Mapping a Tariff-Resistant Real Estate Strategy

by

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and

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ABSTRACT

This paper examines the relationship between U.S. import tariff policy and freight volumes at ports of entry, with implications for supply chain real estate (SCRE) investment strategy. Using a partial equilibrium simulation model grounded in the Armington framework, which treats imports from different countries as imperfect substitutes, we analyze how tariff-driven price changes redistribute import market share across sourcing countries and redirect cargo flows through U.S. ports. As global sourcing patterns shift away from China toward lower-cost alternatives including Vietnam, India, and Mexico, the geographic distribution of port activity is changing in ways that create both risk and opportunity for SCRE investors. The model is calibrated using U.S. Census trade data and applied to a practical investment context: a private equity firm managing a $13.1 billion portfolio of high-flow-through logistics properties. These findings inform a data-driven framework for assessing port-level freight exposure and guiding capital allocation decisions amid ongoing trade policy uncertainty. This research also contributes to the broader literature on how trade policy transmits through logistics infrastructure, offering a replicable methodology for practitioners operating in tariff-sensitive real estate markets.

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1. INTRODUCTION

1.1 Background

Our project sponsor is a private equity firm that specializes in supply chain real estate (SCRE) investments. It has grown its portfolio to $13.1B USD in assets under management, spanning over 400 investments across North America, Europe, and Asia Pacific. It acquires, develops, and owns SCRE properties, leasing them primarily to retail and logistics service providers that require network flexibility or lack the capital to deploy into real estate.

Specifically, these investments are transportation-related industrial properties. Our sponsor focuses its investment and management on what it calls high-flow-through (HFT) logistics properties, such as final-mile delivery facilities, truck terminals, and port-related yards for trailer or container storage. Items in these facilities often need to be received, broken down, and repalletized, typically in under 24 hours. HFT properties are located near ports of entry to allow for companies to quickly pivot from offloading international container ships and onto truck or rail transportation.

1.2 Motivation

Over the past two decades, global manufacturing has been undergoing a major shift, largely due to cost considerations. The growth of the world's dependence on Chinese manufacturing began in the early 2000s when companies began to take advantage of China's significantly lower cost of labor. But as China's technology advanced, and its economy grew, its labor costs grew rapidly. Between 2001 and 2012, the country saw an increase of 11.9% in hourly labor cost each year (Economist Intelligence Unit, 2014). Due to these increases, as well as concerns over supply chain resilience, American companies' dependency on Chinese manufacturing has since decreased. As of 2023, China fell from the U.S.'s top source of internationally manufactured goods for the first time in 20 years (Boston Consulting Group, 2024). Instead, companies have begun favoring other growing, low-cost manufacturing locations, such as India, Vietnam, and Mexico.

These manufacturing shifts were exacerbated by 2018 tariffs imposed on China by President Trump during the US-China trade war. A study done by the *Journal of Economic Perspectives* (Amiti et al., 2019) found that by December 2018, import tariffs were costing US companies and their consumers an additional $3.2 billion per month in added tax costs. These substantial costs further increased price concerns and incentivized companies to diversify sourcing.

As U.S. importers shift sourcing to different manufacturing countries, trade routes to the United States shift accordingly. For example, imports from China predominantly enter the United States through California, while goods from Mexico rely on land border crossings, typically through Texas. Thus, as imports from China decrease and goods from countries such as Mexico increase, traffic at ports of entry shifts accordingly.

Since our sponsor's investment success is tied to current and future transportation activity at ports of entry in the United States, knowledge of how traffic will shift in the next three years is critical.

1.3 Problem Statement and Key Questions

Our objective is to develop a methodology that quantifies the impact of tariffs on inbound freight flows through U.S. ports of entry. To do so, we must understand the historical effects of previous tariffs on freight flows, assess and forecast alternate options for trade routes, and evaluate current and project future activity at ports of entry. We illustrated our findings through a scenario planning model displayed in an interactive dashboard. For this exercise, we focused our research on the immediate and near-term impacts.

Therefore, the research questions are:

1. What has been the historical impact of prior U.S. tariff increases on inbound freight flows?
2. What trade patterns are most likely to shift under the new tariffs, and which U.S. points of entry are likely to experience significant changes in freight tonnage?
3. What are the current trade routes for the selected commodities, and how will these routes shift if U.S. import tariffs persist?

1.4 Project Goals and Expected Outcomes

Our sponsor seeks to proactively identify which U.S. ports are likely to experience sustained import growth or decline as global sourcing patterns adjust to tariff changes. The objective is to inform investment decisions regarding where to acquire, develop, or lease SCRE in the immediate to near-term future.

Our project goal is to build a framework that links tariff scenarios to shifts in country-of-origin sourcing and downstream port utilization. The model will:

- Establish baseline trade patterns for U.S. imports.
- Quantify the impact of tariff changes on the source country's market share.
- Map potential sourcing changes to historical country-to-port routing patterns.
- Estimate the resulting volume redistribution across U.S. ports.
- Enable structured scenario testing by commodity, country, and tariff level.

The final deliverable is an interactive dashboard, delivered through a web-based app, that allows our sponsor company to simulate multiple tariff environments. These simulations will allow it to identify ports with the highest projected growth or decline, supporting data driven and forward-looking SCRE investment decisions.

2. STATE OF THE PRACTICE

The objective of this capstone is to provide our sponsor company with a structured framework for evaluating how tariff changes may alter import flows across U.S. ports and, in turn, influence demand for SCRE. Rather than relying solely on historical correlations of previous tariff increases, this project seeks to understand the underlying mechanisms through which tariff shocks affect country-of-origin sourcing decisions. It then examines how those sourcing shifts ultimately translate into changes in port-level import volumes. This State of the Practice summarizes the relevant literature that informs our methodological choices and guides the development of our scenario-based modeling framework.

2.1 Previous Tariff Impact – 2018

A study done by the *Journal of Economic Perspectives* estimates that the 2018 trade war between the United States and China cost U.S. consumers and importing firms an additional $3.2 billion per month in tax costs. Although several economic theories suggest that tariffs drive down exporter prices, this study concluded that no such decrease existed, and U.S. domestic agents absorbed the full burden of these magnified costs (Amiti et al., 2019). As of a result of these large cost increases, American companies have been pressured to intensify their manufacturing shifts.

2.2 Model Selection

Several quantitative methods were explored to explain the relationship between tariffs and inbound freight flows. There are two distinct approaches to modeling the impact of tariffs: regression models and economic models. Economic models are simulation-based such as the models proposed by economists Krugman (1980) and Armington (1969). They are built on supply and demand relationships and use assumed behavioral parameters to predict how markets respond to a policy change. By contrast, regression models are empirical, and data driven. They use historical data to estimate the observed relationship between tariff changes and import volumes before and after implementation.

2.2.1 Regression Model

Amiti et al. (2019) examines the impact of the 2018 U.S. tariffs using a difference-in-differences (DiD) regression framework that exploits variation across products that are subject to different tariff increases. DiD estimates a treatment effect by comparing outcome changes between affected and unaffected groups over time, making it well-suited to settings where tariffs apply to some products or countries but not others.

2.2.2 Economic Model - Krugman

Krugman (1980) develops a model of trade based on economies of scale and product differentiation under monopolistic competition, where each firm produces a unique variety. Trade is driven by increasing returns rather than comparative advantage, and products are differentiated at the firm level rather than by country of origin. The model attributes trade flows to firm-level variety and scale economies, and therefore does not isolate the effect of a tariff on a specific sourcing country's import market share.

2.2.3 Economic Model - Armington

Armington (1969) proposes that goods of the same type produced in different countries are imperfect substitutes for one another. Demand for imports from any given country is a function of relative prices and the elasticity of substitution between competing source countries. Substitution elasticities are constant but finite, meaning a tariff applied to one country's exports shifts demand toward other supplying countries rather than eliminating import demand entirely.

2.2.4 Model Selection

Initially, we evaluated the use of a DiD regression model. However, DiD is most effective when a tariff change for a given product applies to one country but not another with similar characteristics, allowing the tariff to be isolated as the cause of any observed difference in trade flows. As seen with the 2025 U.S. tariffs, it is possible for tariff changes to apply to all major sourcing countries simultaneously, rendering DiD ineffective in this context. This limitation led us to evaluate structural economic models more deeply.

Both the Armington and Krugman frameworks treat demand shares as a function of relative prices. However, they differ in their unit of analysis. The Krugman (1980) model differentiates products at the firm level and incorporates firm entry and exit dynamics. This level of granularity does not align with our research question, as tariffs are applied at the country level rather than the firm level. The Armington (1969) model, by contrast, models substitution between competing supply sources by country of origin, which directly maps to how tariffs shift import volumes across sourcing countries. The Armington framework is a Constant Elasticity of Substitution (CES) model that differentiates imported goods by country of origin. Because the tariff changes under analysis are applied at the country level, it is the more appropriate theoretical foundation for our scenario-based modeling approach.

2.3 Economic Modeling Scope

When selecting an economic simulation model, it is important to define the analytical scope. In this context, scope refers to the set of inputs the model accounts for and the range of outputs it is designed to produce. Economic models used in trade policy analysis generally fall into two categories: partial equilibrium and general equilibrium.

2.3.1 Partial Equilibrium

Partial Equilibrium models isolate a single market or sector by holding all other macroeconomic variables constant. This approach produces outputs that are directionally informative but do not fully replicate real-world complexity. The key advantages are modest data requirements and interpretive transparency, making results accessible to a broad audience. The primary limitation is that indirect effects across other markets, such as cross-industry price adjustments or factor reallocation, are not captured (Hallren & Riker, 2017; World Trade Organization [WTO], 2012).

2.3.2 General Equilibrium

General Equilibrium models solve for multiple economic variables simultaneously, including wages, consumption, production, trade flows, and prices across industries. These models account for interdependencies throughout the economy. Therefore, they provide a more complete picture of how a policy shock, such as a tariff change, ripples across markets and affects global production and trade patterns. However, general equilibrium analysis demands substantially more data, involves greater computational complexity, and makes it more difficult to isolate the effect of a single variable on a specific outcome (WTO, 2012; UNCTAD, 2012).

2.3.3 Scope Selection

Given the objective of this research, a partial equilibrium framework is more appropriate. When the policy change is narrowly focused on a single input, partial equilibrium models are the right tool. This is because they are easier to set up, require fewer data inputs, and directly isolate substitution effects without requiring full economy-wide adjustment modeling (Hallren & Riker, 2017).

2.4 Armington-Style Elasticity Calculation

To evaluate the effects of tariffs using the Armington model, a crucial parameter, the elasticity of substitution, must be determined. Elasticity of substitution represents how a product's demand responds when tariffs or other financial costs (taxes, duties, fees) are imposed; the higher the value, the more the product's sourcing will shift in response. Elasticity of a product can be characterized by its attributes such as cost of the good, seasonality, and market concentration.

In the Armington model, each country's import share is proportional to its price raised to the power $-\sigma$, where σ is the elasticity of substitution. Although σ itself is always positive, it enters the formula as a negative exponent, meaning a higher σ produces a larger negative power and therefore a more dramatic shift in import shares in response to a price change.

Research done by the *Journal of International Economics* suggests that most elasticity estimates vary widely across studies, often due to publication bias against statistically insignificant estimates, and that the true elasticity in practice should be in the range of 2.5–5.1, with a median of 3.8 (Bajzik et al., 2020). Therefore, we decided to use this range and median when calculating elasticities for our model.

$$CV(h,c) = \sigma(h,c) / (\mu(h,c) + \varepsilon)$$

Where:

- h: HS code
- c: Country
- ε: 10^{-9} (used for the prevention of a division by 0)

The coefficient of variation measures how volatile a country's import share is for a given HS code. Using monthly total customs value for consumption for 2024 and 2025, this calculates the country's standard deviation divided by its overall average. It also includes a small buffer to avoid a division by 0. A low coefficient of variation means that an HS code's standard deviation is not far from the average, meaning that the product is stable and consistent over time.

3. METHODOLOGY

Based on our review of the literature, we developed a methodology to answer the research questions. Our methodology takes U.S. Customs trade data at the product, country, and port level as inputs, which we compiled and aggregated into baseline sourcing and routing matrices. We then applied the Armington model to simulate tariff-driven shifts in import market share, using clustering to provide rigor to the elasticity estimation. The resulting output is an interactive simulation that displays the current baseline trade scenario and allows users to manipulate tariff levels across products and countries to project changes in freight volume at U.S. ports of entry.

3.1 Methodology Selection

We have built a partial equilibrium simulation model that redistributes market share while keeping all other macroeconomic factors fixed. For the purposes of this research, we use the total customs value for consumption as a proxy for volume due to data limitations. In addition, we define market share as the customs value for consumption for a given country or port divided by the total customs value for consumption of its peers over a period. We also hypothesized that goods are historically produced in the same countries of origin with year-over-year stability. In turn, we projected that there is consistency in the U.S. ports that are linked to the countries of product origin. We used these links to establish the status quo prior to any significant tariff shifts.

To operationalize this model, products must be classified at a consistent level of specificity. In the context of U.S. trade data, products are classified under the Harmonized Tariff Schedule (HTS), which is maintained and published by the U.S. International Trade Commission (USITC). Every product is assigned a 10-digit HTS code, with each pair of digits representing a higher level of specificity. The first six digits correspond to the Harmonized System (HS), the globally standardized product classification used across nearly all trading countries. The final four digits are assigned by the United States to provide additional tariff and statistical detail. The structure is hierarchical and mutually exclusive, meaning that at each level of aggregation, a product belongs to one and only one category.

Tariffs in the United States are legally defined at the 8-digit HTS level, while trade flows are typically reported at the 10-digit level. The hierarchy increases in specificity as follows: HS2-chapter, HS4-heading, HS6-subheading, HTS8-tariff line, and HTS10-statistical reporting number. Each broader category is composed of the more detailed codes nested beneath it.

In our model, we establish the baseline country-of-origin distribution at the HS4 level. Although tariffs are applied at the 8-digit level, aggregating to HS4 provides a practical balance between granularity and usability. Specifically, it preserves meaningful product differentiation while limiting instances of sparse or obsolete product categories. Substitution elasticities are calibrated at the HS2 level, where broader supply chains and input materials are more structurally differentiated between HS2 codes. The model allows users to simulate tariff shocks at either the HS2 or HS4 level, depending on the desired level of analysis.

After establishing our product taxonomy at the HS2 and HS4 levels, we identified three research questions to guide model development:

- Can we identify a subset of countries that consistently account for the majority of imports for each HS4 code?
- Can we identify a subset of U.S. ports that consistently account for the majority of volume for each country and HS4 code pairing?
- For each HS2 category, what is the implied elasticity of substitution based on observed historical tariff changes, and how sensitive are import market shares to tariff-inclusive price changes?

3.2 Data Collection and Preparation

Our model relies on public datasets, including some that were inaccessible during the U.S. government shutdown that occurred between October 1, 2025, and November 12, 2025. This temporary impediment forced us to evaluate multiple alternative data sources (most notably the World Bank and the USITC) to build our model. However, we couldn't access the specific data points needed at the level of granularity necessary with either source.

Once the shutdown concluded, we were able to access the U.S. Census Bureau's USA Trade Online database. This gave us the ability to access the granular data we need. With USA Trade, we accessed HS code, production country-of-origin, and U.S. port of entry data. Additionally, due to the size of the database, we had to separate our queries into three datasets.

The product categories that most frequently move through our sponsor's facilities are products that are transported by ocean container and tractor-trailers. Therefore, we selected the HS2 codes and their respective HS4 codes that are most likely to be transported in this manner. Selected HS2 codes and product categories in Figure 1:

HS2 Code(s)	Product Description
HS 33–34	Personal care and cleaning
HS 39	Plastics and articles thereof
HS 48–49	Paper goods and printed materials
HS 61–63	Apparel and textiles
HS 64	Footwear
HS 70	Glassware
HS 73	Articles of iron or steel
HS 76	Articles of aluminum
HS 82	Tools and cutlery
HS 83	Miscellaneous articles of base metal

HS 84–85	Machinery and electrical equipment
HS 87	Automotive and bicycle parts
HS 94	Furniture and bedding
HS 95–96	Toys, sporting goods, and miscellaneous manufactured articles

Figure 1. Table of Selected HS2 Codes

Due to the size of the USA Trade Online files, we divided our queries into three distinct datasets, each serving a specific role in the model: the first establishes baseline country-of-origin market shares by product, the second maps those country-of-origin relationships to U.S. ports of entry, and the third captures monthly tariff and customs value trends used to calculate product-level elasticities of substitution.

Dataset 1: Six-Year Import Country of Origin Trends (2020-2025)

This dataset is critical in the baseline calculation of market share for the primary, secondary, and tertiary countries of origin for our selected products' HS2 and HS4 codes. In our analysis, we found the top ten countries of origin comprised 80% or more of the total market share for nearly every product. Therefore, we limit the country-of-origin count to ten for each product and normalize each country's share to 100%. With this data, we were able to understand the collection of countries impacted by a tariff change for each product.

Relevant features of the dataset included:

- HS2: Classification of imported product at the two-digit chapter level
- HS4: Classification of imported product at the four-digit heading level
- Year: Calendar year in which the import transaction was recorded by U.S. Customs
- Country of Origin: Country where imported product was manufactured or substantially transformed
- Customs Value $ (General): Total value of product as appraised by U.S. Customs for General Imports for a given product, year, and country
- Customs Value $ (Consumption): Value of product as appraised by U.S. Customs for final consumption in the U.S. for a given product, year, and country
- Calculated Duty ($US): Estimates of the duty paid for a given product, year, and country
- Effective Tariff Rate: Calculated Duty divided by Customs Value for consumption for a given product, year, and country
- % of HTS Code Market Share: Customs Value for a specific country, product, and year divided by the total Customs Value for the product and year

Dataset 2: Six-Year U.S. Port of Entry Trends (2020-2025)

This dataset establishes the baseline relationship between countries of origin and the most frequent U.S. ports of entry. In our analysis, we found the top ten ports for each product-country pair comprised 80% or more of the total market share for nearly all the product-country pairs. Therefore, we limit the port of entry count to ten for each product-country pair and normalize each port's share to 100%. This data helped us understand which ports are available for a change in market share should tariffs impact their respective source countries.

Relevant features of the dataset included:

- All features in Dataset 1
- U.S. Port District: Collection of ports within a city's metro area
- U.S. Port Region: Collection of ports within a region composed of multiple states

Dataset 3: Monthly Breakdown of Tariff Trends (2024-2025)

Our final dataset is used to measure the impact of tariffs on market share distribution by country of origin. We have conducted this analysis for every individual HS2 code. The result is an output of elasticity of substitution for each product at the HS2 level of classification.

Relevant features of the dataset:

- All features in Datasets 1 & 2
- Month: Calendar month in which the import transaction was recorded by U.S. Customs

3.3 Model Application

Our model will apply a simulation framework to display the impact of tariffs on U.S. import flows. The answers to the questions listed in the methodology selection served as key parameters to our model. Figure 2 shows the five-step process to build the model.

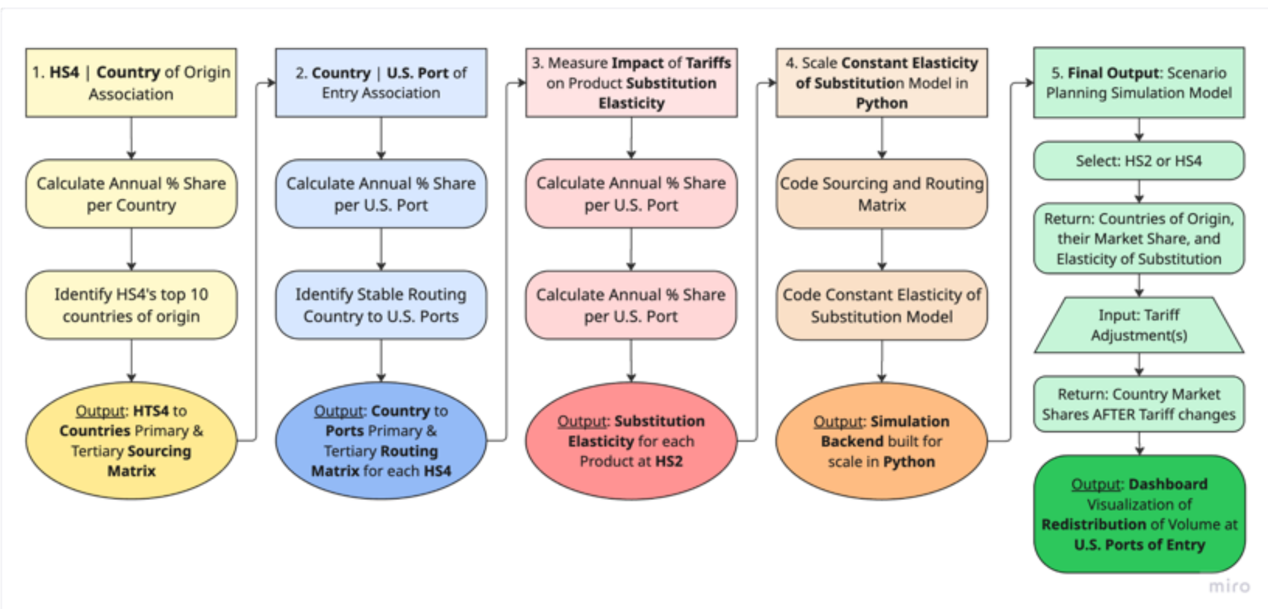

Figure 2. Capstone Methodology Steps

First, we established baseline sourcing and routing matrices, linking country-level market shares to port-level flows. For example, if China accounts for 50% of U.S. imports of a product and the Port of Los Angeles receives 60% of China's imports of that product, then the baseline China-to–Port of Los Angeles flow represents 30% of total imports for that product. Next, we analyzed 2025 tariff changes to estimate product-level substitution elasticities. Finally, we used 2025 effective tariff rates as the current baseline for each product-country pairing, with user-defined changes applied relative to these levels. With these relationships calibrated, we assembled the components required to construct the simulation model.

The model captures the chain reaction from tariff changes to port-level freight flows. Tariffs alter a country's relative price for a given product, and the elasticity of substitution determines how importers shift sourcing in response. These shifts redistribute market share across countries, which ultimately translate into changes in freight volume at specific U.S. ports of entry. While sourcing shifts typically occur over several months or years due to procurement, production, and logistics constraints, the model does not incorporate these time lags and instead assumes immediate adjustment.

Building on this framework, the sourcing and routing matrices are developed in Python. Additionally, the elasticity estimation and CES simulation model were also developed in Python. To improve usability for the sponsor, we deployed a user-friendly interface through an app hosted on Streamlit, a front-end visualization tool, with a map visual in addition to a table output.

3.3.1 Adapted Armington Import Share Model

The following formula estimates the predicted import share for commodity *c* sourced from country *i*:

$$s_{ic} = \alpha_{ic} \cdot p_{ic}^{(-\sigma_c)} \; / \; \Sigma^{N}_{j=1} \; \alpha_{jc} \cdot p_{jc}^{(-\sigma_c)}$$

Model Properties:

$$\Sigma_{i \in S} \; s_{ic} = 1, \quad \forall \, c \in C$$
$$s_{ic} \geq 0, \quad \forall \, i \in S, \forall \, c \in C$$

Sets:

- S: Set of source countries
- C: Set of commodities
- P: Set of ports of entry

Decision Variables:

- s_{ic}: Predicted import share of commodity *c* sourced from country $i \in S$

Parameters:

- α_{ic}: Baseline attractiveness weight for country *i* and commodity *c* prior to tariff change
- p_{ic}: Price factor for country *i* and commodity *c*, defined as $1 + \tau_{ic}$, where τ_{ic} is the applicable tariff rate
- σ_c: Elasticity of substitution across source countries for commodity *c*, entered as a positive value and applied as a negative exponent
- N: Number of source countries considered, restricted to the top 10 origins per commodity

The Adapted Armington Import Share Model estimates how import demand for each commodity is redistributed across source countries in response to tariff changes. For each commodity, a country's predicted import share is calculated based on its pre-tariff attractiveness weight, capturing baseline trade relationships, and its tariff-adjusted price factor (1 + tariff rate). The elasticity of substitution controls how dramatically importers shift sourcing away from more expensive origins, and enters the formula as a negative exponent, meaning a higher σ produces a stronger substitution response. The model properties ensure that the resulting shares are non-negative and sum to one, producing an interpretable reallocation of import volumes that can be mapped to port-level freight flows.

3.3.2 Model Application – Elasticity Calculation

When computing the Armington model, inputting the product's correct elasticity is crucial. Elasticity measures how sensitive the quantity demanded of a good is to a change in its price. Typically, it is measured by taking the percentage change of the demand quantity of the good demanded and dividing it by the percentage change in price of the good.

Unfortunately, the U.S. Census Bureau – the best possible public source for this information – does not reliably report the quantity of imports; there are many missing or incorrect fields throughout the dataset. Thus, to determine the elasticity of a product using only the only reliable field in the U.S. Census Bureau (customs value), we calculated the coefficient of variation (CV): the standard deviation divided by the sample mean.

We chose to determine elasticity at the two-digit HS code level for our chosen set of HS codes. We extracted monthly customs value data for each selected HS code from all countries for 2024 and 2025 and created a data table in Python. Our model then creates an average customs value for every HS code for every country for both 2024 and 2025 and stores it in a separate table.

Since the Armington model requires a single elasticity per product, our model aggregates the CV across all countries for a given HS code into one overall average, yielding a single CV value for each selected HS code. This value captures how far individual months typically deviate from the mean, expressed as a proportion of that mean.

For simplicity of use by our sponsor company, we then clustered these HS codes into three categories:

- Inelastic (low volatility staples)
    - Mean <= 25th % of all CVs
- Moderately Elastic (regularly traded standard goods)
    - Between 25th % and 75th % of all CVs
- Highly Elastic (volatile, price-sensitive goods)
    - Mean >= 75th % of all CVs

A study done by *The Journal of International Economics* determined that Armington elasticity most likely ranges between 2.5 to 5.1 with a median of 3.8 (Bajzik et al., 2020). We used this study to assign elasticities to each cluster:

- Inelastic = 2.5
- Moderately Elastic = 3.8
- Highly Elastic = 5.1

The lower a product's elasticity, the less likely importers are to shift sourcing when a tariff is imposed. Inelastic goods are typically necessities or lack suitable alternatives, such as soap, medication, or gasoline. Highly elastic goods, like apparel, can be sourced from many competing countries, meaning even a small tariff-driven price increase may prompt importers to shift to an alternative origin.

In addition to the clustering-based approach, the model offers an alternative elasticity estimation option using Claude's Sonnet 4.6, a large language model. To generate these estimates, we provided Claude with the raw customs value data and the Armington model formulation and prompted it to estimate the elasticity of substitution for each selected HS2 code. This produced 20 unique elasticity estimates ranging from 2.0 to 7.5 in increments of 0.5, offering the sponsor a more granular set of inputs compared to the three clusters produced by the clustering-based approach.

3.3.3 Model Assumptions Summary

Like all simulation models, this model requires a set of simplifying assumptions. The assumptions fall into two categories: those governing the CES model itself, and those governing port-level routing behavior. The CES assumptions primarily address how import volumes, sourcing shares, and tariff changes are treated within the simulation, while the port assumptions define how freight is routed and what operational factors are held constant. These assumptions reflect the limitations of publicly available trade data and the inherent complexity of modeling real-time macroeconomic conditions. Figure 3 summarizes the full set of assumptions for both categories.

CES Model Assumptions	Port Assumptions
Total U.S. import volume is fixed; the model reallocates market share but does not change aggregate demand.	A country's port distribution remains constant year over year unless tariffs change (e.g., if China routes 30% through LAX in the baseline, that share remains 30% absent tariff shifts).
Baseline customs values and relative competitiveness are embedded in initial market share calibration.	Ports are assumed to operate without disruptions or temporary diversions.
The top 10 countries represent the full competitive set and remain stable except for tariff-driven shifts.	Ports are assumed to have no capacity constraints.
No switching costs or adjustment lags; sourcing adjusts immediately to tariff changes.	Port delays and temporary closures are not considered in this model.
Tariffs remain constant unless modified by the user; changes to selected countries do not affect others.	Geographic considerations do not influence routing decisions; inherently assumed in the baseline calculations.
No transshipment is considered; reported country of origin is treated as the sole manufacturing source.	Secondary network impacts (e.g., warehouse relocation, incremental trucking, or rail requirements) are not modeled.
Transport modes are not separated (ie. Air freight); customs value aggregates all modes.	Changes in shipping lane costs or transit times are not considered when routing shifts occur.

We apply a linear time-weighting function when calculating baseline market shares for product-country and country-port, assigning greater weight to more recent years to better reflect most realistic trade patterns in the future while smoothing impact of outliers.

Figure 3. Table of Model Assumptions

4. RESULTS AND DISCUSSION

4.1 Results

We downloaded raw CSV trade data from the U.S. Census Bureau and built a Python script to clean and aggregate two key relationships: product-to-country and country-to-port. Within that script, we identified the top 10 source countries for each product and the top 10 ports for each country-product pair. We then normalized import volumes using a time-weighted average across 2020–2025. The processed data files were stored in a GitHub repository, which the application pulls from directly at runtime. Finally, we used Python and Streamlit to build a web-based application that allows users to interact with the Armington trade simulation model, accessible at https://mitcapstone2026realterm-ecdbwg66shkz46hwhzjo8z.streamlit.app/.

From there, we began running various simulations in the model, and we found some insights relevant to our sponsor's use case. The following insights assume a Claude-determined elasticity.

Baseline — HS2 95 — Toys, sporting goods, and misc. manufactured articles

2025 Total Imports: $34.7B | **σ = 6.5** | Shares time-weighted 2020–2025, normalized to top-10

#	Country	Baseline Share	Old Tariff
1	China	73.5%	23.3%
2	Vietnam	10.8%	13.6%
3	Mexico	4.3%	1.4%
4	Taiwan	3.9%	13.1%
5	Japan	1.7%	9.6%
6	Indonesia	1.5%	11.3%
7	Thailand	1.3%	12.3%
8	Canada	1.1%	1.3%
9	Malaysia	1.0%	11.4%
10	Cambodia	0.9%	12.6%

Figure 4. App - HS Code 95 Manufacturing Country of Origin

HS codes 95 (toys and sporting goods) and 63 (apparel - other) have the highest reliance on Chinese manufacturing, with a share of 73.5% and 54.3% respectively. This is not surprising; China has long been the largest producer of these product categories, and therefore, has the infrastructure in place to produce much larger volumes of these goods than up-and-coming manufacturing countries such as Bangladesh and Vietnam (Economist Intelligence Unit, 2014).

HS code 73 (iron and steel) in China has the highest effective tariff rate -- 53.9% -- followed by HS code 76 (aluminum) in China, which has an effective tariff rate of 53.7%. These tariffs were first imposed by President Trump in his first term. He then further increased tariffs in June 2025, citing a national-security threat and a goal of revitalizing manufacturing within the United States (The White House, 2026). As a result, these elevated duties are expected to accelerate manufacturing shifts away from China for these goods.

HS code 61 (apparel - knit) has the highest risk of leaving China. The elasticity determined by Claude is 7.5 (the highest elasticity in our product list) and China has a 44.7% effective rate as of 2025. A product with this high of a tariff rate, combined with a high elasticity, allowing companies to substitute manufacturing locations easily, amounts to a good that companies are most willing to change country of origin in response to a tariff increase.

One of the biggest questions from our sponsor was, when looking at the Canadian border versus the Mexican border, who is most likely to win in the production race if China has more tariffs imposed upon it? To answer this question, we simulated a flat increase of 5% across all of the products coming from China, and kept all other countries' tariffs the same. The result was close; Ports along the Mexican border would see a gain of 5.6% volume, while locations on the Canadian border would see an increase of 4.9% in volume. The top gaining U.S. ports were Nogales, AZ (7.6%) and San Diego, CA (7.3%). The top losing U.S ports were Los Angeles, CA (-4.8%) and San Francisco (-2.7%). Overall, the west coast ports were down by 4.1%, and Mexican and Canadian ports were up by 5-8% on average.

4.2 Interactive Dashboard

Visualization is key for our capstone sponsor's implementation of our findings for their future investment strategies. We created an app with interactive features for our sponsor company to assess future scenarios at a high level, with the opportunity to delve deeper into details when required.

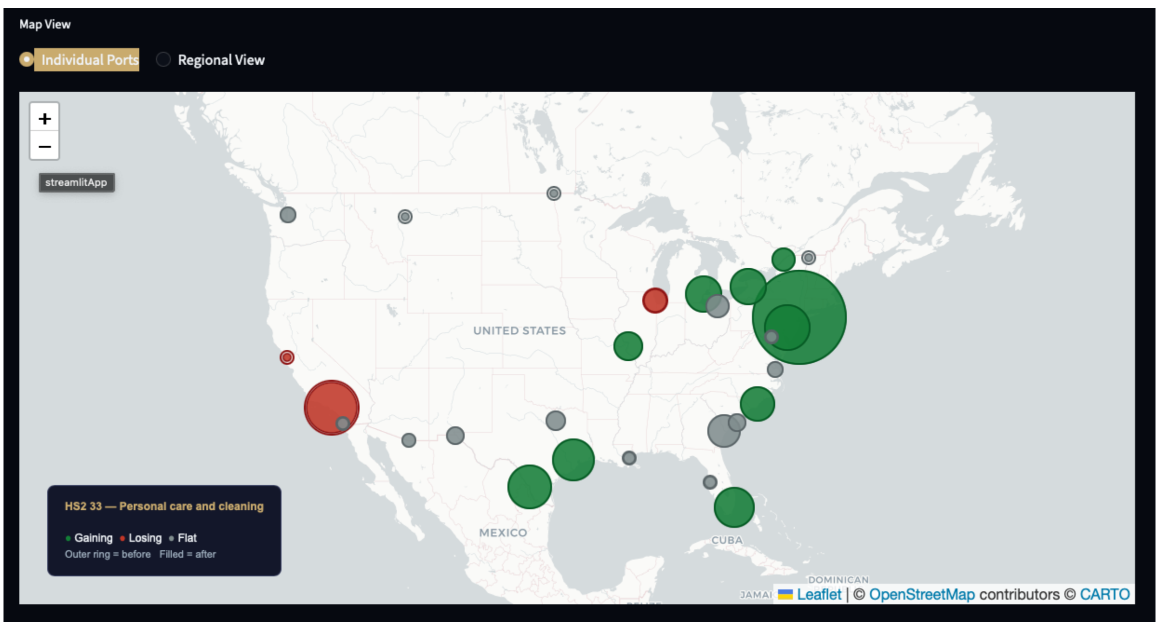

Figure 5. Port Traffic App Visualization

Port Impact Summary						
Port / Region	Before	After	Change (pp)	Before ($)	After ($)	Volume Δ
▸ **West Coast**	**51.21%**	**50.88%**	**-0.33pp**	**$17.8B**	**$17.6B**	**($114.3M)**
Los Angeles, CA	39.18%	37.66%	**-1.52pp**	$13.6B	$13.1B	**($526.7M)**
Seattle, WA	11.09%	11.85%	**+0.76pp**	$3.8B	$4.1B	**+$262.0M**
San Diego, CA	0.63%	0.92%	**+0.29pp**	$216.8M	$317.5M	**+$100.7M**
San Francisco, CA	0.31%	0.45%	**+0.14pp**	$107.5M	$157.2M	**+$49.7M**
▸ **Northern Border**	**14.33%**	**14.36%**	**+0.03pp**	**$5.0B**	**$5.0B**	**+$10.2M**
Chicago, IL	10.56%	10.18%	**-0.39pp**	$3.7B	$3.5B	**($133.6M)**
Cleveland, OH	2.83%	2.82%	**-0.02pp**	$982.5M	$976.6M	**($5.9M)**
Detroit, MI	0.44%	0.65%	**+0.21pp**	$153.4M	$224.5M	**+$71.1M**

Figure 6. Port Traffic App Table

We chose to present the data output in two formats, a table as well as a map, so our sponsor would have the flexibility of using one or both visualizations to present to a wide variety of internal teams throughout.

The percentage change of each port's traffic is presented as a proportional symbol map. We used a circle to represent the size of the change. Red represents a port that is losing share, green represents a port that is gaining share, and gray represents a port where the traffic rate remained flat rate (0-0.05% change). The user can toggle between two visual displays of ports (the individual port or a regional collection of ports) allowing our sponsor to decide in what granularity they would like to see the data.

In the app, we allowed the user to decide if they would like to use our elasticity determined by our clustering code, a Claude AI decision, or a manual entry to allow flexibility for our sponsor. On average, the Claude AI elasticity is about 1.65 σ higher than our cluster-determined elasticity. This is most likely due to our code assigning all HS codes, whose CV falls within the 25-75%, to an elasticity of 2.5, therefore, lowering the average.

4.3 Big Three Scenario – Mexico, China & Canada

Building on the sponsor question raised in 4.1, we selected a single product to examine how tariff shifts redistribute import volume among the Big Three trading partners. We chose a product where Mexico, China, and Canada were the three largest import sources, since they are currently the three largest exporters to the U.S. overall. HS 8708, automobile parts, fit our criteria with $80 billion in U.S. imports in 2025 and a price elasticity of 2.0. Mexico held the largest share at 43.7% with an effective tariff rate of 7.6%, Canada was second at 14.6% at 7.9%, and China was third at 12.0% but faced a significantly higher effective tariff rate of 55.4%. We modeled three scenarios: Mexico raised to China's tariff rate, Canada raised to China's tariff rate, and China reduced to the Mexico-Canada average of 7.8%, with all other variables held constant.

When Mexico is taxed at China's tariff level, its market share falls by nearly two thirds, dropping 17.5% to 26.2%. Canada is the largest beneficiary, gaining 4.5%, followed by China at 3.7%. At the port level, Northern U.S. Border ports collectively gained 8.73% in volume. Individually, Detroit, MI saw a 6% increase, Chicago, IL gained 1.7%, and the Port of Los Angeles saw the largest single-port gain outside the northern border at 2.4%. Laredo, TX experienced the largest decline, falling 14.9%.

When Canada faces China's tariff rate, its market share is cut nearly in half, falling to 7.3%. Mexico becomes the largest beneficiary at 3.7%, with China gaining an additional 1.0%. Detroit saw the sharpest port-level decline at 6.3%, and Laredo was the only port to gain more than 1.0%, picking up 3.2%.

The most notable result comes from the third scenario. Reducing China's tariff to 7.8% produces a significant volume shift, with China's market share jumping from 12.0% to 33.2%, a 177% increase. Mexico absorbs the largest loss, declining 10.5%, with Canada falling an additional 3.5%. The Port of Los Angeles gains the most at 4.2%, followed by Chicago at 2.0%. Laredo declines 9.2%, dropping from 38.0% to 28.8%.

The core takeaway is that large tariff increases affect Mexico the most given its dominant market position, but even an eightfold increase only reduces its share by 17.5%, leaving it in first place. What is more notable is that the third scenario produces a larger redistribution than either of the first two. This comes down to how the model responds to a tariff reduction versus an increase. When China's tariff drops from 55.4% to 7.8%, it moves from a largely uncompetitive position back into the feasible substitution set. The negative exponent in the model amplifies this change, producing a sharp reallocation of share. In Scenarios 1 and 2, Mexico and Canada are already deeply embedded in sourcing decisions at low tariff rates, so even a large increase is absorbed more gradually. For our sponsor, the key implication is that tariff reductions have the potential to be more disruptive than tariff increases of the same magnitude.

5. RECOMMENDATIONS

5.1 Recommendations for Future Work

There are three key areas where we see the most immediate opportunity for future work:

One of the limitations to our model is the lack of a lag component. Our model assumes an immediate manufacturing and traffic reorganization following a tariff change, and realistically, there would be a lag, most likely between 1-3 years. We recommend that a lag be calculated and added to this model to best estimate when these changes will occur after a new tariff goes into effect.

We also recommend that our sponsor continue an in-depth exploration of elasticity. This characteristic plays a significant role in percentage changes in the Armington model, and a more robust calculation for each HS code would aid in accuracy. Currently, clustered elasticity is determined at the HS 2-digit level, and Claude-aided elasticity is determined at the HS 2 or 4-digit level. It is recommended that further analysis be done to calculate elasticity to at least the HS 6-digit level.

Finally, our app only includes 20 out of a possible 97 2-digit HS codes. We chose products from a variety of categories, however, for a more robust scope, we recommend expanding the number of HS codes to cover all possible products that come through our sponsor's properties.

5.2 Implications for Future Use

In the future, there are two things in the model that would need to change as conditions evolve:

The model uses time-weighted (2020–2025) port-of-entry share data, which will shift over time as trade patterns evolve. Updating the model currently requires manual data entry. Full automation would require programmatic retrieval from the U.S. Census Bureau each time new data is published;

however, the Census Bureau API does not expose the specific data elements this model needs. Producing a real-time version would therefore require a substantial investment in custom data collection infrastructure.

Additionally, the World Customs Organization (WCO) updates HS codes every five years to reflect changes in technology, trade patterns, and add new products. The next schedule update will occur on January 1, 2028. When that happens, our sponsor will need to make any changes to the current list of HS codes.

5.3 Sponsor Company Application

The model visualization will serve as a starting point for discussions with company executives. From an investment standpoint, our sponsor's goal is to find out where it should be focusing on future investments. With our app, it plans on targeting its market in areas of growth, starting with the areas circled in green on our regional map.

On the other side of the business, our sponsor plans to use our tool to raise capital. Its executives often attend fundraising events, and they plan on showcasing our tool to investors to help them better understand freight flows, and therefore, their future investment decisions.

Prior to our model, our sponsor only had a static tool using outdated data. Our model is more dynamic and enables our sponsor to update the data as often as possible, and from an easily accessible, public source. For future use, our model also enables our sponsor to begin building a more robust quantitative model, using our work as a starting point.

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