Supply Chain Uncertainty as a Trade Barrier

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Abstract

This paper examines the impact of supply chain uncertainty and ordering costs on trade. Importers hold safety stock to hedge against delays in delivery. An increase in supply chain uncertainty raises safety stocks, increases inventory costs, and reduces imports from locations with high delivery time uncertainty. An increase in order costs reduces a firm's shipping frequency and increases average inventory holding cost for the firm's base inventory stock. As a result, firms import less from locations with high ordering costs to reduce average inventory holding costs. Detailed data on actual and expected arrival times of vessels at U.S. ports serve to measure supply chain uncertainty consistent with the theory. Combined with detailed data on U.S. imports, freight charges and unit values, a 10 percent increase in supply-chain uncertainty lowers imports by as much as 3.7 percent. This is evidence that delivery uncertainty imposes a cost on imports according to the management of safety stocks. A one percent increase in ordering costs lowers imports by as much as 1.2 percent. Ordering costs impact the intensive margin of trade due to the management of base inventory stocks.

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1 Introduction

Goods traded over long distances are subject to unexpected delays in delivery. At U.S. ports over forty percent of vessels arrive one or more days late. In 2007 the average vessel arriving from China at U.S. ports was 3 days late and the average vessel from Europe missed the arrival date by 2.7 days. Vessels also often arrive early, requiring storage until the date of delivery to a customer or absorption in a production process. This matters for importers that rely on timely delivery, because late arrivals may result in lost demand and early arrivals increase storage costs.

This paper identifies the impact of supply chain uncertainty and inventory management on international trade. The theory examines how inventory management impacts import demand if importers hedge against bad arrival shocks by holding safety stock. The empirics identify the impact of supply chain uncertainty on import demand and quantify the inventory management costs associated with managing supply side risk.

The theory employs a stochastic inventory model from the logistics and economics literature (Song et al. (2009), Wisner et al. (2005), Eppen and Martin (1988), Baumol and Vinod (1970)) to derive two testable hypothesis. First, to avoid disruptions due to unexpected delays in delivery, importers respond to an increase in delivery time uncertainty with an increase in their safety stock. This increase raises inventory holding costs and reduces import demand relative to locations with a lower degree of supply chain uncertainty. Second, to minimize base-stock inventory costs, an importer trades off a higher order frequency at a fixed ordering cost for lower average inventory holding costs. As a consequence, an importer responds to an increase in order costs with a reduction in shipping frequency which implies an increase in average inventory holding costs. The importer responds to this increase in average inventory holding costs by reducing demand from locations with high ordering costs relative to other locations subject to lower ordering costs.

To test these two predictions we combine several sources of information. To measure supply chain uncertainty across source countries for U.S. imports and districts of entry we employ expected vessel arrival dates filed by shippers and actual arrival dates at U.S. ports for 2007-2009 from Import Genius[1]. We obtain ordering costs from Doing Business and import, freight charge and unit value data from the U.S. Census Imports of Merchandise. With these data sources at hand, we construct a panel data set of imports that arrive in the U.S. via ocean vessel reported by district of unloading, source country, year of entry and HS 10 product. This rich source of variation allows us to account for several unobservable variables that are suggested by the theory, but are not directly observable. Exploiting variation across source countries of imports within district-by-product pairs the results imply that a 10 percent increase in supply chain uncertainty lowers trade by up to 2.7 percent. A one percent increase in the ordering costs lowers imports by as much as 1.2 percent. This is evidence that supply chain uncertainty and ordering costs impact the intensive margin of trade consistent with the inventory process from the theory.

A back of the envelope structural model shows that a one standard deviation increase in supply chain uncertainty from the mean raises inventory holding costs by \$2,354,005 per year if the total shipping quantity is unchanged. This cost is based on an estimated daily per unit inventory cost of about \$2. This is about twice as much as the average per kg ocean freight rate found in U.S. improt data. In other words, supply chain uncertainty raises the costs of importing and is therefore a friction to trade.

Identifying sources of trade costs that are otherwise difficult to observe is an

[1]importgenius.com

ongoing area of research. Hummels and Schaur (2012) quantify the impact of transit time as a trade barrier. Djankov et al. (2010) identify the impact of time delays within countries on trade and Carballo et al. (2012) examine the impact of trade and customs delay on firm level imports and exports. Blonigen and Wilson (2008) identify the impact of port efficiency on trade. While all of these articles have examined some aspect of the supply chain in determining trade flows, to our knowledge we are the first to identify supply chain uncertainty as a trade barrier.

In our empirical application we account for several other mechanisms that firms may use to mitigate the impact of uncertainty. However, contrary to the existing literature, we consider how these mechanisms may mitigate supply side as opposed to demand side shocks. Hummels and Schaur (2010) show that firms subject to demand uncertainty speed up their supply chain by substituting into expensive air transport. Also with demand uncertainty in mind, Evans and Harrigan (2005) provide evidence that firms move closer to the destination market to speed up delivery. We provide evidence that inventories are an alternative means to manage uncertainty. Nevertheless, we also provide evidence that air transport as well as sourcing from close by markets such as Canada and Mexico are relevant strategies to manage supply chain uncertainty.

Alessandria et al. (2010) examine how firms use inventories to respond to demand uncertainty. In their calibration exercise they find that the volatility necessary to explain the large inventory holdings found in the data is about 5 times bigger than the demand volatility found in Khan and Thomas (2007) and therefore must include other sources of uncertainty not specified in the model. We provide evidence that supply side shocks in the form of unexpected delays in delivery are an additional source that contributes to a firm's inventory. Their dynamic model examines a firm's optimal inventory and pricing behavior. We abstract from optimal price adjustments when firms run out of inventory. The logistics literature suggests that firms hold safety stock such that they satisfy between 95-99 percent of demand.[2] While Alessandria et al. (2010) show that price adjustments are important, we use this fact to assume that firms hold enough safety stock to satisfy all of their demand. Therefore, our theory focuses on the year to year problems and costs imposed by inventory management as opposed to the extreme event when firms run out of safety stock.

This paper is also related to literature on trade in intermediate inputs. This type of trade is growing and comprises 40 to 60 percent of total international trade in the modern world (Ramanarayanan (2006)). About one-third of all international trade is intra-firm trade and for the U.S. this number is about 46%, as shown by Antràs (2003). Recent research derives intermediate input demand from a CES production functions that exhibits love of variety; firms import all available varieties to lower their production costs (e.g. Kasahara and Lapham (2012) or Amiti and Davis (2012)). We also derive our import demand from a CES production function and we allow for heterogeneity in productivity of importing firms. However, assuming homogeneity in productivity the import demand is akin to the import demand in a standard Melitz (2003) type model. Therefore, our model can be easily interpreted in terms of final goods or intermediate inputs.

Section 2 derives the import demand as a function of supply chain uncertainty and ordering costs to derive the main predictions for the empirics. Section 3 derives the empirical specifications, details the data construction and identification approach to discuss results and robustness checks. Section 4 finishes with some broad conclusions and ideas for future research.

[2] For example, see Dullaert et al. (2007) and Fortuin (1980)

2 Theory

This section derives a firm's import demand taking into account that the importer holds inventory to smooth supply chain uncertainty. An increase in the uncertainty of the arrival time of ordered products requires firms to hold a larger amount of safety stock to hedge against bad arrival shocks. As a result, an increase in supply chain uncertainty increases inventory costs and lowers the import demand.

2.1 Import Demand

Consider an importer indexed by i who sells a final bundle of goods Q_{it} on the home market. To produce the final good the importer orders products q_{ijt} from international markets indexed by $j \in J$, where J is an exogenous set of source countries[3] and combines them to the product bundle $Q_{it} = \varphi_i \left(\sum_j q_{ijt}^{\rho} \right)^{\frac{1}{\rho}}$.[4] Importers differ in productivity φ_i. For a given optimal bundle Q_{it} the firm wants to supply on the home market, the importer minimizes the costs of importing $\sum_j \left(m_{ijt} q_{ijt} + F_{jt} \right)$ such that $Q_{it} = \varphi_i \big(\sum_j q_{ijt}^{\rho} \big)^{\frac{1}{\rho}}$, where m_{ijt} is a constant marginal cost of importing and storing and F_{jt} is a fixed cost of importing from country j. The optimal import demand is then

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

Without the productivity parameter φ_i this import demand is similar to Melitz (2003). Therefore, we can interpret q_{ijt} as the demand for the variety i from the

[3] Similar to the existing literature we do not solve for the endogenous number of source countries. For example, Amiti and Davis (2012) assume that firms import inputs from all available markets, due to the CES production function's love of variety. For the empirics this assumption is innocuous, as we absorb the aggregate variable with fixed effects.

[4] Finally, $0 < \rho < 1$ is a parameter that determines the elasticity of substitution between imported goods $\theta = 1/(1-\rho) > 1$.

aggregate consumption bundle Q_{it} demanded by the representative consumer in any period t. We now derive the constant import cost m_{ijt} as a function of factory gate prices, transit costs and inventory costs.

2.2 Importer's Costs

The importer holds inventory to serve gradually arriving demand on the home market. Assume that there is no uncertainty in the arrival of ordered products. In that case the firm trades off ordering costs with inventory holding costs to determine the optimal amount of inventory and the cost minimizing number of shipments within a planning period t. Figure (1) shows an importer who orders half of his yearly imports in the beginning of the year and uses it up gradually until the next shipment arrives. More frequent shipping lowers the average amount stored in inventory, but comes with additional ordering costs. Let ordering costs o_{jt} represent all the expenses associated with ordering a shipment from country j. Total ordering costs per year are then $o_{jt}n_{ijt}$, where n_{ijt} is the total number of orders the firm places during the planning period t. Let w denote the unit annual inventory cost. Because the withdrawal from inventory is linear, the average amount of inventory is $\frac{1}{2}\frac{q_{ijt}}{n_{ijt}}$ and the base stock inventory cost is $\frac{1}{2}w\frac{q_{ijt}}{n_{ijt}}$.

Now suppose that the firm holds safety stock to hedge against delays in the arrival time of ordered products.[5] Let l_{sjt} denote the lead time, the time that passes between ordering and receiving a shipment s in a year t. Let v_{ijt} denote the daily inventory a firm withdraws to supply the home market. If the firm does not hold

[5] We assume that varieties imported from different locations are not substitutable in the short run and therefore firms hold buffer stock. Even though goods are substitutable according to the elasticity of substitution framework over longer planning periods, we assume that it is too costly to substitute varieties imported from, say, Germany with varieties from Russia in the short run.

safety stock, then it will stock out (run out of inventory), if $l_{sjt} > \bar{l}_{jt}$, where $\bar{l}_{jt}$ is the expected delivery time. The logistics literature suggests that firms hold safety stock to keep the probability of stocking out between 1-5 percent.[6] How much safety stock must a firm hold to stock out with a probability of 1 percent? Let l_{jt}^{99} be a threshold such that $l_{sjt} > l_{jt}^{99}$ with a probability of one percent, $P(l_{sjt} > l_{jt}^{99}) = 0.01$. Then, if the firm can cover the potential wait time $l_{jt}^{99} - \bar{l}_{jt}$ at a withdrawal rate of v_{ijt}, the firm stocks out with a probability of 1 percent. To guarantee a 1 percent stock-out probability, safety stock must then be $(\text{safety stock})^{1\%} = (l_{jt}^{99} - \bar{l}_{jt})v_{ijt}$. The logistics literature shows that $(l_{jt}^{99} - \bar{l}_{jt})v_{ijt} = k\sigma_{ijt}v_{ijt}$, for a normal distribution of the lead time in days with a standard deviation σ_{ijt}. The exogenously given parameter k is called a services factor such that for a 1 percent probability of stocking out k is the 99th percentile of the standard normal distribution. For daily withdrawal rates $v_{ijt} = q_{ijt}/365$ the total expected costs of base and safety stocks are then the standard expected inventory cost[7]

$$\text{IC} = o_{jt}n_{ijt} + \frac{1}{2}w\frac{q_{ijt}}{n_{ijt}} + w\frac{k}{365}\sigma_{ijt}q_{ijt}. \tag{2}$$

This inventory cost reflects the key issues of inventory management. First, for a given stock-out probability and annual quantity q_{ijt}, an increase in the lead time uncertainty raises inventory holding costs due to an increase in the safety stock. Second, an increase in the number of shipments raises ordering costs but lowers average inventory holding costs, reflecting a trade-off between ordering costs and the base stock. To obtain the optimal shipping frequency as a function of q_{ijt}, minimize (2) with respect to n_{ijt} and solve for $n_{ijt}(q_{ijt}) = \sqrt{\frac{wq_{ijt}}{2o_{jt}}}$. Substitute the number of

[6](See Dullaert et al. (2007) and Fortuin (1980))

[7]For examples in the logistics literature see: Baumol and Vinod (1970), Tyworth and O'Neill (1997) or Ray et al. (2005)

shipments into the inventory cost (2) to obtain the equilibrium inventory cost

$$\text{IC} = \sqrt{2 o_{jt} w q_{ijt}} + w \frac{k}{365} \sigma_{ijt} q_{ijt}. \tag{3}$$

First examine the special case where per unit inventory costs are $w_{ijt} = 1/q_{ijt}$. Then the inventory costs are not a function of q_{ijt} and are fully captured by the fixed costs of importing F_{jt}. However, across countries j, the fixed costs of importing vary due to uncertainty in the delivery time and ordering costs. In a standard trade model based on firm level selection into export markets such as Melitz (2003), this suggests that inventory costs impact the extensive margin of trade.

Now examine the impact of an increase in ordering costs and supply chain uncertainty if the per unit inventory holding costs are constant. Note that an increase in the ordering costs o_{jt} increases the inventory costs for any given q_{ijt}. However, the ordering cost is not a fixed cost, but the impact of an increase in the ordering costs on the total inventory costs depends on q_{ijt}. To obtain intuition for this result note that firms that ship a larger quantity spread this quantity over more shipments. As a result, the same increase in the ordering costs impacts a firm that absorbs a large quantity more than a firm that absorbs a small quantity. For this reason, a firm with a larger q_{ijt} lowers the number of shipments faster in response to an increase in o_{jt}, raising the average inventory holding costs by more compared to a firm with a smaller q_{ijt}. Therefore, an increase in ordering costs has a larger impact on costs for firms that ship a larger quantity. It is straightforward to see that an increase in supply chain uncertainty raises inventory costs due to an increase in the safety stock.

For large q_{ijt}, the derivative $\frac{\partial IC}{\partial q_{ijt}} = \sqrt{2 o_{jt} w / q_{ijt}} + w \frac{k}{365} \sigma_{ijt} \approx w \frac{k}{365} \sigma_{ijt}$. In other words, for large quantities the total inventory cost is linear in q_{ijt} and we can approximate it well with the first order Taylor approximation around some constant

c:

$$\text{IC} \approx \sqrt{\frac{o_{jt}wc}{2}} + \left(\sqrt{\frac{o_{jt}w}{2c}} + w\frac{k}{365}\sigma_{ijt}\right)q_{ijt} \tag{4}$$

In this case the importer's fixed cost, F_{jt}, depends on ordering and per unit inventory holding costs, but the marginal inventory cost is a function of supply chain uncertainty as well as ordering costs. Assuming that the importer takes any varieties' factory gate price, p_{ijt}, and per-unit freight rate, f_{ijt}, as given, the constant marginal cost of importing then equals

$$m_{ijt} = p_{ijt} + f_{ijt} + \sqrt{\frac{o_{jt}w}{2c}} + w\frac{k}{365}\sigma_{ijt}. \tag{5}$$

All else equal, supply chain uncertainty and ordering costs impact the constant marginal cost of importing and storing a variety. Therefore, ordering and per unit inventory costs impact the intensive margin of trade. Substitute m_{ijt} into the firms import demand (1) to obtain

$$q_{ijt} = \frac{\left(p_{ijt} + f_{ijt} + \sqrt{\frac{o_{jt}w}{2c}} + w\frac{k}{365}\sigma_{ijt}\right)^{\frac{1}{\rho-1}}}{\left(\sum_{jt} m_{ijt}^{\frac{\rho}{\rho-1}}\right)^{\frac{1}{\rho}}} \cdot \frac{Q_{it}}{\varphi_i}. \tag{6}$$

Supply chain uncertainty and ordering costs impact the intensive margin of trade. To derive this import demand we make an additional simplifying assumption. We assume that firms do not take into account the small chance that they run out of safety stock when they derive the import demand. In other words, we are violating some form of Jensen's inequality. This assumption is based on the fact from the logisitics literature that firms hold safety stock to satisfy 95-99% of their demand. Therefore, firms act as if they are not really planing to run out of inventory. In theory, we can always increase k to lower the probabiliy of running out. This assumption emphasizes that we are concerned with the average long run cost of inventory as opposed to the issue of short term adjustments when firms run out of inventory as discussed by Alessandria et al. (2010). With this in mind, the following two prediction summarize the impact of supply chain uncertainty and ordering costs on import demand.

Prediction 1. *All else equal, an increase in the 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 that an increase in the supply chain uncertainty leads firms to increase their safety stock to hedge against bad arrival shocks. Therefore, an increase in the supply chain uncertainty of country j raises inventory holding costs for imports from country j relative to other source countries and lowers the firms' import demand relative to all other source countries.

The ordering costs impact the intensive margin of trade as follows.

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

The intuition follows the discussion above. Firms that ship a large total quantity split this quantity over a larger number of shipments to economize on average inventory holding costs. As a result, the same increase in ordering costs has a greater impact on the inventory costs of firms that ship a large quantity. As a consequence, for large quantities ordering costs are linear in the quantity and an increase in the ordering costs raises the cost of importing.

3 Data, Estimation and Results

To test the predictions we need information on imports, uncertainty, ordering and delivery costs, and prices. This section describes the specification, the data sources and how the variables were constructed. We finish with presenting results as well as robustness checks.

3.1 Specification

We employ a highly disaggregated panel dataset of U.S. imports for three years with four dimensions of variation: across districts of entry d, across commodities h, across source countries j and across time t. We do not observe data at the firm level. For all regressions we assume that every district-commodity combination represents one firm. In other words, the firm indicator i in the theory gets replaced with a $h - d$ couple in the empirical section.

Note that the main equation of interest (6) is nonlinear in the variables of interest. This poses a challenge for the estimation. While non-linear estimators are available, the difficulty is that identification requires that we absorb several unobserved variables with fixed effects. Given the large dimensions of products and countries this is difficult with a non-linear estimator and we work with two linear approximations instead. First approximate the sum of trade costs in (6) by

$$\frac{1}{\rho - 1} ln(p_{ijt} + f_{ijt} + \sqrt{\frac{o_{jt}w}{2c}} + w\frac{k}{365}\sigma_{ijt}) \approx \beta_0 + \beta_1 ln(\sigma_{djt}) + \beta_2 ln(p_{hdjt}) + \beta_3 ln(o_{jt}) + \beta_4 ln(f_{jt}). \tag{7}$$

Then we obtain the empirical model

$$ln(q_{hdjt}) = \beta_0 + \beta_1 ln(\sigma_{djt}) + \beta_2 ln(p_{hdjt}) + \beta_3 ln(o_{jt}) + \beta_4 ln(f_{jt}) + \epsilon_{hdjt} \tag{8}$$

where

$$\epsilon_{hdjt} = ln \frac{Q_{hdt}}{\left(\sum_{jt} m_{hdjt}^{\frac{\rho}{\rho-1}}\right)^{\frac{1}{\rho}} \varphi_{hd}} + u_{hdjt} = v_{hdjt} + u_{hdjt} \tag{9}$$

captures approximation error, unobserved variables such as productivity differences and aggregate demand. The rich variation in our panel data set allows us to accommodate several assumptions about the disturbance ϵ_{hdjt}. If ϵ_{hdjt} is not correlated with the trade costs, then an OLS estimator provides consistent estimates for $\beta_o, ..., \beta_4$. If firms and demands are symmetric across districts but vary across commodities, then $v_{hdjt} = \delta_h$, a commodity fixed effect. If demands vary systematically across districts due to differences in productivity or market size, then $v_{hdjt} = \delta_{hd}$. If aggregate demands vary by districts, commodities and time then $v_{hdjt} = \delta_{hdt}$. This specification of the disturbance accounts for variation in import demands driven by the financial crisis over the sample period. Even though we do not model quality differences explicitly, differences in quality of a product h across source countries may change the relative import demands. To account for this unobserved variation we specify $\epsilon_{hdjt} = \delta_{hdj} + u_{hdjt}$ where δ_{hdj} is a product-by-district-by-exporter fixed effect. In summary, the rich variation of the data allows us to account for several sources of unobserved variation that may impact the identification of the parameters with a dummy variable estimator that pools the data over all dimensions. Specification (10) has several advantages. The coefficients are easy to interpret in terms of elasticities and fixed effects are easy to accommodate in the log-linear model. A further advantage is that it solves an identification problem related to the fact that we only observe import weights instead of quantities. Let q_{hdjt} be the imports measured in weights and suppose that a constant conversion factor λ_h translates weights to quantities. 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

$$ln(q_{hdjt}) = \beta_0 + \beta_1 ln(\sigma_{hdjt}) + \beta_2 ln(p_{hdjt}) + \beta_3 ln(o_{jt}) + \beta_4 ln(f_{jt}) + \gamma ln(\lambda) + \epsilon_{hdjt} \quad (10)$$

where $\gamma = 1 - \beta_2 - \beta_4$. Therefore, the product level fixed effect accounts for this conversion problem in the log-linear model. The main disadvantage of the log-linear model is that the coefficient estimates do not have a structural interpretation. To obtain a "back-of-the-envelope" structural model, we can approximate $ln(q_{hdjt})$ with a first order Taylor approximation around the variable means based on equation (6). Let $B = \left(\bar{p} + \bar{f} + \sqrt{\frac{\bar{o}w}{2c}} + w\frac{k}{365}\bar{\sigma}\right)$ and $\frac{1}{\rho-1} = \alpha$. Then we obtain

$$ln(q_{hdjt}) = \beta_0 + \beta_1 \sigma_{hdjt} + \beta_2 p_{hdjt} + \beta_3 o_{jt} + \beta_4 f_{jt} + \epsilon_{hdjt} \quad (11)$$

where $\beta_1 = \frac{\alpha}{B}\frac{wk}{365}$, $\beta_2 = \frac{\alpha}{B}$, $\beta_3 = \frac{\alpha}{B}\sqrt{\frac{w}{2c}}$ and $\beta_4 = \frac{\alpha}{B}$.[8] The constant, β_0, absorbs all constant terms around which the linearization is centered. Combining the coefficient estimate β_4 with the coefficient estimate β_1 we can then back out $wk/365$ and quantify changes in the total costs of holding safety stock $\frac{wk}{365}\sigma q$.

3.2 Data

3.2.1 U.S. Import Data

For most of our variables we rely on U.S. Imports of Merchandise dataset. These data report imports into the U.S. at monthly frequencies disaggregated by district

[8]For a detailed derivation of this linearization see appendix x.

of entry, HS10 product, mode of transportation (air or ocean) and country of origin. Constrained by the data sources we discuss below, we use the data for 2007-2009. We have quantities (kg), the total value of the shipment (U.S.$) and the total freight charges (U.S.$). Our theory applies to products that can be stored and managed in inventories. Therefore we focus the identification on manufacturing imports and exclude all other commodities from the sample. We also drop all shipments that come from Canada and Mexico, because most of these shipments use ground transportation.

Let q^o_{hdjt} be the total quantity of good h imported via ocean transport from country j in year t arriving in district d. Price per kg is denoted as p^o_{hdjt} and is calculated as total value of the shipment divided by weight. Let f^o_{hdjt} 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^o_{hdjt}. Similarly for air shipments we obtain q^a_{hdjt}, f^a_{hdjt} and p^o_{hdjt}.

3.2.2 Shipment level data

We now describe how we generate a proxy for supply chain uncertainty. The data source we employ is a transaction level import database that includes vessel arrival information purchased for the years 2007 to 2009 from Import Genius[9]. The main dataset contains information on every import that arrives at a U.S. district by day of entry. For each import we observe the vessel that delivered the product, the country of origin, the last foreign port the vessel cleared and the expected arrival date. 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 and compiles the

[9] importgenius.com

information. Similar to the imports of merchandise data we focus on manufacturing goods. Eliminating non manufacturing goods from the sample is more difficult because the data does not report HS10 product codes. To solve this problem we drop all products that include bulk shipments and liquid-carrying containers. This reduces the number of observations by about 12%.[10]

We compute a district-by-country-by-year measure of supply chain uncertainty.[11] This measure captures the idea that for a given exporter it may be more difficult to be on time at different districts. Across the east and west coasts this may be due to longer travel times and the necessity to cross the Panama Canal. At a given coast, it may be more difficult to be on time at certain districts due to weather and possibly congested ports.

Let S_{dtj} be the total number of vessels that arrive in district d in year t that unload imports sourced from origin country j. Let s_{dtj} identify a unique vessel arrival in S_{dtj} and let $AD(s_{djt})$ and $ED(s_{djt})$ denote the actual and estimated arrival day of the shipment. Let $\Delta(s_{djt}) = AD(s_{djt}) - ED(s_{djt})$ denote the number of days the actual arrival deviates from the expected arrival date. Figure 2 plots the distribution of $\Delta(s_{djt})$ over all shipments.

We define supply chain uncertainty as the standard deviation of the difference between the actual and expected arrival date:

$$\sigma_{djt} \equiv \sqrt{\frac{\sum\limits_{s \in S_{dtj}} \Delta(s_{djt})^2}{S_{dtj}}}$$

[10] In the robustness section we experiment with a sample that includes only intermediate inputs.

[11] The data does not include HS10 codes. Therefore it is difficult to combine any product level information from the Import Genius data with the imports of merchandise. Unfortunately we cannot generate a product specific measure of supply chain uncertainty and merge it with the imports. With our calculation of uncertainty we assume that firms in a certain district are faced with the same variation in the delivery time from a certain country.

In the strictest sense this variable measures how punctual vessel arrivals are. On the other hand, if export countries that have difficulty keeping a timely shipping schedule are likely subject to other sources of supply chain uncertainty that we do not observe, then our measure of uncertainty is a proxy for overall supply chain uncertainty.

See histogram 3 and table 1 for the statistics of the uncertainty variable. Uncertainty seems to be lower for higher-income countries, it is very high for Central America and Africa, and the share of shipments that are early is higher whenever the share of late shipments is low. Also, uncertainty is higher for 2008 and 2009 compared to 2007. All these correlations are supported by the descriptive regression results given in Table 2.

3.2.3 Additional Control Variables

The theory asks that we control for ordering costs o_{jt} to identify the impact of supply chain uncertainty on trade. We obtain proxies for ordering costs from the Doing Business database. They include the costs for documents, administrative fees for customs clearance and technical control, customs broker fees, terminal handling charges and inland transport. In addition we collect GDP, and GDP per capita from the World Development Indicators to account for a source countries' level of development. Both variables are in 2000 constant U.S. dollars, foreign currencies converted using the official exchange rate. See Table 3 for the summary statistics of all variables used.

3.3 Results

Table 4 reports the coefficient estimates for specification (10) with standard errors clustered by commodity-country-year. Column 1 reports benchmark OLS estimates.

Across columns 2 to 6 we include alternative fixed effects to account for unobserved variation that impact the identification. Across all columns, the coefficient estimates on the supply chain uncertainty are consistent with Prediction 1, an increase in the supply chain uncertainty lowers imports. Column 2 introduces commodity fixed effects, columns 3 and 4 introduce commodity-district fixed effects, column 5 presents commodity-district country fixed effects, and column 6 finishes with commodity-district year fixed effects. Consistent with our assumption that product-district pairs identify firms, this means that the coefficients are identified within firms by the variation in uncertainty across importer's sources of products. In other words, the coefficient estimates suggest that all else equal, a given firm imports relatively less from locations that exhibit a greater degree of supply chain uncertainty.

After accounting for commodity fixed effects, the coefficient estimates are relatively stable across the specifications. The one outlier is the estimate of Model 5 that introduces commodity-by-district-by-exporter fixed effects. This specification is robust with respect to unobserved variation in quality of imports by product across export locations, and it is comforting that even at this level of rigor the estimates are still consistent with Prediction 1. However, the particular fixed effect regiment of this specification eliminates the main source of identifying variation; the fixed effects absorb the cross-exporter-cross-district variation and rely only on variation across time within countries to identify the coefficients. If supply chain uncertainty is driven for example by port infrastructure, then we would not expect to see a large amount of useful variation that helps identify the impact of uncertainty on imports over time. Therefore, while this specification is robust to several sources of unobserved information, we prefer the specifications that exploit the main source of identifying variation such as the specification presented in Model 6.

Next we turn to Prediction 2. Across all but one model, an increase in order costs lowers imports. This results is surprising, as we identify an impact of a variable on the intensive margin of trade that usually is thought of as a fixed cost and therefore mainly operates on the extensive margin of trade. A caveat is necessary. It is difficult to find information that separates fixed ordering from variable trade costs. While several costs reported in the World Bank's doing business data reflect costs that an importer incurs by order, some reflect more of a variable cost. This means that our estimates are not precise about separating fixed ordering costs from variable costs. However, most of the costs are fixed per order in nature and according to the theory they should be included in the specification. This suggests that specifications that identify import demand omit an important source of trade costs if they do not include fixed ordering costs and the fact that importers hold inventory.

An increase in per unit transport costs and factory gate prices lowers the import demand. This is what we would expect from the theory, but several identification issues need to be addressed. First, as of now we are not really interested in the coefficients on these variables but are mainly concerned with absorbing the variation to identify the impact of supply chain uncertainty and ordering costs on international trade. However, if firms are small and supply curves are flat such as with constant marginal costs, then importers take the factory gate prices as given and the impact of a price change on imports is identified. Similarly, if individual importers are small such that they do not impact the per unit shipping charges set by shippers that serves many firms within a given period, then also the impact of an increase in the per unit freight charge on import demand is identified. Hummels and Schaur (2012) discuss this identification assumption and perform robustness checks using prices and freight rates from lagged periods. They do not find evidence that freight rates are endogenous even at the higher level of aggregation of HS6 commodities.

Columns 4-6 augment the specification with export country GDP and GDP per capita. Both variables have a significant impact on imports as we would expect from a long list of gravity estimation. However, including this information in our model does not change our conclusions about supply chain uncertainty or ordering costs.

All of the specifications in Table 4 include some sort of year effect. Accounting for systematic differences across years is important due to the potential trade effects of the financial crisis. While models 1 to 5 allow for systematic changes in the overall average import demand, specification allows for time effects that are specific to commodities and districts. Therefore, model 6 is robust with respect to shocks driven by the financial crisis that vary across industries and districts.

3.4 Robustness Checks

3.4.1 Intermediate Inputs

First we repeat the specifications from Table 4 on a sample of inputs and report the results in Table 5. The sample for Table 5 is notably smaller than the sample employed in Table 4. The reason is that we restrict the sample only to products that include the words "part", "component", "ingredient" or "detail" in their 10 digit commodity description. The impact of supply chain uncertainty is not as conclusive as in Table 4. While for our preferred model (Model 6) the impact of supply chain uncertainty is still negative, it is not significant in many other models and even positive in Model 3. There are several possible explanations. First, it could be that inputs where hit harder by the financial crisis than other goods and therefore the identification is more difficult for this particular sample. It could also be that firms that import inputs hold inventory in final output as opposed to inputs and the import cost due to inventory is average over all sources of inputs. Furthermore, Hummels and Schaur (2012) provide evidence that inputs are among the most time sensitive commodities in trade. As a result, firms that require timely delivery may have other sourcing strategies such as purchasing inputs from close by locations or flying them in by more expensive air transport. We examine these alternative channels in section 3.4.3.

3.4.2 Alternative Measures of Supply Chain Uncertainty

Next, we use alternative measures of uncertainty and report estimation results in table 6. We re-estimate Model 6 of the previous tables, but examine different ways of computing supply chain uncertainty. The estimated date of arrival is supposed to be the same for all shipments on a vessel, and it is for about 70% of observations. Other vessels happen to have different estimated dates of arrival for different shipments due to data entering error or other reasons. To solve this problem we take the most common estimated date for the vessel (mode), obtaining an alternative measure of the difference between the actual and estimated dates of arrival. The uncertainty obtained this way is denoted $\sigma_{djt}^{\mathrm{mode}}$ and its impact on trade is still negative.

Another indicator of uncertainty in the supply chain is the share of shipments that are late or early, $\mathrm{share\_not}_{djt}$. It can be interpreted as a probability of a shipment from a certain country to be not on time. To obtain that variable we calculate the share of vessel trips for district d from country j in year t that were late or early out of the total number of vessel trips for that district-country pair. As expected, the results of Model 6.2 show that an increase in the probability of late arrival lowers the import demand.

The third measure of uncertainty comes from the Logistics Performance Index developed by the World Bank. Specifically we employ the timeliness component. This timeliness parameter is very similar to what we estimate as delivery time uncertainty: "timeliness of shipments in reaching destination within the scheduled or expected delivery time". It is an index that ranges from 1.38 for Somalia to 4.48 for Germany. Since this measure is increasing with better timeliness, the expected sign on the LPI variable is positive. Column 3 shows that an increase in timeliness raises imports.

3.4.3 Alternative Theories

We now explore mechanisms that firms employ to smooth uncertainty other than inventory management. The literature provides two competing theories. Evans and Harrigan (2005) provide evidence that firms move closer to the destination market to ensure timely delivery if there are demand shocks. Hummels and Schaur (2010) provide evidence that firms substitute into fast transport to hedge against demand shocks. To identify the possibility of switching between ocean and air transport we introduce the variable rate-mile$^{a}_{hdt}$. This variable captures the average unit freight rate for air shipping per mile traveled for a particular commodity h. Distance is measured as a straight line from the capital of country j to the U.S. capital.

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

This variable is an indicator of how expensive it is to ship via air as opposed to shipping by ocean. Next denote the share of trade value that comes from Mexico and Canada as mcshare$_{it}$ for each commodity i.

Table 7 provides evidence for the mechanisms introduced by Evans and Harrigan and Hummels and Schaur based on the specification including commodity-district-year fixed effects. To test Hummels and Schaur (2010) we include an interaction term between uncertainty and air unit charges per mile. Products with higher air unit charges make it more difficult to substitute for faster transport, therefore the expected result is that uncertainty in ocean shipping would matter more for those products. The coefficient on the interaction term is negative, which makes the overall effect of uncertainty larger in absolute value.

To examine the mechanism proposed by Evans and Harrigan we interact the trade share that comes from Canada and Mexico with the supply chain uncertainty. A higher share means that importers source a large amount of a commodity from close-by countries allowing for a fast response time in case an importer runs out of inventory instead of waiting for ocean shipments to arrive from far away. The expected result is that for goods with a high share of trade coming from Canada and Mexico uncertainty in the ocean transit time matters less. The coefficient on the interaction term between the uncertainty and import share from Mexico and Canada is positive. Therefore, supply chain uncertainty has less of an impact for commodities that are heavily sourced from close by locations.

In conclusion, while we still find that supply chain uncertainty has a negative impact on imports as predicted by the theory, this impact is heterogeneous in an importer's ability to source from close by locations or air ship. If importers of intermediate inputs mostly use air shipments or sourcing strategies that involve close by exporters, then this could be the reason why we find that the inventory impact on intermediate inputs is weak.

3.5 Structural Estimation

Finally we estimate the "structural model" equation (11). The results of this specification are given in table 8, models 1 through 6 repeat the specifications described above. From the six specifications the largest coefficient on σ is -0.16, and the smallest is -0.016. Using the smallest value, the coefficient on σ divided by the coefficient on f is equal to

$$\frac{\beta_1}{\beta_4} = w\frac{k}{365} = 5.33.$$

For $k = 2.33$, per kilogram inventory holding costs are equal to 834 U.S.$ per kg. Then, for a one standard deviation increase in uncertainty ($sd(\sigma) = 0.97$), the safety stock costs (3) will increase by

$$0.97w\frac{k}{365}\bar{q}_{ijt} = 0.97 \cdot 834 \cdot \frac{2.33}{365} \cdot 455834 = 2354005.$$

In other words, the cost of additional safety stock due to a one standard deviation increase in σ, holding the total inventory quantity fixed, is about 2.3 million dollars per year. This means that if a firm orders the same quantity from two different countries, it has to spend 2.3 million dollars more per year to store products obtained from the country with a one standard deviation higher uncertainty. Inventory holding costs represent the annual cost of adding one more unit to the safety stock. Our estimate shows that these marginal costs are rather large: 834 dollars per kg per year. Freight charges are equal to only 1.1 dollars/kg for ocean shipping or 6.1 dollars/kg for air shipping. Inventory costs are also high compared to unit values, U.S.$ 35 on average. However, it is important to note that this is the cost if the unit is stored for an entire year. At daily withdrawal rates, the cost of inventory per day is $834/365 \approx 2.3$U.S.$.

4 Conclusions

This paper investigates the impact of supply chain uncertainty and ordering costs on trade flows. 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 from locations with high delivery uncertainty. High ordering costs reduce shipping frequency, increase average inventory holding cost for a firm's base inventory stock, and result in fewer imports from locations where ordering costs are high. Supply chain uncertainty is measured using detailed data on actual and expected arrival times of vessels at U.S. ports. Results indicate delivery time delay significantly reduces trade volumes. A 10 percent increase in supply chain uncertainty reduces imports by as much as 3.7 percent. When ordering costs rise one percent, imports fall by up to 1.2 percent.

Late shipments may be due to factors beyond shipping lines' control. Included here are bad weather, labor strikes, fires, ship collusions, groundings, and delays at previous ports of call. A large nation, like the U.S., imports most shipments over direct trade routes. Trade costs associated with supply chain uncertainty are more important for lower income countries with inadequate port facilities that ship through multiple ports of call. A container ship that misses its contractually negotiated birthing window affects both berth and yard planning at seaport terminals, leading to port congestion. High trade costs associated with supply chain uncertainty suggest much can be gained from reducing port congestion. Countries can reduce congestion at ports by investing in additional container handling capacity and by improving infrastructure. Reductions in supply chain uncertainty can stimulate trade and lead to significant cost savings for the shipper, importing firm, and final consumers.

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Figure 1: Inventory Process Illustrated

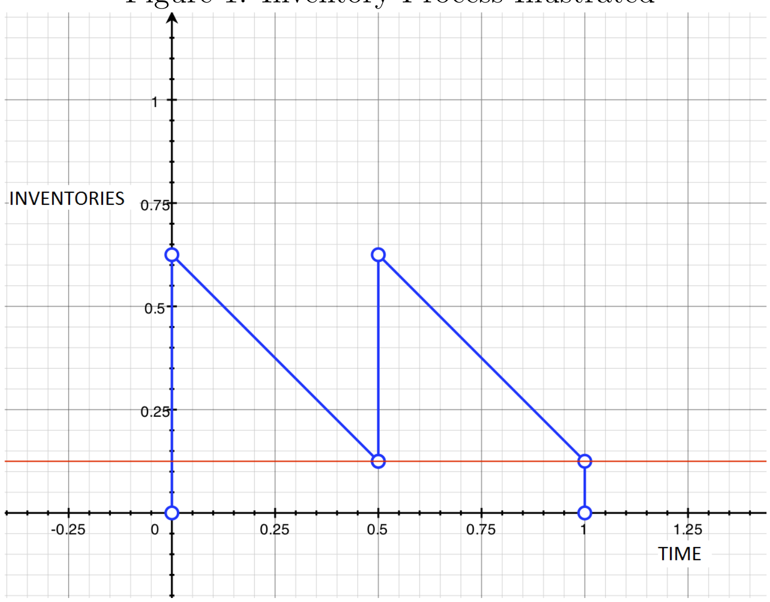

Figure 2: Difference between the actual date of arrival and the estimated date of arrival

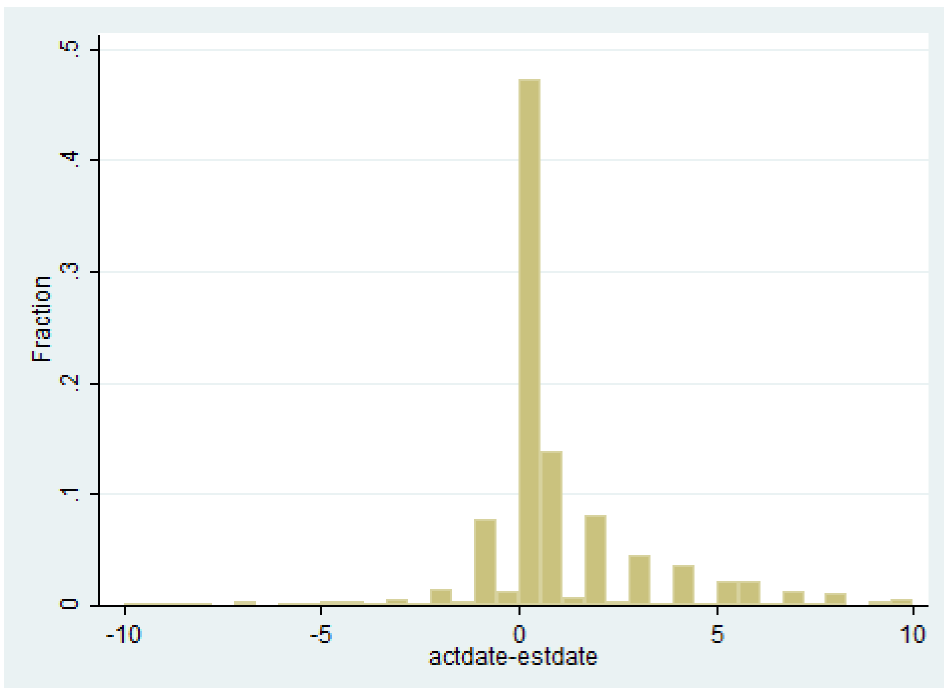

Figure 3: Uncertainty for district d and country j

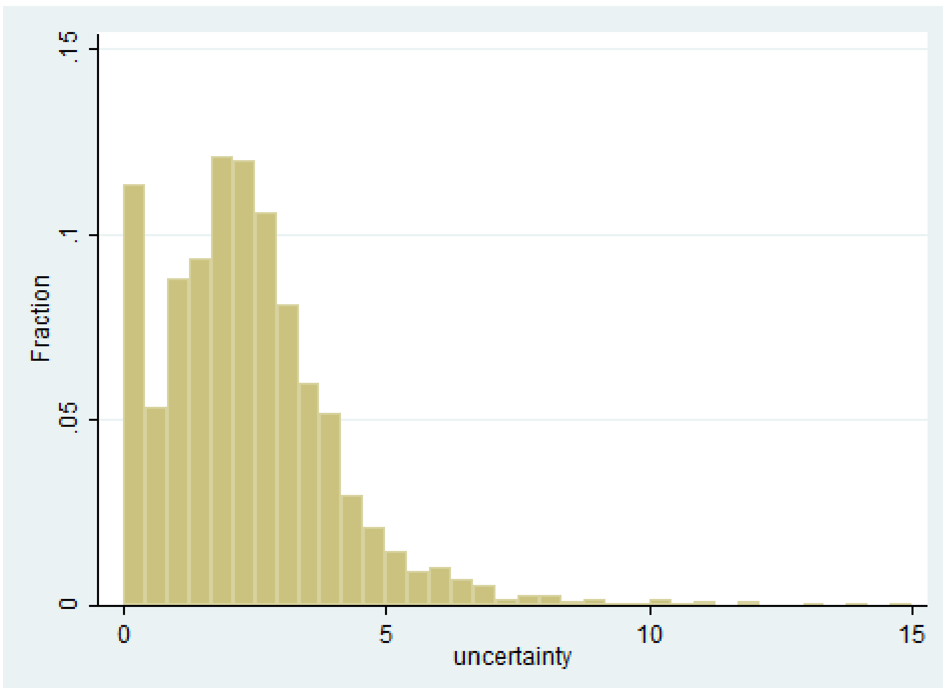

Table 1: Table of summary statistics of uncertainty

		Δ_{vdjt}				Late shipments only				Early shipments only			
		N	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
	europe	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: Descriptive regressions

Variables in logs	σ_{djt}	share_not$_{djt}$
GDP$_{jt}$	0.034**	0.014
	(0.016)	(0.013)
GDPC$_{jt}$	-0.055**	-0.031*
	(0.022)	(0.018)
2008 dummy	0.269***	0.141***
	(0.033)	(0.029)
2009 dummy	0.172***	0.057
	(0.046)	(0.036)
Constant	0.370	-0.825***
	(0.329)	(0.254)
R-squared	0.109	0.044
N	355	356

* p<0.1, ** p<0.05, *** p<0.01

Table 3: Summary statistics

Variable		**Source**	**Mean**	**Std. Dev.**	**N**
σ_{djt}	uncertainty by district	Import Genius	2.177	0.97	852385
$\sigma_{djt}^{\text{mode}}$	uncertainty by district, mode	Import Genius	2.457	1.225	852385
share_not$_{djt}$	share not on time	Import Genius	0.47	0.231	848210
lpi	logistics performance index	World Bank	4.005	0.332	850870
q_{ijdt}^{o}	ocean weight (tons)	US Census	455.834	9073.292	852385
p_{hdjt}^{o}	value per kg	US Census	35.493	1112.377	852385
f_{ijdt}^{a}	air unit freight rates	US Census	6.072	29.423	269275
f_{ijdt}^{o}	ocean unit freight rates	US Census	1.123	33.083	852385
rate-mile$_{it}^{a}$	air freight rates per mile traveled	US Census	0.001	0.004	269275
share$_{it}^{MC}$	Mexico and Canade trade share	US Census	0.177	0.214	852376
o_{jt}	ordering costs	Doing Business	773.654	287.619	852139
GDP$_{jt}$	GDP (bln $ US)	World Development Indicators	1480.450	1351.434	852385
GDPC$_{jt}$	GDP per capita ($ US)	World Development Indicators	13181.042	12616.566	852385

Table 4: The effect of uncertainty on log of ocean-shipped weight

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(in logs)	No FE	Comm FE	Comm-dist FE	Comm-dist FE	Comm-dist-ctry FE	Comm-dist-yr FE
σ_{djt}	-0.114***	-0.259***	-0.351***	-0.352***	-0.042***	-0.372***
	(0.005)	(0.004)	(0.009)	(0.008)	(0.009)	(0.010)
p_{hdjt}	-1.045***	-1.105***	-1.122***	-1.052***	-0.868***	-1.076***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
o_{jt}	-0.789***	-1.030***	-1.195***	-0.750***	-0.015	-0.779***
	(0.011)	(0.010)	(0.012)	(0.010)	(0.025)	(0.012)
f_{jt}	-0.207***	-0.131***	-0.133***	-0.145***	-0.117***	-0.152***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
year8	0.051***	0.039***	0.035***	0.021***	-0.036***	
	(0.010)	(0.008)	(0.009)	(0.008)	(0.005)	
year9	-0.068***	-0.066***	-0.068***	-0.146***	-0.300***	
	(0.010)	(0.008)	(0.009)	(0.008)	(0.007)	
GDP_{jt}				0.385***	-0.260	0.401***
				(0.003)	(0.272)	(0.003)
$GDPC_{jt}$				-0.250***	1.174***	-0.255***
				(0.003)	(0.277)	(0.004)
Constant	16.538***	18.472***	19.673***	8.229***	7.958	8.049***
	(0.074)	(0.066)	(0.081)	(0.101)	(5.074)	(0.116)
R-squared	0.315	0.440	0.496	0.524	0.861	0.460
N	850766	850766	850766	850766	850766	850766

* p<0.1, ** p<0.05, *** p<0.01

LHS variable - $\ln(q_{hdjt})$

Table 5: The effect of uncertainty on log of ocean-shipped weight (inputs only)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
(in logs)	No FE	Comm FE	Comm-dist FE	Comm-dist FE	Comm-dist-ctry FE	Comm-dist-yr FE
σ_{djt}	-0.013	-0.115***	0.079***	0.015	0.020	-0.054***
	(0.011)	(0.010)	(0.015)	(0.014)	(0.015)	(0.007)
p_{hdjt}	-1.040***	-1.057***	-1.070***	-0.967***	-0.836***	-1.073***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.014)	(0.005)
o_{jt}	-0.723***	-1.030***	-1.152***	-0.798***	0.119*	-0.775***
	(0.028)	(0.026)	(0.032)	(0.027)	(0.067)	(0.013)
f_{jt}	-0.155***	-0.122***	-0.147***	-0.158***	-0.145***	-0.153***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.003)
year8	0.084***	0.064***	0.049**	-0.005	-0.025*	
	(0.026)	(0.021)	(0.023)	(0.021)	(0.013)	
year9	-0.014	-0.032	-0.001	-0.116***	-0.299***	
	(0.027)	(0.022)	(0.024)	(0.021)	(0.018)	
GDP_{jt}				0.471***	0.173	0.409***
				(0.008)	(0.743)	(0.004)
GDPC_{jt}				-0.226***	0.733	-0.252***
				(0.008)	(0.756)	(0.004)
Constant	16.178***	18.391***	19.080***	5.617***	-1.132	7.543***
	(0.195)	(0.175)	(0.215)	(0.254)	(13.849)	(0.121)
R-squared	0.265	0.362	0.422	0.468	0.836	0.457
N	110472	110472	110472	110472	110472	110472

* $p<0.1$, ** $p<0.05$, *** $p<0.01$

LHS variable - $\ln(q_{hdjt})$

Table 6: Alternative measures of uncertainty

Variable (in logs)	Model 6.1 Comm-dist-yr FE	Model 6.2 Comm-dist-yr FE	Model 6.3 Comm-dist-yr FE
$\sigma_{djt}^{\text{mode}}$	-0.208***		
	(0.009)		
share_not_{djt}		-0.040***	
		(0.007)	
LPI			0.923***
			(0.066)
p_{hdjt}	-1.077***	-1.078***	-1.087***
	(0.005)	(0.005)	(0.005)
o_{jt}	-0.757***	-0.775***	-0.768***
	(0.012)	(0.012)	(0.012)
f_{jt}	-0.152***	-0.152***	-0.151***
	(0.003)	(0.003)	(0.003)
GDP_{jt}	0.404***	0.401***	0.392***
	(0.003)	(0.003)	(0.003)
GDPC_{jt}	-0.253***	-0.247***	-0.277***
	(0.004)	(0.004)	(0.004)
Constant	7.712***	7.673***	6.916***
	(0.115)	(0.116)	(0.132)
R-squared	0.523	0.522	0.522
N	850097	845530	861161

* p<0.1, ** p<0.05, *** p<0.01

LHS variable - $\ln(q_{hdjt})$

Table 7: Testing other theories

Variable (in logs)	Model 6.4 Comm-dist-yr FE	Model 6.5 Comm-dist-yr FE
σ_{djt}	-0.534***	-0.460***
	(0.016)	(0.012)
$\sigma_{djt} \cdot$ rate-mile$^a_{it}$	-0.022***	
	(0.002)	
rate-mile$^a_{it}$	dropped	
$\sigma_{djt} \cdot$ mcshare		0.375***
		(0.037)
mcshare		dropped
p_{hdjt}	-1.075***	-1.077***
	(0.005)	(0.005)
o_{jt}	-0.153***	-0.152***
	(0.003)	(0.003)
f_{jt}	-0.788***	-0.777***
	(0.012)	(0.012)
GDP$_{jt}$	0.402***	0.400***
	(0.003)	(0.003)
GDPC$_{jt}$	-0.259***	-0.256***
	(0.004)	(0.004)
Constant	8.079***	8.061***
	(0.116)	(0.116)
R-squared	0.456	0.460
N	837213	849173

* p<0.1, ** p<0.05, *** p<0.01

LHS variable - ln(q_{hdjt})

Table 8: The effect of uncertainty on log of ocean-shipped weight (structural estimation)

Variable (in abs.val)	Model 1 No FE	Model 2 Comm FE	Model 3 Comm-dist FE	Model 4 Comm-dist FE	Model 5 Comm-dist-ctry FE	Model 6 Comm-dist-yr FE
σ_{djt}	0.10062***	-0.11035***	-0.16157***	-0.13505***	-0.01655***	-0.14662***
	(0.00362)	(0.00287)	(0.00510)	(0.00492)	(0.00512)	(0.00609)
p_{hdjt}	-0.00008**	-0.00007**	-0.00007***	-0.00007***	-0.00003*	-0.00029***
	(0.00004)	(0.00003)	(0.00002)	(0.00002)	(0.00002)	(0.00006)
f_{jt}	-0.00323***	-0.00281***	-0.00307***	-0.00300***	-0.00290**	-0.00320***
	(0.00124)	(0.00090)	(0.00079)	(0.00075)	(0.00113)	(0.00102)
o_{jt}	-0.08213***	-0.11087***	-0.12103***	-0.05670***	-0.00727***	-0.05890***
	(0.00096)	(0.00078)	(0.00093)	(0.00079)	(0.00181)	(0.00092)
year8	-0.13327***	-0.10991***	-0.10735***	-0.10745***	-0.11957***	
	(0.01276)	(0.00929)	(0.00992)	(0.00896)	(0.00533)	
year9	-0.13482***	-0.12444***	-0.12471***	-0.27098***	-0.34423***	
	(0.01290)	(0.00954)	(0.01029)	(0.00913)	(0.00760)	
GDP_{jt}				0.00000***	0.00000***	0.00000***
				(0.00000)	(0.00000)	(0.00000)
$GDPC_{jt}$				-0.00006***	0.00003***	-0.00006***
				(0.00000)	(0.00001)	(0.00000)
Constant	11.48622***	12.25173***	12.52838***	10.53220***	9.45541***	10.46411***
	(0.02908)	(0.02356)	(0.02790)	(0.02360)	(0.04840)	(0.02660)
R-squared	0.034	0.297	0.359	0.413	0.828	0.338
N	850766	850766	850766	850766	850766	850766

* p<0.1, ** p<0.05, *** p<0.01

LHS variable - $\ln(q_{hdjt})$