

Supply Chain Uncertainty in Ocean Transit as a Trade Barrier

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Abstract

Importers hold safety stock to hedge against delays in delivery. An increase in supply chain uncertainty raises safety stocks, increases inventory holding costs, and reduces imports from locations with high delivery time uncertainty. Supply chain uncertainty is measured using detailed data on actual and expected arrival dates of shipments at U.S. ports. A 10 percent increase in supply-chain uncertainty reduces imports by 1 to 2 percent. Assessing costs associated with shipment delays quantifies the economic impact of policies intended to facilitate trade such as streamlined cargo screening and investment in port infrastructure. For the average importer, the cost of safety stock ranges between 2 and 4 percent of import unit value and is comparable to an ad valorem ocean freight charge of about 3 percent. Depending on the number of shipments, average total inventory costs per unit of imports are as high as 27 percent.

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1 Introduction

Goods traded over long distances are subject to unexpected delays in delivery. Over fifty percent of shipments arrive one or more days late at U.S. ports. When vessels arrive early, shipments require storage until delivery to a customer or absorption into the production process. Late shipments put an importer at risk of losing sales, market share and highly valued customer relationships.

We test two predictions to quantify the impact of supply chain uncertainty and inventory management on international transactions. First, to avoid disruptions due to unexpected delays in delivery, importers respond to greater delivery time uncertainty with an increase in safety stock that is expected to raise inventory holding costs and reduce import demand relative to locations with a lower degree of delivery time uncertainty. Second, order costs constrain an importer's ability to split total import demand over multiple shipments. An increase in ordering costs will raise base-stock inventory holding costs and impact the intensive margin of trade. Hypotheses are formalized by combining a static trade model with a stochastic inventory model from the logistics and economics literature (Wisner et al., 2005; Eppen and Martin, 1988; Baumol and Vinod, 1970). Our model shows how to interpret inventory risk management costs in terms of fixed and variable trade costs.

Predictions are tested using a panel of annual U.S. vessel imports, freight rate charges and a supply chain uncertainty measure by district of arrival, source country and 10-digit product for years 2007-2009. Shipment-level data at U.S. ports from Import Genius include expected and actual arrival dates. We compute supply chain uncertainty as the standard deviation of the difference between actual and expected

arrival dates by district of arrival, country of loading and year. Import Genius does not report information on import values or freight charges. Our supply chain uncertainty measure is merged with manufacturing imports from the U.S. Census Imports of Merchandise.

The dataset provides several dimensions of variation that are useful for examining our hypotheses. For example, let purchasers in New York import ball bearings from Germany and China. If shipments from Germany to New York are more reliable, we expect New York importers will source relatively more from Germany. On the other hand, if shipments from China to Los Angeles (LA) are more reliable, we would expect LA importers would source relatively more from China. This variation across exporters and ports of arrival allows us to absorb unobserved exporter-specific information such as quality of infrastructure with fixed effects.

Results show delivery time uncertainty and higher ordering costs significantly reduce trade volumes like other non-tariff barriers such as transit time within and across countries (Hummels and Schaur, 2013; Djankov et al., 2010), time delays at customs (Carballo et al., 2012) and port efficiency (Blonigen and Wilson, 2008). We find a 10 percent increase in supply chain uncertainty reduces imports by about 1 to 2 percent. Our study is the first to provide a measure of supply chain uncertainty and to estimate its restrictive impact on trade.

Depending on the number of shipments, back-of-the-envelope calculations imply total inventory costs as a fraction of the import value as high as 27 percent. Comparable to our estimates the supply chain literature argues that inventory holding costs are often underestimated and they can vary from 15% of the cost of goods per

year to as much as 50% (Sanders, 2012). Independent of the number of shipments, safety-stock costs account for 2 to 4 percent of the unit value of the average import. For comparison, in our sample average per-unit freight charges are about 3 percent of the average per-unit import value.

We also provide evidence that during the trade collapse of 2008/2009, the supply chain uncertainty of 2007 works best to predict U.S. imports. This suggests either firms are slow to learn and adjust to their new environment, or firms are fully aware of changes in supply chain uncertainty, but it is too costly to adjust if they expect the trade collapse is temporary.

Previous studies investigate effects of inventory management and demand side shocks on trade. Alessandria et al. (2010) examine how firms use inventories to manage demand uncertainty. Their calibration exercise finds that volatility necessary to explain large inventory holdings observed in the data is about five times larger than the real data-based demand volatility found by Khan and Thomas (2007). Demand volatility exerts an important impact on inventories, but evidence suggests other yet unidentified sources of volatility such as supply chain uncertainty, must be an important source of risk to be addressed with inventory management.

Importers may use supply chain strategies other than holding inventory to manage uncertainty. For example, Hummels and Schaur (2010) show firms facing demand uncertainty speed up deliveries by trading fast and expensive air transport for cheap and slow ocean shipping. Evans and Harrigan (2005) find that firms move closer to the destination market to speed up delivery of time-sensitive goods to optimally respond to demand realizations. Harrigan and Venables (2006) show timeliness im-

poses trade costs that create incentives for clustering production activities. Also, a homogeneous product imported from Germany can be more easily substituted for the same product arriving late from Italy compared to highly differentiated products. Consistent with these theories, we provide evidence that air transport, as well as sourcing from nearby markets such as Canada and Mexico, and product substitutability can be effective supply side risk management strategies in addition to holding inventory.

This paper is organized as follows. The next section provides background information on supply chain uncertainty. Section 3 derives import demand as a function of supply chain uncertainty and ordering costs. Empirical specifications, data, estimation and results are discussed in Section 4. Conclusions are summarized in the final section.

2 Background on Supply Chain Uncertainty

Import Genius receives bill of lading information at the shipment level via U.S. customs feed. We observe the delivery vessel, port of arrival, country of loading, actual and expected arrival dates for each shipment. Vessels have a contractually negotiated berthing window at the destination port. Based on this, each carrier quotes an expected arrival date to the shipper, either an exporter or importer, that is recorded on the bill of lading.

The contractually negotiated berthing window is an agreement that specifies when the vessel is to arrive and how many containers are to be handled. Carriers pay a

lump sum or hourly penalty for missing the berthing window. Terminal operators can pay a penalty for delayed departures. As carriers move through ports of call toward their final destination, picking up additional shipments along the way, new information is gathered on such events as weather delays, delays at ports, and port congestion. Shippers have an opportunity to modify their expected arrival date. Recently loaded shipments on a vessel may have different expected arrival dates than shipments loaded earlier. Figure 1 plots the distribution of the difference between actual and expected arrival dates for manufactured imports excluding those from Canada and Mexico.¹ While the distribution is slightly skewed to late arrivals, a significant fraction of shipments are found to arrive early.

Late shipments may be due to factors beyond carriers' control. Included here are bad weather, labor strikes, ship collisions, groundings, customs delays, and delays at previous ports of call that lead to port congestion. Recent examples include labor strikes at Brazil's Port of Santos, the Chennai Port in India, and at Ports of Los Angeles and Long Beach. A ship collision at India's main port in Mumbai caused unexpected shipment delays. Insufficient cargo handling capacity and inadequate port infrastructure at ports along the U.S. West Coast, and at ports of New York and New Jersey delayed vessel arrivals and departures. The recent U.S. federal government shutdown stranded vessels in ports and shipments at customs clearance warehouses awaiting paperwork. Deviations from the expected arrival date across the east and west U.S. coasts can result from the need to cross the Panama canal. Weather and port congestion affect delivery time at ports along a given coast. Early

¹Sample construction details are discussed in the data section.

arrivals may be due to lower traffic in ports, skipped ports of call, and back winds.

We compute a district-by-country-by-year measure of supply chain uncertainty.² Let S_{dtj} be the total number of shipments arriving in district d in year t that were loaded in country j . Supply chain uncertainty is defined as the standard deviation of the difference between the actual and expected arrival date:

$$\sigma_{djt} \equiv \sqrt{\frac{\sum_{s=1}^{S_{dtj}} (\text{Actual Date}_s - \text{Expected Date}_s)^2}{S_{dtj}}}.$$

Sources of variation in uncertainty are assessed by regressing log uncertainty on country and district-of-unloading indicators and computing r-squares. Country specific and district of arrival specific information in 2007 and 2009 account for about 23 and 13 percent of the variation, respectively. During the trade collapse of 2008, port districts of arrival explain more variation (20 percent) than exporter specific information (16 percent). If supply chain uncertainty increases the cost of trade, then these systematic differences across countries and ports represent trade costs that are subject to exporter-specific policy and port of arrival management. The remaining variation in supply chain uncertainty is due to importer-exporter location-pair specific variation. For example, Germany's supply chain uncertainty with New York is found to be higher than with the port of LA.

Figure 2 shows the relationship between supply chain uncertainty and distance between district of arrival and exporting country. There is a weak positive relationship. A one percent increase in distance raises uncertainty on average by about .14

²Import Genius does not provide product codes needed to compute product level uncertainty.

percent. However, the figure also shows that for any given distance, there is a considerable amount of variation in uncertainty around the expectation. In summary, this suggests there is considerable variation in uncertainty that cannot be explained with variables commonly used to proxy trade costs. Sections that follow explain our model and empirical approach to confirming this variation in uncertainty as an important trade cost.

3 Theory

Importers hold safety stock to hedge against delivery delays. An increase in supply chain uncertainty will raise safety stocks, increase inventory holding costs, and reduce import demand. This section derives the import demand as a function of supply chain uncertainty and ordering costs.

3.1 Import Demand

Each importer i sources inputs q_{ij} from foreign markets j at time t and combines them to produce the final product $Q_{it} = \varphi_i \left(\sum_j q_{ij}^\rho \right)^{\frac{1}{\rho}}$ sold on the home market.³ Importers differ in productivity φ_i . More productive firms produce greater amounts of output with the same mix of inputs. The total cost of sourcing from foreign markets, $\sum_j (m_{ijt}q_{ijt} + F_{jt})$, is determined by the constant marginal import cost m_{ijt} and fixed costs F_{jt} . For a given output Q_{it} the firm plans to sell on the domestic

³The elasticity of substitution is $0 < \rho < 1$ with $\theta = 1/(1 - \rho) > 1$. "Love of variety" imports ensures a variety of the input is purchased from each available source.

market, import demand

$$q_{ijt} = \frac{m_{ijt}^{\frac{1}{\rho-1}}}{\left(\sum_j m_{ijt}^{\frac{\rho}{\rho-1}}\right)^{\frac{1}{\rho}}} \cdot \frac{Q_{it}}{\varphi_i} \quad (1)$$

minimizes the cost of sourcing from foreign markets.⁴

3.2 Inventory and Import Costs

The importer holds inventory to serve gradually arriving demand on the home market. Total inventory management cost

$$\text{IC} = r_{jt}n_{ijt} + \frac{1}{2}w\frac{q_{ijt}}{n_{ijt}} + wk\sigma_{ijt}\frac{q_{ijt}}{365} \quad (2)$$

is the sum of ordering costs, base-stock costs and the cost of holding safety stock as in models used by Baumol and Vinod (1970), Tyworth and O'Neill (1997) or Ray et al. (2005).

Order costs r_{jt} represent the fixed costs of filing documents, fees and processing costs. A firm that orders n_{ijt} shipments to import the total quantity q_{ijt} will pay $r_{jt}n_{ijt}$ in total order costs. The firm gradually withdraws from inventory to serve the local market. This results in average inventory stock $\frac{1}{2}\frac{q_{ijt}}{n_{ijt}}$. Let w be the per-unit storage costs. Base-stock inventory costs are then $\frac{1}{2}w\frac{q_{ijt}}{n_{ijt}}$. Increasing the number of orders spreads the quantity over more shipments and lowers base-stock inventory costs, but raises ordering costs.

⁴Without the productivity parameter φ_i this import demand is similar to Melitz (2003). Therefore, we can interpret q_{ijt} as the demand for variety i from the aggregate consumption bundle Q_{it} demanded by a representative consumer.

The last term in the inventory cost is due to safety stock. The importer holds safety stock to hedge against delays in the arrival time of shipments.⁵ Lead time is the time that passes between ordering and receiving a shipment s , and σ_{ijt} measures the standard deviation of the lead time. The service factor k scales the standard deviation to the desired level of safety stock. For example, in a given year the daily withdrawal rate is $q_{ijt}/365$. If $\sigma_{ijt} = 3$ then the average shipment is 3 days late or early. If the firm sets $k = 2$, it holds enough safety stock to cover a 6 day delay in arrival.

We take the service factor k as an exogenous parameter. The logistics literature suggests that firms hold safety stock to keep the probability of stocking out to 1-5 percent (Dullaert et al. (2007); Fortuin (1980)). If the lead time is normally distributed, firms achieve this by setting $1.64 < k < 2.33$ (Eppen and Martin (1988)). The cost of safety stock is then $wk\sigma_{ijt}\frac{q_{ijt}}{365}$.⁶ With this in mind, we next show that inventory costs can be approximated well in terms of fixed and variables costs of trade.

To obtain the importer's optimal shipping frequency, minimize (2) with respect to n_{ijt} and solve for $n_{ijt}(q_{ijt}) = \sqrt{\frac{wq_{ijt}}{2r_{jt}}}$. Substitute the number of shipments into the inventory cost (2) to obtain the equilibrium inventory cost

$$\text{IC} = \sqrt{2r_{jt}wq_{ijt}} + w\frac{k}{365}\sigma_{ijt}q_{ijt}. \quad (3)$$

⁵We assume varieties imported from different locations are not substitutable in the short run to highlight the role of inventories in managing arrival delays. This assumption is revisited in the empirical section.

⁶The optimal service factor can be determined by setting up expected profits including the possibility of stocking out. While this is interesting from a theoretical point of view, evidence from the supply chain literature suggests k is relatively constant over time.

If $w = 1/q_{ijt}$, then inventory costs are fully captured by fixed costs F_{jt} . In this case, the fixed costs vary across countries due to uncertainty in the delivery time and ordering costs. If per-unit inventory holding costs are constant, then an increase in supply chain uncertainty raises inventory costs because firms hold larger safety stock. Order costs are not separable from the quantity and therefore impact variable costs. High order costs constrain a firm's ability to spread an increase in the quantity over multiple orders. Therefore, an increase in the order cost raises the base stock and average inventory holding costs.

Note that for large quantities total inventory costs are close to linear in q_{ijt} and the first order Taylor approximation

$$\text{IC} \approx \sqrt{\frac{r_{jt}wc}{2}} + \left(\sqrt{\frac{r_{jt}w}{2c}} + w \frac{k}{365} \sigma_{ijt} \right) q_{ijt}$$

is a good representation of total inventory costs. An increase in ordering costs and per-unit inventory costs raises the fixed costs of importing, F_{jt} . Therefore, inventory management impacts the extensive margin of trade. Let p_{ijt} denote the factory gate price and f_{ijt} denote per-unit freight charges of importing. Including inventory costs, the constant marginal cost of importing then equals

$$m_{ijt} = p_{ijt} + f_{ijt} + \sqrt{\frac{r_{jt}w}{2c}} + w \frac{k}{365} \sigma_{ijt}.$$

Substitute m_{ijt} into the firm's import demand (1) to obtain

$$q_{ijt} = \frac{\left(p_{ijt} + f_{ijt} + \sqrt{\frac{r_{jt}w}{2c}} + w \frac{k}{365} \sigma_{ijt}\right)^{\frac{1}{\rho-1}}}{\left(\sum_j m_{ijt}^{\frac{\rho}{\rho-1}}\right)^{\frac{1}{\rho}}} \cdot \frac{Q_{it}}{\varphi_i}. \quad (4)$$

This suggests the following two predictions regarding inventory management and the intensive margin of imports.

Prediction 1. *All else equal, an increase in supply chain uncertainty for country j decreases a firm's imports from country j relative to its imports from all other countries.*

The intuition is straightforward. An increase in supply chain uncertainty raises the costs of holding safety stock. All else equal, importers shift their import mix toward locations with lower supply chain uncertainty.

Prediction 2. *All else equal, an increase in ordering costs for country j decreases a firm's imports from country j relative to its imports from all other countries.*

High order costs raise base-stock inventory costs because it is more expensive for importers to split the desired quantity over multiple shipments. As a consequence, firms import less from locations with high order costs.

4 Specifications, Data, Estimation and Results

Our empirical model requires data on imports, prices, supply chain uncertainty measures, ordering and delivery costs. This section describes our empirical specification,

data sources, and details regarding variable construction. Empirical predictions are tested. Robustness tests are also performed.

4.1 Specification

We use a highly detailed panel dataset of U.S. imports for three years with four dimensions of variation: across districts of arrival d , across products h , across source countries j and across years t .

The starting point for our empirical model is equation (4), which specifies import quantity as a function of variable trade costs.⁷ An estimation challenge is that the import demand is nonlinear in the variables of interest. Identification requires that we account for unobserved variables. Given the large number of products and countries this is difficult as we cannot difference a nonlinear model to eliminate the fixed effects. Instead, we log-linearize $\ln(q_{hdjt})$ around the variable means based on equation (4). Let $B = \bar{p} + \bar{f} + \sqrt{\frac{\bar{r}w}{2c}} + w \frac{k}{365} \bar{\sigma}$. Then we obtain

$$\ln(q_{hdjt}) = \beta_0 + \beta_1 \ln(p_{hdjt}) + \beta_2 \ln(f_{jt}) + \beta_3 \ln(r_{jt}) + \beta_4 \ln(\sigma_{hdjt}) + \epsilon_{hdjt}, \quad (5)$$

where

$$\epsilon_{hdjt} = \ln \frac{Q_{hdt}}{\left(\sum_{jt} m_{hdjt}^{\frac{\rho-1}{\rho}} \right)^{\frac{1}{\rho}} \varphi_{hd}} + u_{hdjt} = v_{hdjt} + u_{hdjt}$$

⁷We work with import quantity instead of values because our model highlights quantity management as opposed to price adjustments. For a model and empirical evidence that highlights price adjustments, see Alessandria et al. (2010). We also estimated our model with log import values as a dependent variable. Results are qualitatively the same.

and $\beta_1 = \frac{B}{\rho-1}\bar{p}$, $\beta_2 = \frac{B}{\rho-1}\bar{f}$, $\beta_3 = \frac{B}{\rho-1}\sqrt{\frac{w}{2c\bar{r}}}\bar{r}$ and $\beta_4 = \frac{B}{\rho-1}\frac{wk}{365}\bar{\sigma}$.⁸ The advantage of specification (5) is that coefficients are easy to interpret in terms of elasticities and fixed effects are easy to accommodate. This solves several identification problems.

First, we observe import weights instead of quantities. Let q_{hajt} be the imports measured in weights and suppose that a constant conversion factor λ_h translates weights to quantities.⁹ Then, we can convert variables measured in kg to quantities by multiplying by λ_h . However, given the log separability of the model we obtain

$$\ln(q_{hajt}) = \beta_0 + \beta_1 \ln(p_{hajt}) + \beta_2 \ln(f_{jt}) + \beta_3 \ln(r_{jt}) + \beta_4 \ln(\sigma_{hajt}) + \gamma \ln(\lambda_h) + \epsilon_{hajt},$$

where $\gamma = 1 - \beta_1 - \beta_2$. Therefore, a product level fixed effect accounts for this conversion problem in the log-linear model.

Second, firm-level data are not available. Instead, we let every district-product combination represent one firm. Therefore, the firm indicator i is replaced with $h - d$ in the empirical section. We do not observe if there is more than one importer for a given product in each district. As long as the importers are homogeneous, the number of importers is relegated to the error term and the rich variation in our panel data set allows us to accommodate several assumptions about the disturbance ϵ_{hajt} . If demands vary systematically across districts due to differences in productivity or market size, then $v_{hajt} = \delta_{hdt}$. Across all products and districts, U.S. importers may favor certain export partners for quality of infrastructure, product quality and country level differences in reliability. This extends to $v_{hajt} = \delta_{hdt} + \delta_j$ to account for

⁸Appendix A presents a detailed derivation of this linearization.

⁹See Appendix B for a more detailed discussion.

these systematic differences.

Third, we can use coefficient estimates to back out information related to inventory costs. The constant, β_0 , absorbs all constant terms that center the linearization. Combining the coefficient estimate β_4 with the coefficient estimate β_2 we can back out $wk/365$ and quantify changes in the total costs of holding safety stock $\frac{wk}{365}\sigma q$.

Higher product prices reduce the quantity of imports demanded. This raises endogeneity concerns common to simultaneous equation models. The standard solution for this problem is to use supply shocks as instruments. Unfortunately, we do not know of any foreign shocks that vary across products and countries. However, if firms are small and supply curves are flat, such as with constant marginal costs, then importers take factory gate prices as given and the impact of a price change on imports is identified. Similarly, if individual importers are small so they do not impact the per-unit shipping charges set by shippers that serve many firms within a given period, then the impact of an increase in the per-unit freight charge on import demand is identified.

4.2 Data

4.2.1 U.S. Import Data

Monthly figures on U.S. imports disaggregated by district of arrival, HS 10 product code, mode of transport, and country of origin for the 2007-2009 period are from the U.S. Imports of Merchandise dataset. Quantities are measured in kilograms. The total value of shipments and total freight charges are measured in U.S. dollars. Our theory applies to products that can be stored and managed in inventories so we

exclude bulk and perishable goods. HS 10 codes are merged with SITC codes for industries SITC 5 to SITC 9. Imports from Canada and Mexico are dropped because most shipments use ground transportation. We use information related to Canada and Mexico as an alternative to inventory management in the robustness section. Finally, we exclude Hawaii, Puerto Rico and the Virgin Islands to focus on imports of the continental United States.

Our main specification focuses on imports that arrive on ocean vessels. The total value of imports arriving on ocean vessel in 2007, 2008 and 2009 is 926, 1040, and 715 billion dollars, respectively. Our estimation sample captures 70, 65, and 70 percent of total vessel imports. We do not mean to imply that supply chain uncertainty is not important for industries or locations excluded from our sample. We focus on a sample of industries where our supply chain management process is most applicable.

Let q_{hdjt}^o be the total quantity of good h imported via ocean transport from country j in year t arriving in district d . Price per kg, denoted as p_{hdjt}^o , is calculated as total value of the shipment divided by weight. Let f_{hdjt}^o denote the unit ocean freight rate associated with the shipment computed as the total freight charge associated with the shipment divided by the shipping weight, q_{hdjt}^o . Similarly for air shipments we obtain q_{hdjt}^a , f_{hdjt}^a and p_{hdjt}^a .

4.2.2 Shipment-Level Data

We employ transaction-level import data that include vessel arrival information available for the years 2007-2009 from Import Genius. This dataset contains information on every import that arrives at a U.S. port by date of arrival. For each import we

observe the delivery vessel, actual date of arrival, the country of loading, the last foreign port the vessel cleared, and the expected arrival date based on the contractually negotiated berthing window at the final destination. All information is collected from the electronic bills of lading filed by the shipper. Import Genius receives this information via a U.S. customs feed.

We drop bulk and liquid shipments. This is not straightforward as the dataset does not report HS10 product codes. Product descriptions are used to identify and drop observations that include bulk shipments and liquid-carrying containers. The number of observations is reduced by about 12%.

The Import Genius data are highly disaggregated, but do not include freight cost or value information. To estimate the impact of supply chain uncertainty on imports we generate a measure of supply chain uncertainty based on the arrival information and merge it with the import information from the Imports of Merchandise. This is accomplished by assigning the arrival ports in the Import Genius data to customs districts consistent with the Imports of Merchandise. We then compute a district-by-country-by-year measure of supply chain uncertainty for the years 2007, 2008 and 2009 defined as the standard deviation of the actual relative to the expected arrival date for each district of arrival and country of loading.

It is not possible to develop a product-specific measure of supply chain uncertainty. Import Genius reports only product descriptions. Without commodity codes, it is difficult to match products in the Imports of Merchandise data. As a consequence, our measure of uncertainty assumes that importers in a given district are faced with the same variation in delivery time from each source country indepen-

dent on the product. Given that many different products are imported on the same vessel, this assumption is not unreasonable if much of the uncertainty is driven by scheduling issues for vessel transport.

Summary statistics for our supply chain uncertainty measure are reported in Figure 3 and Table 1. Initially we have 1,096,770 observations for uncertainty. Three percent are zeros. These observations are dropped when making log transformations. We lose an additional 10% of observations because of merges with other variables. Table 1 shows uncertainty is lower for North America and Asia, and higher for South America and Africa. Late shipment shares are lower for North America, Central America, and Asia, and higher for South America and Africa.

4.2.3 Merging Import Data with Arrival Data

There are several challenges in merging the data worthy of mention. Imports of Merchandise reports the country of origin for each import based on the production location. Import Genius reports the country where the product was loaded on the vessel. These locations may not coincide. Our uncertainty measure is based on products loaded at a country's ports even though not all products might have been produced in that country. For example, the supply uncertainty measure for Holland that includes the Port of Rotterdam may contain some products produced in Germany that were transshipped to the Port of Rotterdam. Similar issues arise when we regress aggregate trade flows on distance. We do not observe inter- or intra-country movements of products on the way to their destinations.

An additional discrepancy between country of origin and loading is attributed

to landlocked countries (e.g., Switzerland) or countries that do not ship directly to the United States. For example, small countries may ship to a “hub” port where shipments are unloaded, consolidated, and reloaded for the voyage to the United States. Because we do not observe the entire voyage, only the last leg, we cannot generate supply chain uncertainty measures in these cases. As a consequence, we lose some district-exporter pairs that are observed in the Imports of Merchandise dataset. Fortunately, these observations only account for about 3.3 percent of the total value of vessel imports across all three years.

4.2.4 Additional Control Variables

Our theory requires that we control for fixed ordering costs r_{jt} when identifying the impact of supply chain uncertainty on trade. We obtain proxies for ordering costs from the Doing Business database. Included here are costs for documents, administrative fees for customs clearance and technical control, customs broker fees, terminal handling and inland transport.¹⁰ Summary statistics for variables are presented in Table 2.

We also generate a U.S. district-by-exporter specific measure of distance. GPS coordinates of domestic and foreign ports from the U.S. Army Corps of Engineers are used to generate the average distance between a U.S. district and all ports for each exporter. Compared to standard country-level measures, this measure has the advantage that it is sensitive to the location of the exporter relative to the United States. While countries to the east or west face variation in distances across coasts,

¹⁰It is not possible to separate variable ordering costs, such as inland transport charges, from fixed ordering costs in the Doing Business ordering cost measure.

countries to the south face variation along the coasts, for example, between New Orleans and New York.

4.3 Results

4.3.1 Main Estimation Results

Table 3 reports coefficient estimates for equation (5). Our first prediction is that firms will import more from countries with low supply chain uncertainty. Consistent with this prediction, an increase in supply chain uncertainty is found to lower imports across all specifications. Specification 1 includes country and district-by-commodity-by-year fixed effects. Specification 2 includes exporter-by-year and district-by-commodity-by-year fixed effects. We cannot estimate the impact of order costs because they only vary across exporters and time. Pooled over all years, a unit increase in log uncertainty lowers imports by 0.103 log points. A unit increase in log prices or log freight rates lowers imports by 1.072 and 0.148 log points, respectively.

Specifications 3 to 5 report estimates by year for the 2007-2009 period that are used to examine the stability of our estimates during the trade collapse. Compared to pooled estimates, the impact of supply chain uncertainty more than doubles for 2007, drops by about 63 percent in 2008 and is about 16 percent lower in 2009. Freight charges and prices, on the other hand, have a similar impact as in the pooled estimates. We conclude that during the trade collapse, the impact of supply chain uncertainty drops in magnitude, but the impact of realized prices and freight charges remain relatively unchanged. This is what we would expect if the trade collapse changed supply chain uncertainty in ways that importers did not anticipate, but

transactions were based on realized and perfectly observed prices and freight charges. This leads us to expect that realized uncertainties before the trade collapse predicted trade flows during the trade collapse. Specifications 6 and 7 relate 2008 and 2009 imports to the supply chain uncertainty experienced in 2007. The impact of the 2007 supply chain uncertainty on 2008 and 2009 trade flows is similar in sign and magnitude to the impact of the 2007 supply chain uncertainty on 2007 imports. This suggests that the trade collapse changed uncertainties, but firms acted based on their experience before the trade collapse.

Our second prediction is that an increase in order costs reduces imports. Specification 1 delivers the appropriate sign, but an insignificant estimate. There are two reason for this outcome. First, order costs vary only across countries and years. As a result, after accounting for country fixed effects, we have little information left to identify the impact. We also experimented with specifications excluding country fixed effects. In this case order costs have a negative and significant impact, as predicted. The tradeoff is a less rigorous identification strategy.¹¹ The second reason is that order costs aggregate over many costs related to trade and therefore are only a proxy for ordering costs. This issue may be magnified during the time of the trade collapse when some of these costs may be more difficult to measure.

4.3.2 Alternative Theories

Table 4 augments specification 3 of Table 3 to examine alternative theories. We focus on the year 2007 to alleviate concerns regarding the trade collapse.

¹¹Results are available upon request.

The first question we want to examine is whether supply chain uncertainty is captured by trade costs proxies such as distance, or if supply chain uncertainty is an independent source of such costs. Specification 1 of Table 4 augments our main specification with the distance from each U.S. port district to the exporter’s capital. Proxying for all other distance related costs, an increase in supply chain uncertainty is still found to have a negative and significant impact on trade. This implies that supply chain uncertainty is not simply a proxy for distance related costs. It is a barrier to trade even among countries that are at a similar distance from the U.S. market, but, compared to the estimates of Table 3, the impact of uncertainty on imports drops in magnitude by about half.

Next, we explore mechanisms other than inventory management that firms may use to smooth uncertainty. In the case of demand volatility, Evans and Harrigan (2005) show firms move closer to the destination market to ensure timely delivery and Hummels and Schaur (2010) provide evidence that firms use expensive air transport. We expect supply chain uncertainty matters less for firms that can easily respond to bad arrival shocks by sourcing from nearby markets or emergency deliveries via air transport.

To identify the possibility of switching between ocean and air transport let

$$\text{rate-mile}_{it}^a = \sqrt{\frac{\sum_{j=1}^J \frac{\sum_{d=1}^D f_{ijdt}^a}{\text{distance}}}{J}}$$

be the average unit freight rate for air shipping per mile traveled for a particular

product h .¹² This variable is an indicator of how expensive it is to ship via air as opposed to shipping by ocean. Specification 2 of Table 4 interacts the log of supply chain uncertainty with the log of the cost of air shipping. As we would expect, the cheaper it is to substitute to air shipment, the lower the impact of supply chain uncertainty on imports. Evaluated at the mean of 0.001, the impact of an increase in the log uncertainty on imports equals about -.235.¹³

To examine the impact of sourcing from nearby markets, we interact supply chain uncertainty with the share of imports of a given product from Canada and Mexico. A higher share means importers source a larger amount of a product from nearby markets, allowing for a fast response time in case of a bad arrival shock. Therefore, we expect that uncertainty matters less for goods that can be sourced from the Canadian and Mexican markets.¹⁴ Specification 3 of Table 4 interacts supply chain uncertainty with the Canada/Mexico import share. As we would expect, supply chain uncertainty matters more for products that are not heavily sourced from nearby markets.

4.3.3 Uncertainty impact by product category

Our estimates of the uncertainty impact are averaged across all commodities, hiding some variation in how imports of different commodity groups respond to changes in delivery time uncertainty. One important classification distinction is differentiated versus homogeneous products. An importer facing large delivery shocks should be harmed less if products are easily substitutable. This expectation is supported by

¹²Distance is measured as a straight line from the capital of country j to the U.S. capital.

¹³ $\frac{\partial \ln q}{\partial \ln \sigma} = -0.518 - 0.041 \times (\ln(0.001))$.

¹⁴Unfortunately we do not have data for alternative suppliers to the U.S. market.

our data based on the preferred specification with commodity-country-year fixed effects. Using the Rauch (1999) classification, results shown in Table 5 reveal the uncertainty impact is higher than average for differentiated goods and about average for homogeneous goods.

We also employ the U.S. Census end use classification to study different impacts of uncertainty based on products' end use characteristics. Imports of goods that are more difficult to store in inventory, such as foods and beverages, are found to respond less to uncertainty and ordering costs than other product groups. Industry supplies and capital goods are associated with a smaller uncertainty impact than consumer products. This result is not surprising because time sensitive goods used in manufacturing require more efficient supply chains. Hummels and Schaur (2013) provide evidence that inputs are among the most time sensitive commodities in trade. Firms that require timely delivery often use other sourcing strategies such as purchasing inputs from nearby locations or using expensive air transport. We examined these alternative channels in section 4.3.2. Final products might also be ordered by a larger number of importers, which means uncertainty will impact more entities and have a greater cumulative effect. For example, imports of footwear fall by 6.7% in response to a 10% increase in uncertainty, which is much larger than the average impact.

4.3.4 Additional Robustness Exercises

We also take advantage of an outside measure of supply chain uncertainty based on the timeliness component of the World Bank's Logistics Performance Index (LPI)

that measures the “timeliness of shipments in reaching destination within the scheduled or expected delivery time.” This index ranges from 1.38 for Somalia to 4.48 for Germany. Since this measure is increasing with improvements in timeliness, the expected sign on the LPI variable is positive. The disadvantage of this measure of uncertainty is that it only varies across countries and years. Therefore, we exclude country fixed effects when we test the impact of this measure of supply chain uncertainty on imports. As expected, better supply chain performance of the export country based on timeliness is found to have a positive impact on U.S. vessel imports. Results are available upon request.

4.4 Back of the Envelope Computation of Inventory Costs

Based on linearization of the import demand equation, we can back out per-unit storage costs from coefficient estimates of equation (5). Dividing coefficient estimates on the supply chain uncertainty measure by the coefficient on the freight rate yields

$$\frac{\hat{\beta}_4}{\hat{\beta}_2} = \frac{wk\bar{\sigma}}{365f}. \quad (6)$$

When this is multiplied by the average freight charge, we obtain the marginal cost of safety stock with respect to an increase in the total quantity that cycles through inventory over a given planning period.

Combining coefficient estimates of specification 1 in Table 3 with the mean ocean freight rate of 1.148 yields a per-unit cost of holding safety stock equal to \$.67. When compared to the average import unit value of \$36.82, per-unit safety stock costs are

found to be equivalent to a 2 percent ad valorem cost. Applying coefficient estimates of equation 3 yields a higher cost of about 4 percent.¹⁵

For comparison, in our sample per-unit freight charges are about 3 percent of the unit value of the product. Hummels (2001) reports an average ad valorem freight charge for the U.S. of 3.8 percent. According to Hummels (2007), ad valorem ocean freight charges decreased to about 5 to 6 percent by 2004. Hummels argues that ad valorem freight charges pose a barrier to trade that is equal to or greater than that associated with tariffs.

Total per-unit inventory costs can be calculated from our estimates and assumptions about the number of shipments. Applying coefficient estimates of specification 1 in Table 3 with the mean uncertainty value and freight rate reported in Table 2, and setting $k = 2.33$, we obtain $\hat{w} = 56.6 \frac{\$}{kg}$. If instead we apply the estimates of specification 3 of Table 3 we obtain $\hat{w} = 134.6 \frac{\$}{kg}$. Total storage cost is $\frac{1}{2}w\frac{q}{n} + \frac{wk\sigma q}{365}$. Dividing total storage cost by the import value $p \times q$, we obtain $(\frac{1}{2}w\frac{1}{n} + \frac{wk\sigma}{365})/p$.

Inventory costs increase as the number of shipments decreases due to a larger average base-stock cost.¹⁶ To evaluate the costs of inventory relative to the import value therefore requires information on the number of shipments between an importer and exporter, n . The Census Import data reports the number of records for a given HS10 product in a given month.¹⁷ In our sample the average number of shipments

¹⁵Safety stock costs increase with unusually high uncertainty. We estimate them to be equivalent to a 3.5% - 8.5% tariff if uncertainty is equal to 3.6, which is the mean plus two standard deviations.

¹⁶This does not impact the costs of holding safety stock. Based on the above example, the cost of holding safety stock is still between 2 and 4 percent of the average import unit value.

¹⁷This number of records is disaggregated by HS10 product, exporter, district and month but not by mode of transportation. In the few cases where we observe both air and ocean shipments at this level of disaggregation we split the number of shipments by the value share.

equals 40. This number likely overestimates the average number of shipments because it potentially includes multiple importer-exporter pairs that transact the same product. Based on detailed data from El Salvador, Carballo et al. (2014) report that the average exporter makes about 8 shipments per product and destination.

Evaluated at $w = 56.6$, with $n=40$ and $n = 8$ shipments and the mean unit value reported in Table 2 shows that per-unit storage cost is about 4 and 11 percent of the average import unit value. At the high end, if we set $w = 134.6$, this cost increases to about 9 and 27 percent of the average import unit value.

5 Conclusions

This paper investigates the impact of supply chain uncertainty and ordering costs on trade. Previous studies have been preoccupied with the effects of demand uncertainty on trade. An increase in supply chain uncertainty raises safety stocks, increases inventory holding costs, and reduces imports. Results indicate that unforeseen delays in shipment significantly reduce trade volumes in the same manner as other non-tariff barriers. A 10 percent increase in supply chain uncertainty reduces imports between 1 and 2 percent.

For the average importer inventory costs per unit of import are as high as 27 percent of the unit import value. Per-unit safety stock costs range between 2 and 4 percent of the per-unit import value and are comparable to the cost of average per-unit freight charges relative to the unit import value of about 3 percent.

Late shipments may be due to factors beyond shipping lines' control. Included

here are bad weather, labor strikes, fires, ship collisions, groundings, delays at previous ports of call, and customs delays. We find that shipment delays significantly reduce U.S. trade flows. A large nation, like the U.S., imports most shipments over direct trade routes. Trade costs associated with supply chain uncertainty are even higher for lower income countries with inadequate port facilities that ship through multiple ports of call. A container ship that misses its contractually negotiated berthing window affects both berth and yard planning at seaport terminals, leading to port congestion. Measuring supply chain uncertainty can help us assess costs associated with both unforeseen and deliberate shipment delays, and the economic impact of policies intended to facilitate trade such as streamlined cargo screening, improved customs procedures, and investment in infrastructure to ease port congestion.

High trade costs associated with supply chain uncertainty suggest much can be gained from reducing these costs. Trade costs affect the fragmentation of production (Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008; Yi, 2003). Safety stocks are a coordination cost that firms incur to hedge against the failure of timely arrival or faulty inputs. Coordination costs and failure rates determine comparative advantage in the supply chain and vertical specialization (Costinot et al., 2013). Reductions in supply chain uncertainty from investments in additional container handling capacity, port and screening infrastructure will lead to significant cost savings for shippers, importing firms, and final consumers and will affect the location of production and pattern of trade.

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Figure 1: Difference between the actual date of arrival and the estimated date of arrival

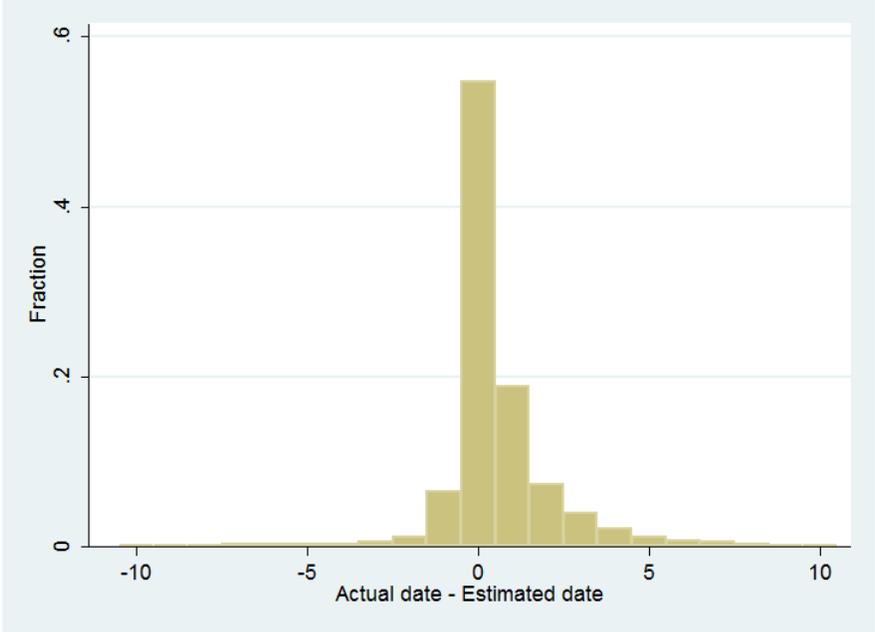
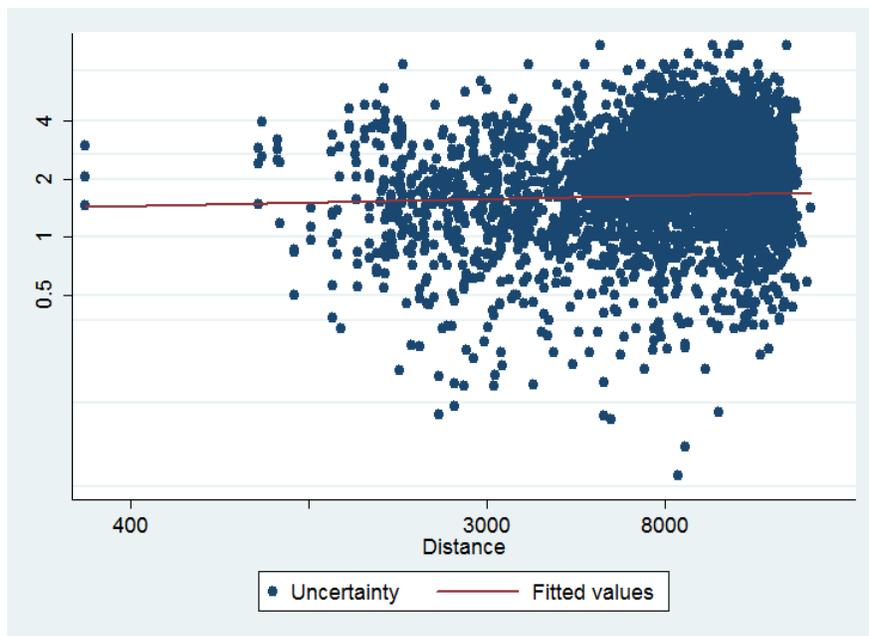


Figure 2: Supply Chain Uncertainty and Distance



Note: Horizontal and vertical axes are log scaled.

Figure 3: Uncertainty for district d and country j

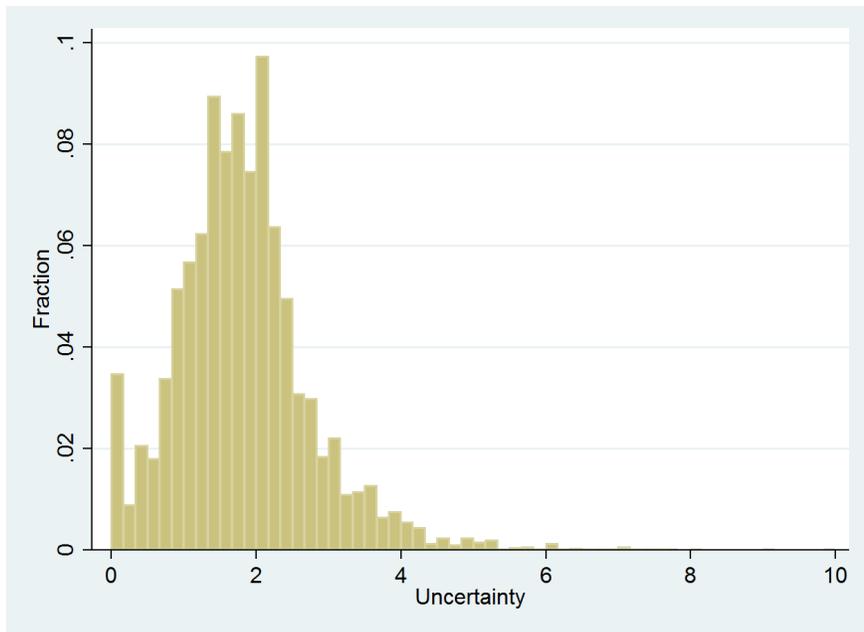


Table 1: Table of summary statistics of uncertainty

	N	Δ_{odjt}			Late shipments only			Early shipments only				
		avg	med	sd	share	avg	med	sd	share	avg	med	sd
all observations	566453	0.58	0	1.96	0.34	2.3	1.53	2.09	0.13	1.6	1	1.98
years												
2007	236781	0.7	0	1.96	0.38	2.35	2	2	0.12	1.55	1	1.85
2008	171290	0.56	0	2.06	0.33	2.4	1.64	2.24	0.14	1.71	1	2.13
2009	158382	0.41	0	1.82	0.3	2.1	1.02	2.05	0.14	1.53	1	1.97
regions												
n america	10937	0.45	0	1.5	0.27	2.07	1	1.75	0.075	1.6	1	1.82
c america	78462	0.53	0	1.8	0.31	2.28	1.09	2	0.11	1.64	1	1.78
s america	47273	0.85	0	2.22	0.39	2.69	2	2.27	0.12	1.68	1	1.84
europa	156878	0.71	0	2.05	0.37	2.49	2	2.1	0.14	1.56	1	1.85
asia	247074	0.45	0	1.88	0.32	2.06	1	2.04	0.14	1.59	1	2.13
australia	10998	0.55	0	1.87	0.35	2.25	1.88	1.86	0.16	1.45	1	1.86
africa	12985	1	0	2.29	0.44	2.82	2	2.25	0.1	1.76	1	1.76
puerto rico	1846	0.29	0	1.08	0.26	1.52	1	1.19	0.075	1.32	1	1.43
coasts												
east coast	385502	0.66	0	1.96	0.35	2.4	1.98	2.11	0.12	1.56	1	1.84
west coast	156240	0.38	0	1.92	0.32	2.04	1	2.02	0.17	1.6	1	2.15
income												
low income	6278	0.71	0	1.85	0.37	2.34	2	1.95	0.097	1.6	1	1.67
lower-middle income	193622	0.63	0	2.02	0.35	2.38	1.67	2.19	0.12	1.64	1	2.04
upper-middle income	73977	0.53	0	1.86	0.33	2.24	1.14	1.98	0.13	1.6	1	1.85
higher income non-oecd	65420	0.44	0	1.84	0.31	2.1	1	2.01	0.13	1.62	1	2.14
higher income oecd	207325	0.61	0	1.98	0.35	2.35	1.91	2.06	0.14	1.57	1	1.9

Table 2: Summary statistics

Variable	Source	Mean	Std. Dev.	N
σ_{djt}	Import Genius	1.854	0.869	1008097
distance _{dj}	distance between a district and a country	9935.755	3094.587	1008097
q_{ijdt}^o	US Census	441.029	8895.522	1008097
p_{hdjt}^o	US Census	36.822	2513.224	1008097
f_{ijdt}^a	US Census	6.065	29.077	310917
f_{ijdt}^o	US Census	1.148	33.392	1008097
rate-mile _{it} ^a	US Census	0.001	0.004	310902
share _{it} ^{MC}	US Census	0.176	0.212	1008090
r_{jt}	Doing Business	767.106	281.747	1008097

Table 3: Coefficient Estimates of the Main Specification

Variable (in logs)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
uncertainty	-0.087 (0.008)***	-0.103 (0.008)***	-0.211 (0.017)***	-0.038 (0.014)***	-0.087 (0.013)***		
uncertainty of 2007						-0.176 (0.019)***	-0.215 (0.02)***
price	-1.072 (0.004)***	-1.072 (0.004)***	-1.072 (0.007)***	-1.083 (0.008)***	-1.06 (0.008)***	-1.084 (0.008)***	-1.062 (0.008)***
ordering cost	-0.027 (0.042)						
freight rate	-0.149 (0.003)***	-0.148 (0.003)***	-0.152 (0.004)***	-0.149 (0.005)***	-0.142 (0.005)***	-0.148 (0.005)***	-0.142 (0.005)***
Fixed Effects:							
Country	yes	no	yes	yes	yes	yes	yes
Country-year	no	yes	no	no	no	no	no
Product-dist	no	no	yes	yes	yes	yes	yes
Product-dist-year	yes	yes	no	no	no	no	no
Year	all	all	2007	2008	2009	2008	2009
N	1008097	1008097	364047	332508	311542	338941	312617

Note: The dependent variable in all specifications is the log of imports in kgs. The unit of observation is at the product-district-country-year level. Standard errors are robust and clustered by product-district-year.

Table 4: Robustness checks

Variable (in logs)	(1)	(2)	(3)
uncertainty	-0.095 (0.016)***	-0.518 (0.125)***	-0.271 (0.022)***
distance	-2.581 (0.054)***		
uncertainty · air rate per mile		-0.041 (0.016)**	
air rate per mile		dropped	
uncertainty · MexicoCanada share			0.33 (0.065)***
MexicoCanada share			dropped
price	-1.074 (0.007)***	-1.067 (0.007)***	-1.072 (0.007)***
freight rate	-0.151 (0.004)***	-0.156 (0.004)***	-0.152 (0.004)***
Country FE	yes	yes	yes
Comm-dist-year FE	yes	yes	yes
Year	2007	2007	2007
N	364047	346297	364045

Note: The dependent variable in all specifications is the log of imports in kgs. The unit of observation is at the product-district-country-year level. Standard errors are robust and clustered by product-district-year.

Table 5: The effect of uncertainty on log of ocean-shipped weight by category

Product category	Uncertainty impact	Obs N
Homogeneous goods	-0.088 (0.045)**	57504
Differentiated goods	-0.238 (0.021)***	252506
End use category (1 digit)		
Foods and beverages	-0.346 (0.537)	700
Industry supplies and materials	-0.087 (0.031)***	109856
Capital goods, except automotive	-0.159 (0.034)***	88613
Automotive vehicles, parts and engines	-0.062 (0.077)	16715
Consumer goods	-0.334 (0.027)***	140211
Nondurable goods	-0.402 (0.039)***	78833
Durable goods	-0.215 (0.038)***	60617
Other goods	-0.023 (0.119)***	3715
End use category 5 digit example		
Footwear (40040)	-0.673 (0.117)***	5077

Note: The dependent variable in all specifications is the log of imports in kgs. The unit of observation is at the product-district-country-year level. Standard errors are robust and clustered by product-district-year. Only observations from 2007 were used.

Appendices

A Log-linearization

For simplification let

$$A = \frac{Q_{it}}{\varphi_i \left(\sum_{jt} m_{ijt}^{\frac{\rho}{\rho-1}} \right)^{\frac{1}{\rho}}}, \text{ and}$$
$$B = \bar{p} + \bar{f} + \sqrt{\frac{\bar{r}w}{2c}} + w \frac{k}{365} \bar{\sigma}.$$

Rewrite the main equation (4) such that every endogenous variable x is replaced with $e^{\ln(x)}$, and take logs of both sides:

$$\ln [e^{\ln(q_{ijt})}] = \ln \left[A \left(e^{\ln(p_{ijt})} + e^{\ln(f_{jt})} + \sqrt{\frac{e^{\ln(r_{jt})}w}{2c}} + w \frac{k}{365} e^{\ln(\sigma_{ijt})} \right)^{\frac{1}{\rho-1}} \right]. \quad (7)$$

Using first-order Taylor approximation of equation (7) for all endogenous variables

around $(\ln(\bar{q}), \ln(\bar{p}), \ln(\bar{f}), \ln(\bar{r}), \ln(\bar{\sigma}))$, we obtain:

$$\begin{aligned}
\text{LHS} &= \ln(\bar{q}) + \frac{1}{\bar{q}} e^{\ln(\bar{q})} (\ln(q_{ijt}) - \ln(\bar{q})) = \ln(q_{ijt}). \\
\text{RHS} &= \ln\left(AB^{\frac{1}{\rho-1}}\right) + \frac{1}{AB^{\frac{1}{\rho-1}}} AB^{\frac{\rho}{\rho-1}} \frac{1}{\rho-1} e^{\ln(\bar{p})} (\ln(p_{ijt}) - \ln(\bar{p})) + \\
&+ \frac{1}{AB^{\frac{1}{\rho-1}}} AB^{\frac{\rho}{\rho-1}} \frac{1}{\rho-1} e^{\ln(\bar{f})} (\ln(f_{jt}) - \ln(\bar{f})) + \\
&+ \frac{1}{AB^{\frac{1}{\rho-1}}} AB^{\frac{\rho}{\rho-1}} \frac{1}{\rho-1} \sqrt{\frac{w}{2c\bar{r}}} e^{\ln(\bar{r})} (\ln(r_{jt}) - \ln(\bar{r})) + \\
&+ \frac{1}{AB^{\frac{1}{\rho-1}}} AB^{\frac{\rho}{\rho-1}} \frac{1}{\rho-1} \frac{wk}{365} e^{\ln(\bar{\sigma})} (\ln(\sigma_{ijt}) - \ln(\bar{\sigma})).
\end{aligned}$$

We then combine the LHS and the RHS and rearrange to get:

$$\begin{aligned}
\ln(q_{ijt}) &= \ln A + \frac{1}{\rho-1} \ln B - \frac{B}{\rho-1} \bar{p} \ln(\bar{p}) - \frac{B}{\rho-1} \bar{f} \ln(\bar{f}) - \\
&- \frac{B}{\rho-1} \sqrt{\frac{w}{2c\bar{r}}} \bar{r} \ln(\bar{r}) - \frac{B}{\rho-1} \frac{wk}{365} \bar{\sigma} \ln(\bar{\sigma}) + \frac{B}{\rho-1} \bar{p} \ln(p_{ijt}) + \\
&+ \frac{B}{\rho-1} \bar{f} \ln(f_{jt}) + \frac{B}{\rho-1} \sqrt{\frac{w}{2c\bar{r}}} \bar{r} \ln(r_{jt}) + \frac{B}{\rho-1} \frac{wk}{365} \bar{\sigma} \ln(\sigma_{ijt}).
\end{aligned}$$

Now rename the coefficients:

$$\begin{aligned}\beta_0 &= \ln A + \frac{1}{\rho-1} \ln B - \frac{B}{\rho-1} \bar{p} \ln(\bar{p}) - \frac{B}{\rho-1} \bar{f} \ln(\bar{f}) - \\ &\quad - \frac{B}{\rho-1} \sqrt{\frac{w}{2c\bar{r}}} \bar{r} \ln(\bar{r}) - \frac{B}{\rho-1} \frac{wk}{365} \bar{\sigma} \ln(\bar{\sigma}), \\ \beta_1 &= \frac{B}{\rho-1} \bar{p}, \\ \beta_2 &= \frac{B}{\rho-1} \bar{f}, \\ \beta_3 &= \frac{B}{\rho-1} \sqrt{\frac{w}{2c\bar{r}}} \bar{r}, \text{ and} \\ \beta_4 &= \frac{B}{\rho-1} \frac{wk}{365} \bar{\sigma}.\end{aligned}$$

Change the subscript from i to hd to match the level of aggregation in our data and obtain:

$$\ln(q_{hdjt}) = \beta_0 + \beta_1 \ln(p_{hdjt}) + \beta_2 \ln(f_{jt}) + \beta_3 \ln(r_{jt}) + \beta_4 \ln(\sigma_{hdjt}) + \epsilon_{hdjt},$$

which is our structural estimation of the model, equation (5).

B Units vs. kilograms

Assume a switching parameter γ that transforms units into kilograms, with γ being constant within one 10-digit industry code: $q_{ijt} = \gamma q'_{ijt}$, where q_{ijt} is quantity in units and q'_{ijt} is quantity in kgs. Similarly the purchasing price per unit and freight charges per unit transform into price per kg and charges per kg as $p_{ijt} = \frac{1}{\gamma} p'_{ijt}$ and

$f_{jt} = \frac{1}{\gamma} f'_{ijt}$. Then import demand equation (4) becomes:

$$\gamma q'_{ijt} = \frac{\left(\frac{1}{\gamma} p'_{ijt} + \frac{1}{\gamma} f'_{ijt} + \sqrt{\frac{r_{jt} w}{2c}} + w \frac{k}{365} \sigma_{ijt} \right)^{\frac{1}{\rho-1}}}{\left(\sum_{jt} m_{ijt}^{\frac{\rho}{\rho-1}} \right)^{\frac{1}{\rho}}} \cdot \frac{Q_{it}}{\varphi_i}.$$

Denote

$$A = \frac{Q_{it}}{\varphi_i \left(\sum_{jt} m_{ijt}^{\frac{\rho}{\rho-1}} \right)^{\frac{1}{\rho}}}, \text{ and}$$

$$C = \frac{1}{\gamma} \bar{p} + \frac{1}{\gamma} \bar{f} + \sqrt{\frac{\bar{r} w}{2c}} + w \frac{k}{365} \bar{\sigma}.$$

After log-linearizing as described in Appendix A we get:

$$\begin{aligned} \ln(q'_{ijt}) = & \ln A + \frac{1}{\rho-1} \ln C - \frac{1}{\gamma} \frac{C}{\rho-1} \bar{p} \ln(\bar{p}) - \frac{1}{\gamma} \frac{C}{\rho-1} \bar{f} \ln(\bar{f}) - \\ & - \frac{C}{\rho-1} \sqrt{\frac{w}{2c\bar{r}}} \bar{r} \ln(\bar{r}) - \frac{C}{\rho-1} \frac{wk}{365} \bar{\sigma} \ln(\bar{\sigma}) + \frac{1}{\gamma} \frac{C}{\rho-1} \bar{p} \ln(p_{ijt}) + \\ & + \frac{1}{\gamma} \frac{C}{\rho-1} \bar{f} \ln(f_{jt}) + \frac{C}{\rho-1} \sqrt{\frac{w}{2c\bar{r}}} \bar{r} \ln(r_{jt}) + \frac{C}{\rho-1} \frac{wk}{365} \bar{\sigma} \ln(\sigma_{ijt}). \end{aligned}$$

Combining all the constant terms into the intercept and renaming coefficients, the structural estimation becomes:

$$\ln(q'_{hdjt}) = \beta_0 + \beta_1 \frac{1}{\gamma} \ln(p'_{hdjt}) + \beta_2 \frac{1}{\gamma} \ln(\gamma f'_{jt}) + \beta_3 \ln(r_{jt}) + \beta_4 \ln(\sigma_{hdjt}) + \epsilon_{hdjt}.$$

Estimates of β_4 and β_2 will give us the following:

$$\frac{\beta_4}{\beta_2} = \frac{\frac{C}{\rho-1} \frac{wk}{365} \bar{\sigma}}{\frac{C}{\rho-1} \frac{1}{\gamma} \bar{f}} = \frac{wk \bar{\sigma}}{365 \bar{f} \gamma},$$

which we estimate to be equal to 0.58. From here we find that the per kg inventory holding costs $w\gamma$ are equal to \$56.6.

The switching parameter does not change the interpretation of the structural estimates.