an initial spike downwards, followed by many up and down trends. This seems reasonable given that tariffs would likely cause a immediate impact on trade flow, but would gradually stabilize in the years following. Japan also follows a similar pattern.

4.5 Simulating Retaliatory Tariffs

In order to draw inferences about economical implications, it is important to consider retaliatory tariffs. These are tariffs that trade partners may impose on the United States in response to the United States placing high tariffs on them. We have created a hypothetical retaliatory tariff scenario to show how they may impact trade flow, specifically exports from the United States.

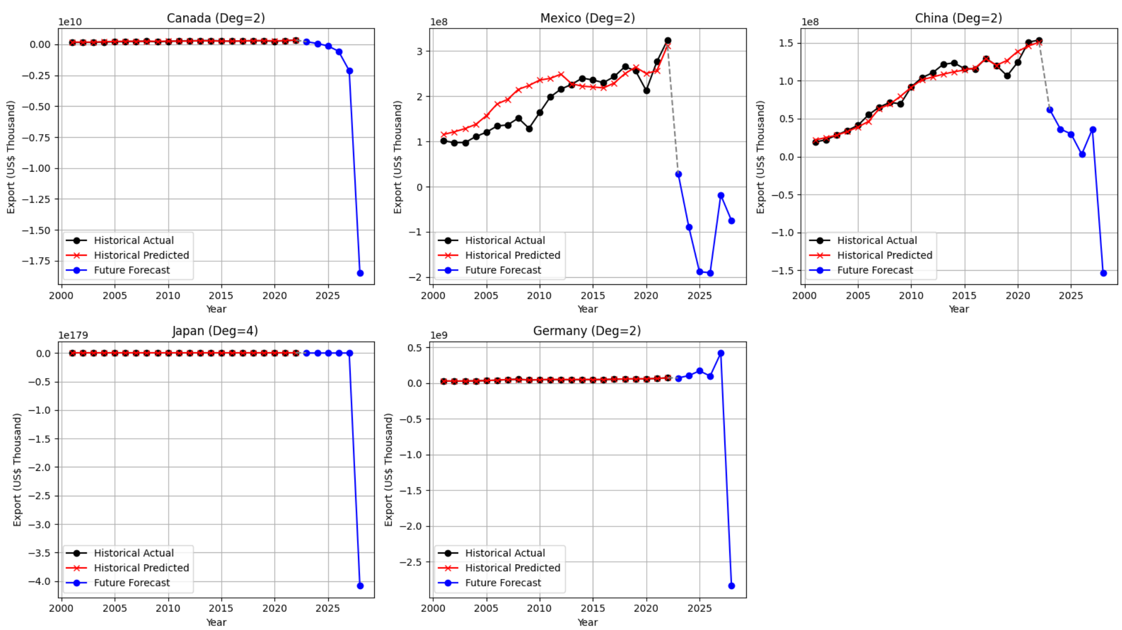

Figure 9: Time-Series Forecasting with Polynomial Regression on Potential Retaliatory Tariffs

Figure 9 shows the results of our forecasting model used to predict the impact hypothetical retaliatory tariffs on exports from the United States. While our results may seem skewed due to the unpredictability of such trade scenarios, it is clear that almost the exports to every country showcase a sharp downwards trend. This means that many of the resources produced in the United States would not be able to be shipped to other countries as a result of high tariffs being placed on U.S. goods. Countries would be more likely to rely on their own domestic production to substitute for this change in trade flow.

5 Discussion & Conclusion

5.1 Results Interpretation

The results from our time-series polynomial regression model suggest that while imports into the United States would not have any significant impact from tariffs imposed by the Trump administration, the exact opposite is true for exports given that countries are likely to place retaliatory tariffs on U.S. goods. Our exports would significantly drop, further increasing the trade balance and making the U.S. even more reliant on foreign goods.

This suggests the tariffs proposed by the Trump administration will result in the exact opposite of what the Trump administration hopes to accomplish by placing these tariffs. While the Trump administration hopes to increase domestic labor, these tariffs will only make the United States even more reliant on foreign goods while paying a higher price, which would in turn result in a drastic increase on goods at the consumer level.

5.2 Future Improvements

If we were to continue this project or repeat it in the future, we can expand on this by incorporating additional economic indicators and refine our current predictive models in order to enhance the accuracy of trade impact. Our current results show a very skewed outcome likely due to the uncertainty of the generated results from the time-series model.

5.3 Conclusion

The findings of this project provide a clear understanding of the economic problems given by tariffs on U.S. trade. By analyzing historical trade data, applying statistical modeling techniques, and conducting tariff scenarios, the project demonstrated how tariff policies influence import and export trade patterns. Our analysis of key trading partners revealed trends in trade volume and tariff impacts, showcasing how changes in tariff rates could lead to shifts in trade flows and their implications for industries, consumers, and the economy. In addition, the inclusion of retaliatory tariffs shows the responses that trade partners may place in reaction to U.S. policy changes.

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