

Analyzing U.S. Maritime Trade and COVID-19 Impact Using Machine Learning

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INTRODUCTION

Americans import and export goods in three primary ways: air, land (truck, rail, and pipeline), and sea. Out of the three methods, maritime trade is the primary vessel of international trade. As of 2013, as much as 53% of imports and 38% of exports move through American ports, measured in U.S. dollars. The deepening of the Panama Canal and local passages around U.S. ports has encouraged ocean carriers to realize economies of scale by using larger vessels. The maximum size of a ship increased from about 15,000 twenty-foot equivalent units (TEUs) in 2010 to 23,000 TEUs in 2020 (Manaadiar, 2020).

Although monetary terms are one form of measuring value, its meaning is relative to the current exchange rate and value of the USD. Economists have traditionally focused on monetary measurements such as the product's value and national GDP. Instead, we opt to measure trade in metric tonnage. Over time, general baskets of goods retain relatively constant weights whereas real values vary based on exchange rates, scarcity, and inflation. When measured in metric tonnage, maritime trade accounts for 72.4% of imports and 74.8% of exports to and from the United States. In 2019, the Bureau of U.S. Customs and Border Protection cleared 11,160,342 shipments. Serious importers and exporters overwhelmingly prefer sending their goods by sea.

Goods can be transported by sea in a variety of ways, including liquid bulk, breakbulk, roll-on/roll-off (ro/ro), and containers, with the latter being the preferred method for most shippers (Mittal, Boile, Baveja, & Theofanis, 2013). Liquid bulk can be measured in ISO tanks, ro/ro in units, and breakbulk in cartoons, bags, or boxes. The variety of measurements can make cross-comparison difficult. This is yet another reason to use metric tonnage as the standard unit of comparison. Although valuations in the U.S. dollar may facilitate understanding in broad economic terms, the analysis is only useful for shorter time intervals, when framed in the specific time period studied.

This paper begins by elaborating on literary, industry, and historical support that justifies the chosen attributes and time period. Next, details related to data collection and methodologies are outlined. Data analysis and results are divided into subcategories for each model. Models are developed and evaluated to

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answer the research questions. This is followed by an analytics section to highlight trends. We conclude with a section with recommendations for future research.

Background

Since the end of WWII, the United States has been the standard bearer of neoliberalism and, an advocate of free trade (Chang, 2002; Steger & Roy, 2010). The U.S. entered the 1950s as the primary engine of growth for the world economy. Over the decades its share of imports and exports declined, relative to the rest of the world (Irwin, 2017; Yildirim & Saccomano, 2021). Beginning in the 2010s, some Americans became skeptical that free trade worked for them. This discontent materialized in abrupt trade policy changes in 2016.

Imports gained market share in the 1980s as policy prioritized inflation mitigation and floating exchange rates at the expense of jobs. Proponents of neoliberalism argued that the consumer benefits from the increased quantity and variety of imports. It is estimated that the annual earning power of the average American has increased by over \$18,000 per annum between 1950 and 2016 (Hufbauer & Lu, 2019). In 2019, 2.5 trillion dollars of goods were exported while 2.6 trillion dollars of goods were imported. Taken together, the U.S. has benefited from increased trade, in measurable, economic terms.

The changing attitudes toward trade were observed through proxy variables such as unemployment, exchange rates, applied tariff rates, and the size of companies who participate in the international market. Changes among these variables can produce a shock to the global supply chain, influencing the behavior of companies and consumers alike. Wars, famine, and plagues and viruses have had impacts, but these risks have been mostly ignored in recent international trade theory (Irwin, 2017). COVID-19 upended various parts of the supply chain as the pandemic spread throughout the world in 2020 (Baldwin & Di Mauro, 2020). The first effect was a dramatic and rapid reduction in the labor force in affected locations, as workers fell ill or were forced to quarantine (Charlton & Castillo, 2021). International trade was impacted further as borders limited the flow of people and products (Kerr, 2020). These restrictions further exacerbated supply chain disruptions within and among countries, as goods themselves were prioritized differently. However, food and agriculture supply lines were relatively unaffected in the short term, due to narrow time windows between harvest, shipment, and consumption. Even during a pandemic, the global population still needed to eat (Kerr, 2020).

Although the period studied does not include the time period post-global vaccination or data about economic stimulus, enough time has passed to assess the impact of the COVID-19 disruption on international trade, considering this disruption in the context of other possible variables such as unemployment, average applied tariff rates, exchange rates, free trade agreements, and other factors.

The applied tariff rates of countries is one change that may prove transitory or could confound the disruptions caused by the direct or indirect measures of COVID-19. It is still too early to tell if the pandemic will lead to a more decentralized global economic system (Anderson, Rainie, & Vogels., 2021).

There are practical implications of this work for supply chain and logistics professionals. Until the tariff disputes in the late 2010s, the supply chain prioritized “just in time” deliveries, stretched over long distances, that delivered the exact goods, in the right quantities, to the right buyers (Kootanaee, Babu, Nagendra, & Hamid, 2013). Supply chain analytics considered scarcity, strikes, changes in domestic and international policies, and natural disasters, but did not generally anticipate a global pandemic.

This study uses tens of millions of records, aggregating quantitative variables by month and year. Time series, tree-based, and artificial neural network models are used in the attempt to answer some of the research questions, using literature from international trade economists, supply chain professionals,

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