Measuring the Impact of Trade Cost Volatility on Supply Chains: An Application to Plastics and Light Truck Manufacturing

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Abstract

This paper employs two methods to estimate the impact of trade cost volatility on U.S. imports of plastic products. First, an econometric model is used to estimate the relationship between trade cost volatility and sourcing of U.S. imports. We find that a one percent increase in trade cost volatility is associated with about a 0.7 percent reduction in U.S. imports. Then, we introduce a partial equilibrium model of the upstream plastic industry and downstream light truck manufacturing industry in the United States. To measure the impact of plastic trade cost volatility on downstream light truck manufacturing, we run a Monte Carlo simulation using a historical distribution of trade costs as model inputs to understand how a reduction in trade cost volatility translates into a reduction in volatility in downstream outcomes.

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1 Introduction

There have been many disruptions to supply chains in recent years, as factors such as the COVID-19 pandemic and Russian invasion of Ukraine have changed trade patterns and caused fluctuating prices. Volatility in trade costs is one source of supply chain disruption, including spikes in shipping costs and changes in tariff rates. This paper describes and employs two methods to estimate the impact of trade cost volatility on U.S. supply chains, using plastic products and light truck manufacturing in an application. First, an econometric model is used to estimate the relationship between trade cost volatility and sourcing of U.S. imports. Then we introduce a partial equilibrium model of the upstream plastic industry and downstream light truck manufacturing industry in the United States. To measure the impact of plastic trade cost volatility on downstream light truck manufacturing, we run a Monte Carlo simulation using a historical distribution of trade costs as model inputs. This model is further used to understand how a reduction in historical trade cost volatility translates into a reduction in volatility in downstream outcomes.

The paper finds that a one percent increase in a country's trade cost volatility over time is associated with about a 0.7 percent reduction in U.S. imports of plastic products, suggesting that import sourcing changes following an increase in the volatility of trade costs. Then, the Monte Carlo simulation shows how plastics trade cost volatility flows through the light truck manufacturing supply chain. Further, plastics trade cost volatility in the Monte Carlo simulation is reduced in 10 percent increments to understand how a reduction in volatility in upstream inputs would affect downstream truck manufacturing. We find that each subsequent reduction in plastics trade cost volatility leads to a roughly constant reduction in volatility in light truck manufacturing output.

2 Literature Review

This research is related to two areas of the literature: literature on pass-through of upstream price changes and literature on trade policy uncertainty. For the former, there are several papers in the literature that discuss the pass through of price fluctuations into downstream prices. Nakamura and Zerom (2010), Bonnet and Villas-Boas (2016), and Shu and Su (2009) analyze the pass through of upstream cost shocks into prices. Nakamura and Zerom (2010) analyze the determinants of incomplete pass-through of cost shocks, uncovering the role of markup adjustment and barriers to price adjustment in determining incomplete pass-through. Bonnet and Villas-Boas (2016) find significant evidence that consumers react differentially to positive and negative price movements. Shu and Su (2009) find significant pass-through of exchange rate changes into import prices. In addition, Meyler (2009), Romano and Scandurra (2012), Chen et al. (2021) and Hollas (1994) examine the pass through of oil price movements into markets. Of the four, Romano and Scandurra (2012) look at volatility in oil prices specifically, analyzing the effect of periods of low volatility and high volatility in oil prices.

There are few studies that analyze pass-through of plastic-specific price movements into downstream prices, and none to our knowledge that describe the effect of plastics trade cost volatility specifically. De Mello and Ripple (2017) analyze plastics price dynamics and whether input costs or downstream demand drive price changes. Hellerstein and Villas-Boas (2010) analyze pass through of exchange rates on outsourced inputs in the auto industry, a related downstream industry to what we analyze in this paper. In this paper, we analyze the pass-through of trade cost volatility in plastics trade into U.S. prices and on downstream-consuming industries. We present new tools that can be used to measure the impact of trade cost volatility in supply chains, building on the analyses described above.

The second area of literature related to this research is the trade policy uncertainty literature. Handley and Limao (2017, 2022) provide a framework to examine the impact of trade policy uncertainty on economic outcomes and provide evidence of large effects of policy uncertainty on economic activity. Graziano et al. (2021) estimate the uncertainty effects of preferential trade disagreements. Ahmad et al. (2023) estimate the impact of increased policy uncertainty from Brexit on UK trade in services, and Graziano et al. (2020) examine if Brexit uncertainty has trade externalities beyond Europe. Finally, Ciuriak et al. (2020) estimate the effect of binding commitments on services trade. In this paper, we do not model trade policy uncertainty explicitly and instead focus on observed trade cost volatility in trade data. As noted in the conclusion, future research could incorporate uncertainty into the model to examine whether volatility and uncertainty have similar effects on international sourcing.

3 Trade Costs in Plastics Supply Chains

There have been many disruptions in plastics trade in recent years, forcing supply chains to adjust to factors such as the COVID-19 pandemic, the war in Ukraine, irregular weather patterns, container shortages, and other logistics issues.[1] For the purposes of this research, we focus on international trade cost disruptions which include volatility in shipping costs and changes in tariff rates. The modeling analyses presented later in the paper measure the economic effects of trade cost changes on downstream purchasers of plastics. Many non-trade cost supply chain disruptions impact trade costs indirectly, such as the increase in oil prices and shipping costs due to the war in Ukraine. This paper only considers observed changes in trade costs in the data and not other supply chain disruptions.

Plastics chemical companies reported in a recent survey that transportation costs increased across all modes of transportation in 2021 and 2022 for nearly all survey respondents, leading to disruptions in supply chains for downstream purchasers.[2] This can be seen

[1] For example, see Vakil (2021).

[2] American Chemistry Council, 2022, "Major supply chain problems persist for chemical manufacturers"

in shipping data; global shipping rates surged during the COVID-19 pandemic as demand increased for goods such as computers, cars, and furniture, while the supply of cargo ships and containers were slow to catch up.[3] The Freightos Baltic Index, a global container freight index, sharply increased in the first two quarters of 2021, followed by a rapid descent in 2022.[4] In addition to shipping cost volatility, the United States implemented a 25 percent tariff on U.S. imports of certain plastic products from China as part of a section 301 investigation on unfair foreign practices affecting U.S. commerce.[5] The impact of these trade cost fluctuations on users downstream in the supply chain is the focus of this paper.

Table 1 lists the top U.S. plastic-consuming industries in 2012. Of the total supply of plastics product manufacturing (NAICS 3261) in the United States, 4 percent is consumed by the non-residential maintenance and repair industry (NAICS 230301). As shown in table 1, the light truck manufacturing industry (NAICS 336112) is the third largest consumer of plastic products in the United States, accounting for 2.4 percent of total U.S. plastic use. This is the downstream industry chosen for the application of the model presented later in the paper, and includes companies that manufacture light trucks and utility vehicles including light duty vans, pick-up trucks, minivans, and sport utility vehicles. In 2012, the purchase of plastic products comprised about 3.5 percent of total light truck intermediate input costs. Additionally, about 17 percent of plastic usage in light truck manufacturing was sourced from imports in 2012.[6] Therefore, it is reasonable to assume that recent trade cost volatility may have an impact on the price of light truck manufacturing in the United States. This impact is explored in section 5.

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at `https://www.americanchemistry.com/chemistry-in-america/news-trends/press-release/2022/major-supply-chain-problems-persist-for-chemical-manufacturers`

[3]For example, see UNCTAD (2022).

[4]The Freightos Baltic Index represents an average spot rate for 40-foot shipping containers using data obtained from hundreds of logistical providers.

[5]See USITC (2023), *Economic Impact of Section 232 and 301 Tariffs on U.S. Industries*.

[6]Bureau of Economic Analysis (BEA), "Input-Output Accounts Data," at `https://www.bea.gov/industry/input-output-accounts-data`

Table 1: Top 10 Downstream Users of Plastic in the United States

NAICS industry name	6-digit NAICS code	Share of U.S. plastic consumption, 2012
Non-residential maintenance and repair	230301	4.0%
Soft drink and ice manufacturing	312110	3.5%
Light truck and utility vehicle manufacturing	336112	2.4%
Limited-service restaurants	722211	2.3%
Couriers and messengers	492000	2.2%
State and local government hospitals	GSLGH	2.1%
Offices of physicians	621100	2.0%
Other residential structures	2334A0	1.9%
Snack food manufacturing	311910	1.8%
Soap and cleaning compound manufacturing	325610	1.7%

Data source: BEA Input-Output Accounts Data.

Notes: The plastic products included in this calculation are all 6-digit NAICS codes within NAICS 3261 (plastics product manufacturing). Excluded from the list are within-plastic manufacturing consumption. The BEA use tables at the NAICS 6-digit level were only available as of 2012 so shares may have changed since then.

To examine trade costs in this section and in the regression analysis below, the analysis uses a 10-year panel of plastics import data from 2013 to 2022 disaggregated at the NAICS 6-digit level obtained from USITC's DataWeb.[7] Trade costs are determined by the difference between imports valued at customs value and at the landed duty paid value. The customs value is the "transaction value" of a good—the price that is actually paid or payable when the goods are sold for export.[8] Landed duty-paid values include trade costs such as insurance, freight, and tariffs paid in addition to the customs value.

The trade cost factor (τ_{ikt}) by 6-digit NAICS industry k, country i, and year t are calculated by dividing the landed duty-paid import value by the customs value. The trade cost factor is equal to one if there are no trade costs and greater than one if trade costs exist. Average trade cost μ_{ik} for each industry k and source country i are calculated for

[7] `https://dataweb.usitc.gov/`

[8] International Trade Administration, "Trade Guide: Customs Valuation," at `https://www.trade.gov/trade-guide-customs-valuation/`

the 10-year period 2013–2022. Volatility in trade costs is measured using the coefficient of variation (CV_{ik}), defined as the standard deviation of trade costs s_{ik} divided by the mean μ_{ik} for the same period.

Table 2 shows overall volatility in plastics trade costs from 2013–2020, and table 3 shows sourcing shares and trade cost volatility by country. Plastics trade costs are becoming significantly more volatile for China, Israel, and Thailand due in part to increased shipping costs and additional duties imposed by the U.S. on plastic from China. The share of U.S. imports of plastic from China has declined since 2013, from 40 percent to 38 percent. At the same time, volatility in trade costs has more than quadrupled. Similarly, Taiwan, Germany, Japan, and the United Kingdom have seen increases in trade cost volatility and decreases in sourcing shares. In the opposite direction, the share of U.S. imports from South Korea increased since 2013 at the same time as a decrease in trade cost volatility. Thailand, however, shows a different trend: both their sourcing share and trade cost volatility measure increased during the previous ten years. The extent to which there is a pattern between sourcing and trade cost volatility is estimated below.

Table 2: Historical Volatility in Trade Costs, 2013–2022

Mean trade cost	1.1052
Standard deviation	0.0323
Coefficient of variation	0.0292

4 Empirical Model

4.1 Econometric Approach

The econometric model employed in this section is based on the approach described in Riker (2022). The model estimates the relationship between trade cost volatility and import

Table 3: Historical Volatility in Trade Costs by Country, 2013–2022

Top 10 Sources of U.S. Imports of Plastic	Sourcing share, 2013 (%)	Sourcing share, 2022 (%)	Coefficient of variation, 2013–2017	Coefficient of variation, 2018–2022
China	40.1	38.1	0.016	0.078
Canada	18.3	15.1	0.009	0.004
Mexico	10.3	11.0	0.008	0.008
Taiwan	4.1	3.6	0.013	0.021
Germany	3.7	3.2	0.019	0.026
South Korea	3.3	4.5	0.020	0.018
Japan	3.0	1.8	0.019	0.027
United Kingdom	1.7	1.3	0.019	0.030
Israel	1.3	1.5	0.031	0.140
Thailand	1.2	1.7	0.035	0.083
Top 10 Sources	86.9	81.8	-	-

sourcing, where volatility in trade costs is measured by the coefficient of variation of the data across years. The dependent variable is the customs value of U.S. imports by industry k, country i, and year t. The independent variable is the log of the coefficient of variation in trade costs by industry and country and a set of industry-year and source country-year fixed effects. The fixed effects capture country-specific and industry-specific factors such as producer price changes, national policies, and other factors that vary across these dimensions. Both Ordinary Least Squares (OLS) and Poisson Pseudo Maximum Likelihood (PPML) regressions are used below. Standard errors are clustered by source country to account for intra-cluster correlation in the error terms at the country level. The regression equations with trade cost volatility terms are:

OLS: $\ln(x_{ikt}) = \beta \ln(\mathrm{CV}_{ik}) + \rho_{kt} + \upsilon_{it} + \epsilon_{ikt}$

PPML: $x_{ikt} = \exp[\beta \ln(\mathrm{CV}_{ik}) + \rho_{kt} + \upsilon_{it}] \times \epsilon_{ikt}$

The specification above assumes that importers maintain a constant value of trade cost volatility for the entire period. If firms instead update their measure of volatility over time, a time-varying measure of trade cost volatility may be more appropriate. Allowing the trade cost term to vary over time also lets us introduce an additional fixed effect into the specification. The time-varying mean trade cost μ_{ikt} is the average cost for each industry and source country for the most recent five years, thus $\mu_{ikt} = \frac{1}{5}\sum_{t-4}^{t} \tau_{ikt}$. The time-varying standard deviation and coefficient of variation are defined over the same period, as $s_{ikt} = \sqrt{\frac{\sum_{t-4}^{t}(\tau_{ikt}-\mu_{ikt})^2}{5}}$ and $\mathrm{CV}_{ikt} = \frac{s_{ikt}}{\mu_{ikt}}$. For consistency with the prior specification, in this model specification we incorporate an additional four years of data (2009–2012), so the time-varying CV is defined for the same 2013–2022 period as the time-invariant CV. The regression equations with time-varying trade cost volatility term are:

OLS: $\ln(x_{ikt}) = \beta \ln(\mathrm{CV}_{ikt}) + \rho_{kt} + \upsilon_{it} + \phi_{ik} + \epsilon_{ikt}$

PPML: $x_{ikt} = \exp[\beta \ln(\mathrm{CV}_{ikt}) + \rho_{kt} + \upsilon_{it} + \phi_{ik}] \times \epsilon_{ikt}$

As noted in section 3 above, the model is estimated using a 10-year panel data set (2013–2022) downloaded from USITC's DataWeb. The panel includes all 6-digit NAICS industries within the NAICS 3261 4-digit plastics grouping, including NAICS 326111 (plastic bag and pouch), 326112 (plastic packaging film and sheet), 326113 (unlaminated plastic film and sheet), 326121 (unlaminated plastic profile shape), 326122 (plastic pipe and pipe fitting), 326160 (plastic bottles), 326191 (plastic plumbing fixtures), 326192 (other plastic product manufacturing), and 326199 (other plastic product manufacturing).[9] In the second set of regressions with the time-varying means, four additional years (2009–2012) are used to calculate the coefficient of variation for the first years of the panel. These additional four years are not included in the estimation, they are only used to calculate the time-varying mean in the first four years of the panel. For the time-invariant mean estimates, countries that have only one year of non-zero trade in the data set (from 2013–2022) are dropped

[9] The Census Bureau changed the HTS concordance for three of these NAICS 6-digit products in 2012. For consistency, when calculating the time-varying mean, we applied a consistent concordance to all years. Specifically, HTS 3923.21 and 3923.29 were concorded to NAICS 326111 from 2009–2011; HTS 3921.90.4010 was concorded to NAICS 326112 from 2012–2022; and HTS 3918.10.1000, 3918.10.2000, 3918.90.1000, 5904.10.0000, 5904.90.10.00, and 5904.90.90.00 were concorded to NAICS 326192 from 2012–2022.

from the analysis as a standard deviation could not be calculated.[10] All other observations are included in the analysis. For the time-varying mean estimates, a mean and standard deviation is calculated only if the observation has more than one non-zero trade flow in the previous five years.

4.2 Regression Results

Tables 4 and 5 present econometric results under different model specifications. In table 4, the coefficient of variation is calculated as the standard deviation of trade costs by country and industry, divided by the mean by country and industry, where the standard deviation and mean are calculated over the entire ten-year panel. Following Borchert et al. (2020), we include two PPML estimates to examine differences between OLS and PPML results. The first, "PPML (no zeros)," includes the same observations as in the OLS dataset, i.e., with zero trade flows excluded.[11] The second, "PPML (with zeros)," includes observations with non-zero trade in the dataset. Only the OLS and "PPML (with zeros)" results are statistically significant. The first model, OLS with industry-year and source country-year fixed effects, finds that a one percent increase in trade cost volatility is associated with a 1.9 percent reduction in imports.[12] The "PPML (with zeros)" regression results differ substantially from the OLS results, finding that a one percent increase in trade cost volatility is associated with about a 0.4 percent reduction in imports.

For regression results in table 5, the standard deviation and mean trade costs are calculated over the previous five year period for each country and industry. Results in table 5

[10] These countries are typically small and would have a negligible impact on the estimates.

[11] The number of observations in the first and second model are different by six because there were six singleton observations dropped when using the ppmlhdfe command in Stata. Inclusion of the six additional observations does not change the estimates or standard errors.

[12] A one percent increase in trade cost volatility, as measured by the coefficient of variation of trade costs, can be placed in context using the data. On average across all countries and industries in the data, the coefficient of variation of trade costs varies by nine percent from 2013 to 2022. That variation fluctuates significantly by industry and source country.

Table 4: Time-Invariant CV Regression Results, 2013–2022

Explanatory variable	OLS	PPML (no zeros)	PPML (with zeros)
$\ln(\text{CV}_{ik})$	-1.94***	-0.40	-0.44*
	(0.11)	(0.22)	(0.19)
Industry-year FE	Yes	Yes	Yes
Source country-year FE	Yes	Yes	Yes
Industry-source country FE	No	No	No
N	6,925	6,919	9,229

Note: clustered standard errors given in parentheses. The dependent variable for the OLS regression is the log of U.S. imports, by source country, 6-digit NAICS industry, and year. The dependent variable in the PPML regressions is the level of U.S. imports by source country, 6-digit NAICS industry and year. The independent variable for both OLS and PPML is the log of the coefficient of variation in trade costs by country and 6-digit NAICS industry across all ten years in the panel.

are quite similar to those in table 4, showing the same large divergence between OLS and PPML. The PPML results are larger, around 0.7, and do not depend greatly on the inclusion or exclusion of zero trade flows in the data. This similarity suggests that the value of using the PPML estimator is to account for the heteroskedasticity in trade data and not to include the information contained in the zero trade flows. As suggested in Borchert et al. (2020), a possible explanation for this is that the source countries with some years of zero U.S. imports are typically the smaller countries that are discounted in the PPML first order conditions.

Table 5: Five-Year Average CV Regression Results, 2013–2022

Explanatory variable	OLS	PPML (no zeros)	PPML (with zeros)
$\ln(\text{CV}_{ikt})$	-1.31***	-0.67***	-0.71***
	(0.04)	(0.07)	(0.07)
Industry-year FE	Yes	Yes	Yes
Source country-year FE	Yes	Yes	Yes
Industry-source country FE	Yes	Yes	Yes
N	6,609	6,596	7,494

Note: clustered standard errors given in parentheses. The dependent variable for the OLS regression is the log of U.S. imports, by source country, 6-digit NAICS industry, and year. The dependent variable in the PPML regressions is the level of U.S. imports by source country, 6-digit NAICS industry and year. The independent variable for both OLS and PPML is the log of the coefficient of variation in trade costs by country and 6-digit NAICS industry for the previous five years in the panel.

The last model, "PPML (with zeros)," is our preferred specification, finding that a one percent increase in trade cost volatility is associated with about a 0.7 percent reduction in U.S. imports. The coefficient of variation in this model, based on trade cost volatility over the previous five year period, is backward looking and includes information relevant to an importer making purchasing decisions. The use of a PPML model allows us to capture information contained in the zero-trade flows and correct for possible heteroskedasticity in the data. Additionally, industry-year, source-country year, and industry-source country fixed effects are similar to current gravity specifications and control for country-specific and industry-specific factors.

5 Monte Carlo Simulation

5.1 Modeling Approach

The previous section found that trade cost volatility is associated with a reduction in U.S. imports of plastics. To further analyze the impact of trade cost volatility in supply chains, particularly in downstream prices and production, we constructed a partial equilibrium supply chain model of the U.S. market with plastics manufacturing and imports in the upstream and light truck manufacturing and imports in the downstream.[13] The downstream light truck manufacturing industry is affected by plastics trade costs through their production costs. Equation 1 is the upstream plastics price index, where, as before, the index i refers to the source country of U.S. imports of plastic, p_{ui} is the producer price of plastic that originated in source i, $(1 + \tau_{ui})$ is the tariff factor on imports from source i, b_{ui} is a demand asymmetry parameter, and σ_u is the elasticity of substitution across sources of plastics supply to the U.S. market.[14]

[13] The model presented here is an extension to the model in Schreiber (2023).

[14] In this section, we no longer index by industry k. We perform the analysis for the 4-digit NAICS 3261 industry, "plastic products manufacturing," including all 6-digit plastics industries discussed above.

$$z = \left(\sum_i \; b_{ui} \; (p_{ui}(1 + \tau_{ui}))^{1-\sigma_u} \right)^{\frac{1}{1 \, - \, \sigma_u}} \tag{1}$$

Equation (2) is the downstream price index, where p_{di} is the price of the downstream good (light trucks) originating in country i and $(1 + \tau_{di})$ is the tariff factor on downstream imports from country i.

$$P = \left(\sum_i \; b_{di} \; (p_{di} \; (1 + \tau_{di}))^{1-\sigma_d} \right)^{\frac{1}{1 \, - \, \sigma_d}} \tag{2}$$

The price of the downstream domestically-produced good is a function of the upstream prices it uses as inputs. Equation (3) represents the price of downstream light truck manufacturing. The parameter c is a calibrated cost parameter and w is the price of all other production inputs, treated as exogenous in the model.[15] The upstream good and all other production inputs are consumed by the downstream in fixed proportions.

$$p_d = (w \; + \; c \; z) \tag{3}$$

Then the demand for the upstream plastic from source country i, q_{ui}, is represented by Equation (4). This equation is a modified version of a constant elasticity of substitution (CES) demand equation that incorporates upstream and downstream prices. Demand for the downstream good produced in country i is represented by Equation (5).

$$q_{ui} \;\; = \frac{k \; c \; b_{ui}}{p_{ui} \; (1 + \tau_{ui})} \left(\frac{p_d}{P}\right)^{1-\sigma_d} \left(\frac{z}{p_d}\right) \left(\frac{p_{ui} \; (1 + \tau_{ui})}{z}\right)^{1-\sigma_u} \tag{4}$$

$$q_{di} \;\; = \;\; k \; b_{di} \; P^{\sigma_d - 1} \; (p_d \; (1 + \tau_{di}))^{-\sigma_d} \tag{5}$$

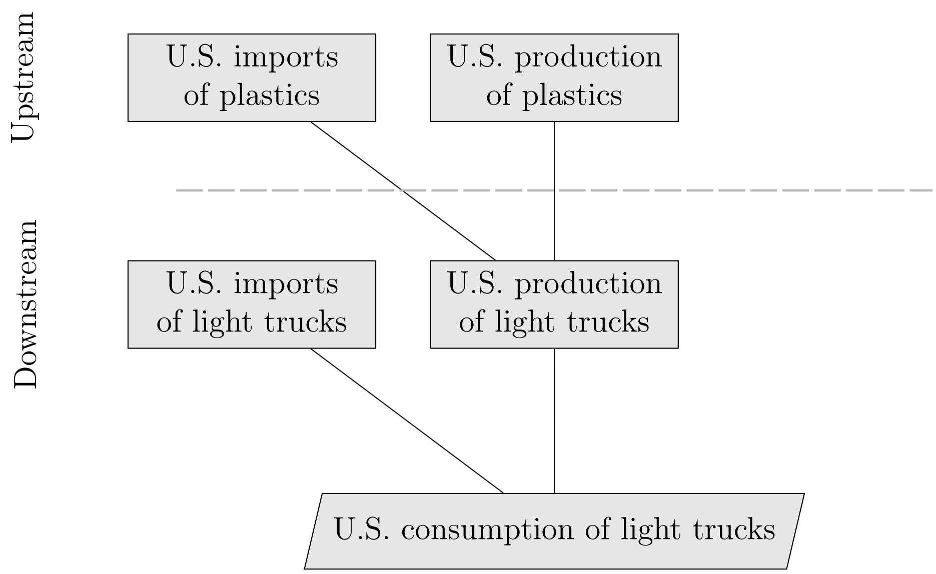
[15]The exogeneity assumption is appropriate when the trade policy shock is small and does not impact the cost of labor and other production inputs.

Equation (6) describes the supply curve for upstream imports and upstream domestic production, where a_{ui} is a supply parameter and ϵ_{ui} is the constant elasticity of supply for upstream goods from country i.

$$q_{ui} = a_{ui}\, p_{ui}{}^{\epsilon_{ui}} \tag{6}$$

The model is illustrated in figure 1.

Figure 1: Model Illustration



5.2 Data Inputs

Several data sources were used to calibrate the model. U.S. imports and exports of plastic products (NAICS 3261) and light truck products (NAICS 336112) in 2021 were obtained from USITC's DataWeb (table 6).[16] U.S. domestic production of plastic products and light truck

[16]The model requires an estimate of U.S. imports of plastic sent to light truck manufacturing. For this estimate, one could either (i) multiply total U.S. imports of plastic by the share of imported plastic sent to light truck manufacturing calculated from the BEA input-output accounts data, or (ii) multiply U.S. domestic production of light trucks by the cost share of imported plastic obtained from the BEA input-output accounts data. We used the latter calculation in this application.

manufacturing in 2021 were obtained from the U.S. Census Annual Survey of Manufactures.[17] The cost share of plastic in light truck manufacturing was calculated from the BEA's 2012 Input-Output Accounts Data, the latest available for NAICS 6-digit level data.[18] The share of plastics used in light truck manufacturing that are sourced from imports was obtained from the BEA's 2012 import matrices data. The 2021 trade cost estimate on U.S. imports of plastics was calculated using U.S. import data by taking the ratio of the landed duty-paid value and customs value.

Table 6: Monte Carlo Simulation Data Inputs, 2021

Data input	Value (in millions of dollars and %)
U.S. imports of light trucks	24,760.1
U.S. exports of light trucks	11,493.7
U.S. domestic production of light trucks	210,491.5
Cost share of plastic in light truck manufacturing	4.6%
Import share of plastic in light truck manufacturing	17.6%
U.S. imports of plastic products used in light truck manufacturing	1,611.1
U.S. domestic production of plastic products used in light truck manufacturing	7,542.8

Note: Import and export data were obtained from USITC's DataWeb. Domestic production data were obtained from the U.S. Census Annual Survey of Manufactures. Cost shares and import shares were obtained from the BEA's Input-Output Accounts Data.

The model also requires a number of elasticity estimates described in the modeling approach above. It requires a price elasticity of supply for domestic plastic and a price elasticity of supply for imported plastic. A medium elasticity value of five was used. The model also needs an elasticity of substitution estimate for upstream varieties of plastic and for downstream varieties of light trucks. In the downstream, the elasticity of substitution across varieties of light trucks is estimated using the trade cost method in Riker (2020). Using U.S.

[17]This analysis used 2021 data to calibrate the model because 2022 domestic production data was not yet available.

[18]The plastics data are at the NAICS 4-digit level of aggregation. Light truck manufacturing data are at the NAICS 6-digit level. Therefore, we use the 6-digit Input-Output data to calculate the cost shares for light truck manufacturing.

import data of light trucks, disaggregated by source country, district of entry, and year, the elasticity of substitution was estimated as 6.22. For the upstream elasticity of substitution between plastics sources, we consider two different specifications. We first test five different values evenly spaced between 2 and 10 to show a range of model outcomes under low, medium, and high elasticity values. Second, we estimate the plastics elasticity of substitution point estimate and standard error (4.17 and 0.22, respectively) using the trade cost method from Riker (2020). In this second specification, a normal distribution of elasticity values is drawn using this point estimate and standard deviation and used as a model input in the Monte Carlo simulation described below.

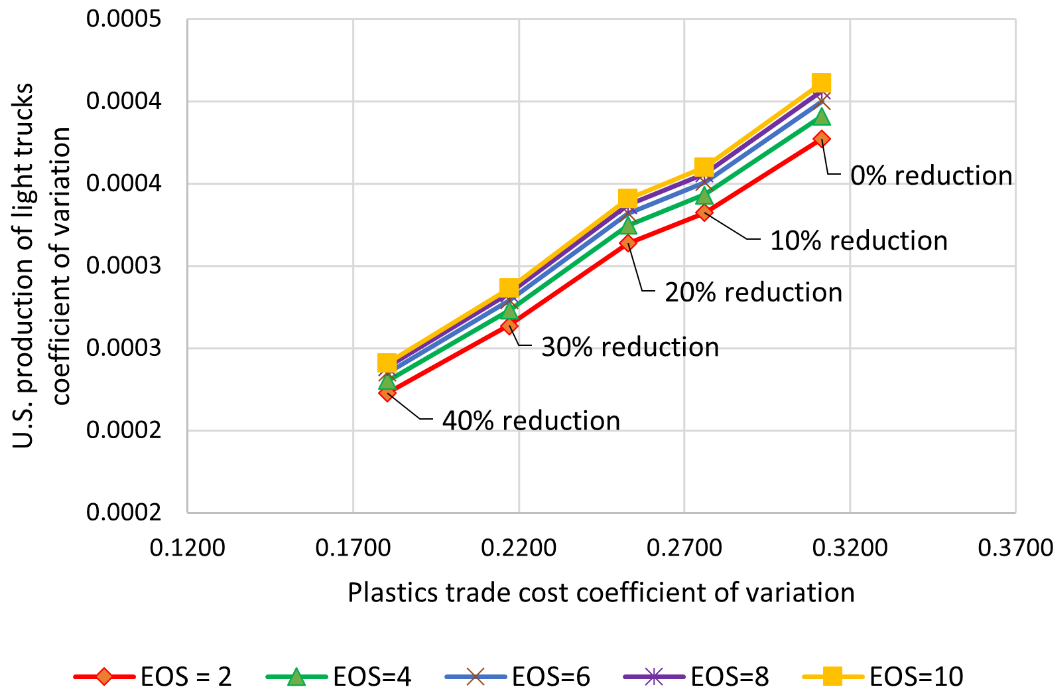
5.3 Monte Carlo Simulation Results

We use Monte Carlo simulation to estimate the impact of plastics trade cost volatility in the light truck manufacturing supply chain. The model incorporates a distribution of trade costs and estimates a distribution of model outcomes (including domestic production of plastics and light trucks). The mean and standard deviation of the trade cost distribution fed into the model is estimated from historical volatility in trade costs from 2013–2022 using U.S. import data, as shown in table 2.

The underlying model is first calibrated to the initial market equilibrium using the data inputs listed above. This includes an estimate of trade costs in U.S. imports in 2021. Then, the model draws 300 observations of trade costs as model inputs and a new market equilibrium is estimated with each realized trade cost value. Economic outcomes are recorded for each of the 300 draws of the trade cost distribution. Then, volatility in the inputs is compared to volatility in downstream domestic production of light trucks.

In the first Monte Carlo simulation, we run the model with a distribution of trade costs under 5 different values of the upstream plastics elasticity of substitution (σ_u). First, the Monte Carlo is run assuming 100% historical variation in trade costs. Then, we reduce the

Figure 2: Comparison of Volatility in Inputs and Outputs, by Upstream Elasticity of Substitution Value

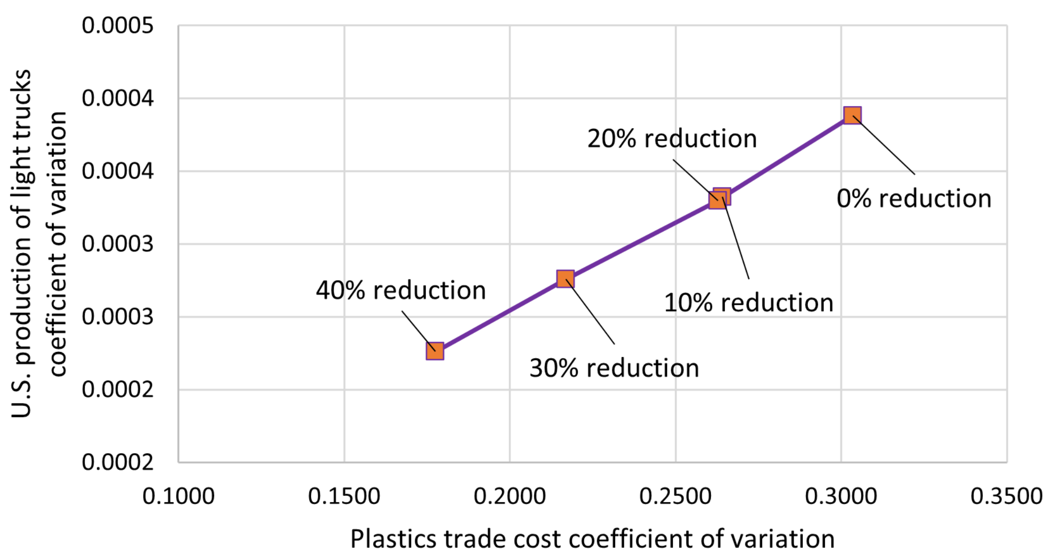


standard deviation used when drawing values for the trade cost distribution by 10 percent, simulating a 10 percent reduction in historical volatility in trade costs. After, we continue to reduce volatility in trade costs (90% of historical volatility, 80% of historical volatility, 70%, and so on) to simulate the effects on downstream outcomes of a reduction in volatility in trade costs. Model results are graphed in figure 2.

Each line in figure 2 represents a different assumption about the elasticity of substitution in the upstream industry. The elasticity of substitution does not affect the plastics cost share coefficient of variation, as that is a model input based on only import data. The elasticity of substitution does impact the U.S. domestic truck production coefficient of variation, as that is a modeled outcome and the magnitude depends on the willingness of truck producers to shift plastics sourcing. A higher elasticity of substitution value shifts the curve vertically as the same level of plastics volatility leads to more volatility in downstream truck manufacturing.

In the second Monte Carlo simulation, we run the model with a distribution of elasticity of substitution estimates. The distribution mean and standard deviation was econometrically estimated using the trade cost method presented in Riker (2020). The econometric method uses the same variation in international trade costs to estimate the elasticity using U.S. import data. Using this method, the elasticity point estimate is 4.17 and the standard error was 0.22. These values were used in the Monte Carlo simulation to draw a normal distribution of elasticity of substitution estimates.[19]

Figure 3: Comparison of Volatility in Inputs and Outputs



Results of the Monte Carlo simulation are illustrated in figure 3. The simulation was run first assuming full 100 percent historical volatility in trade costs first. After, we reduce

[19]Note that the two distributions fed into the Monte Carlo simulation—the trade cost distribution and the elasticity of substitution distribution—were drawn independently. An interesting extension to this research would be to have a joint distribution of trade cost estimates and elasticity of substitution estimates. Since both distributions are dependent on historical variation in trade costs, the model estimates of downstream variability here may be understated.

volatility in trade costs in 10 percent increments to estimate how a reduction in volatility in trade costs transfers to downstream outcomes. The simulations show that each subsequent reduction in plastics trade cost volatility lead to a roughly constant reduction in volatility in light truck manufacturing output.

6 Conclusion

This paper presents and applies two models to illustrates the impact of trade cost volatility on downstream consumers in a supply chain. First, the econometric specification found that an increase in plastics trade cost volatility is associated with a statistically significant decrease in plastics imports from a specific source country. This suggests that import sourcing is changing following the increase in trade cost volatility in recent years. Next, the paper describes a Monte Carlo simulation to estimate the impact of plastics trade cost volatility on downstream outcomes for light truck manufacturing. The underlying model is an upstream-downstream model where changes in plastic prices flow directly into light truck production costs. The Monte Carlo simulation showed how a reduction in trade cost volatility would reduce volatility in downstream outcomes in a roughly proportional manner. This result is intended to be useful for policy makers who want to lower volatility in manufacturing outcomes.

In future versions of this paper, it would be interesting to explore the sensitivity of the Monte Carlo simulation results to model parameters, to test if the linear relationship in figure 3 holds under differing assumptions. Additionally, it would be informative to build uncertainty into the model to compare the estimated effects of trade policy uncertainty and trade cost variability.

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