Hedging Price Volatility Using Fast Transport

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Abstract

Ocean transportation in international trade imposes a time lag between the departure and arrival of a shipment. This arrival lag creates a problem for firms selling in markets with volatile demand. Specifically, the quantity a firm ships via ocean at a given time may not maximize profits when it arrives. This paper examines whether fast but expensive transportation hedges this uncertainty. Fast air shipments allow a firm to wait until the uncertainty is revealed, meaning that high demand volatility urges greater air shipments. On the other hand, a higher price for air shipment raises the cost of waiting and causes a firm to choose greater ocean quantities to minimize the transport bill. The model in this paper identifies the tradeoff between uncertainty and transportation costs. Monthly data for US imports of merchandise separated by transport mode confirm the predictions.

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1 Introduction

Firms in volatile markets would like to respond ex-post to demand shocks by re-optimizing prices charged and quantities sold. In international trade these adjustments face several constraints, including, the time lag between when a good is produced and shipped and when the product arrives in the foreign market. For example, shipping a good on a low-cost container ship from China to the United States requires, on average, 24 days.[1] In a market with volatile demand, the quantity shipped 24 days earlier may not maximize profits ex-post.

In recent years, technological advances in air shipment have dramatically reduced the cost of reaching foreign markets to hours rather than weeks (Hummels 2006). Consequently, it is now feasible for firms to adjust to demand shocks by waiting until the realization of those shocks before deciding on quantities to be sold. Air shipping provides firms with a real option to smooth demand shocks. This paper explores theoretically and estimates empirically the extent to which air shipping functions as a real option in international trade.

This paper presents a model with time dependent transportation costs. A exporter serves uncertain demand in a foreign market with a mix of inexpensive but slow ocean shipping and fast but expensive air shipment. Ocean shipments must depart prior to the resolution of a demand shock, because ocean transport is time consuming. Using only ocean shipping would minimize the total shipping bill, but at some risk. If the realization of the shock is unfavorable, the exporter will have too much quantity on the market and incur losses. Alternatively, the exporter can wait until the demand shock is realized and potentially employ air shipping. The

[1] Average is generated from a master schedule of shipping for 1999 taken from www.shipguide.com.

exporter fills in demand with an air shipment, if the demand shock is sufficiently favorable and demand is high.

In equilibrium, more volatility leads an exporter to reduce the ocean shipment and increases the probability of an air shipment. So in general, an increase in the volatility leads to an increase in the share of trade that is air shipped. A high price, ex-post, calls forth more air shipping in that period. A high relative air freight rate means that the real option of air transport is expensive and less likely to be used.

The empirics in this paper employ 10 digit (HS) *US Imports of Merchandise Data* at monthly frequencies. For each exporter, data is reported for quantity, value and import charges by transportation mode. To measure demand volatility, monthly unit values are normalized by their annual mean. Demand volatility is defined as the standard deviation of the normalized unit values within each year.

The estimation finds a significant positive relationship between the share of trade that is air shipped and the history of demand volatility. Also, higher prices, lower air freight rates, and higher ocean freight rates lead to a larger share of air shipment. These results identify a tradeoff between uncertainty and time dependent transportation cost.

This paper is related to four different literatures. First, the estimation provides empirical evidence for a tradeoff between uncertainty and time dependent transportation costs as first suggested by Aizenman (2004). A key point of Aizenman is that the extent of observed pass through of an exchange rate shock to the price of importables depends critically on the timing of the transaction. For low-speed imports bought before the uncertainty concludes, the prices and the shock are disconnected. For last-minute deliveries after the uncertainty concludes, high-speed shipments connect prices to the shock. The pass through of a shock to the price increases with the share of last minute deliveries, which is equivalent to the share of air shipments in the present paper. Aizenman's work focuses on macroeconomic implications including terms of trade shocks and financing cost. The present paper focuses on micro price volatility and identifies a quantity response in the share of air shipments. This quantity adjustment suggests that the mechanism is empiricaly relevant for pass through and arbitrage.

Second, the literature on the 'border effect' (Engel & Rogers 1996) suggests that price volatility is structurally higher across borders than within borders and that price volatility increases with distance. The standard explanation for this result is that the exogenously higher cost of moving goods across borders and over distance prevents arbitrage and results in volatility. Alternatively, this paper suggests a potential reverse causation. High price volatility urges an exporter into a fast and more expensive transport mix.

Third, in several recent papers James Harrigan has argued that geographical proximity between suppliers and customers is particularly important for solving demand uncertainty and that short reaction times drive the geographical allocation of firms. Timeliness may be a force that leads to clustering in order to smooth uncertainty (Harrigan & Venables 2006) or firms may trade off flexibility gained through proximity to the market with higher cost of inputs (Evans & Harrigan 2005). This paper argues that high-speed shipment is an alternative solution to being proximate to customers by providing micro evidence of its impact for individual products.

Finally, Hummels shows that exporters have a willingness to pay for faster shipping that far exceeds inventory holding cost. Using data on air versus ocean modal usage, he shows that exporters will pay as much as 0.8% ad valorem to save a day in transit, but he does not identify the precise source of this willingness (Hummels 2001). This paper argues that the ability to hedge demand uncertainty with an appropriate transport mix is valuable, and that for exporters subject to high price volatility, the gains from smoothing risk cover the higher expense of air transport.

In section 2, the theory explains how demand volatility and freight costs determine a firm's mix of ocean and air shipment. Section 3 tests the empirical predictions before section 4 concludes.

2 The Exporter's Maximization Problem

2.1 Set-up

Consider an exporting firm that lives for two periods. The firm produces a single good which it sells as a monopolist.[2] The market for the monopolist's good is active only in the second period.[3] The inverse demand in US$ is given by $p = \epsilon(a - bQ)$, where Q is the total quantity sold.[4] ϵ is a uniformly distributed shock over the interval $(\gamma - z, \gamma + z)$ which reveals at the beginning of the second period. Since the final price cannot be negative we require $\gamma - z \geq 0$ and $z \geq 0$. The probability density function for ϵ is $d(\epsilon) = \frac{1}{2z}$ and the mean and the variance of ϵ are $\mu = \gamma$ and $\sigma^2 = \frac{1}{3}z^2$. The firm knows this distribution.

[2] Following the pricing to market literature (Krugman 1986).

[3] Given that there is no trade-off in production, first-period sales would not affect the firm's decisions about the second period.

[4] Goldberg and Tille collect invoicing information on 24 countries and document that the US$ share in import invoicing for the United States in 2003 is at 85% (Goldberg & Tille 2005).

An increase in z raises the variance of ϵ and implies a greater volatility of the monopolist's price.

The firm ships its product to the destination market employing ocean shipment and/or air shipment. Let the quantity shipped over the ocean and air be q^o and q^a, where $Q = q^o + q^a$. Ocean shipment takes one period to arrive, while air shipment arrives immediately. The freight rates f^a and f^o determine the constant marginal cost of shipping an additional unit via air and ocean transport, $f^a > f^o$. We do not allow firms to hold inventory across periods in the US market.[5]

2.2 The Exporter's Problem

The firm's problem is to determine the total quantity with an optimal mix of ocean and air shipment. Without uncertainty, the exporter ships the entire quantity via ocean to minimize the transport bill. With uncertainty, a larger ocean shipment increases the expected loss in the event of a bad demand shock. Waiting until the uncertainty is resolved allows the firm to optimize the total quantity on the market. However, waiting to ship after the realization of the shock necessitates the use of more expensive air transport. The exporter balances the tradeoff between uncertainty and transportation cost to determine an optimal mix of air and ocean shipping.

We solve the exporter's problem backwards. We first derive the exporter's optimal rule for air shipment as a function of the first-period ocean shipment and ϵ. We then employ the optimal rule for air shipment to derive the exporter's first-period expected profits, from which we find the optimal ocean quantity.

[5] We capture inventory costs in the empirical part with real interest rates.

The exporter calculates the second-period US$ dollar profit[6] as total revenue minus the cost of transportation,

$$\pi_2 = \epsilon(a - b(q^o + q^a))(q^o + q^a) - q^a f^a - q^o f^o. \tag{1}$$

Taking the ocean shipment and ϵ as given, the second period objective is to maximize the profit with respect to the amount of air shipment q^a such that $q^a \geq 0$. Take the derivative with respect to q^a to obtain the first order condition

$$\frac{\partial \pi_2}{\partial q^a} = \epsilon(a - bq_o - bq_a) - \epsilon b(q_o + q_a) - f^a + \lambda = 0, \tag{2}$$

where λ is the multiplier on the constrained $q^a \geq 0$. For an interior optimum, the optimal air shipment is strictly greater than zero, $\lambda = 0$, and marginal revenue of shipping an additional marginal unit by airplane must equal the marginal cost.[7] From 2 solve for the optimal interior air-shipment

$$q^a = \frac{\epsilon a - f^a}{2\epsilon b} - q_o. \tag{3}$$

The optimal air-shipment is strictly increasing in ϵ. A greater realization of ϵ raises the marginal revenue and leads to a larger air shipment. For a given q^o, the exporter makes an air shipment if and only if $\epsilon > f^a/(a - 2bq^o)$. For $\epsilon < f^a/(a - 2bq^o)$ the optimal air quantity is negative and the constraint binds q^a to zero.

[6]We can define ϵ as the exchange rate and denote the freight rates in the firm's currency. The tradeoff between risk and transport costs would then be solely based on exchange rate risk.

[7]For $b > 0$, the second order condition, $\frac{\partial^2 \pi_2}{\partial (q^a)^2} = -2b < 0$, is strictly negative for all q^a.

To find the unique threshold, ϵ^*, that separates realizations of the shock that trigger an air shipment, set air shipments to zero and solve 3 for

$$\epsilon^* = \frac{f^a}{a - 2bq_o}. \tag{4}$$

This threshold is a function of the first-period ocean shipment. An increase in the first-period ocean shipment raises the level of the shock necessary to induce an air shipment.

We summarize this results as *the optimal rule for air shipping* and write,

$$q^a = \begin{cases} \frac{\epsilon a - f^a}{2\epsilon b} - q_o & \text{and } \lambda = 0 \text{ if } \epsilon > \epsilon^* \\ 0 & \text{and } \lambda > 0 \text{ if } \epsilon \leq \epsilon^*. \end{cases} \tag{5}$$

The exporter makes an air shipment, if the realization of the shock is strictly greater than ϵ^*; when marginal revenue from making an air shipment is strictly greater than the marginal cost. The quantity the exporter ships via airplane increases as the realization of the shock increases. For a given ocean shipment, a higher realization of the shock results in a higher price for the exporter's good, and the exporter increases the quantity shipped by air plane. A higher air freight rate implies a greater marginal cost of air transport and lower air shipment for all realizations of the shock.

To find the optimal ocean quantity, derive the first-period expected profit function. Substitute *the optimal rule for air shipping* (5) into the second-period profit function (1) to obtain

$$\pi_2(q^o) = \begin{cases} -q^o f^o - f^a\Big(-q^o + \frac{a\epsilon - f^a}{2b\epsilon}\Big) + \epsilon\Big(a - b\frac{a\epsilon - f^a}{2b\epsilon}\Big)\frac{(a\epsilon - f^a)}{2b\epsilon} & \text{if } \epsilon > \epsilon^* \\ -q^o f^o + q^o(a - bq^o)\epsilon & \text{if } \epsilon \leq \epsilon^*. \end{cases} \tag{6}$$

Now take the expectation over all possible realizations of the shock. For $\epsilon > \epsilon^*$, the firm expects to make an air shipment and accounts for this in the expectation. For $\epsilon \leq \epsilon^*$, the firm sets $q^a = 0$ and calculates the expected profit from the revenue and cost generated by the ocean quantity. Apply the density function to derive the first-period expected profit function

$$\begin{aligned} E(\Pi) = &-q^o f^o + \int_{\gamma - z}^{\epsilon^*} \Big[q^o(a - bq^o)\epsilon\Big]\frac{1}{2z}d\epsilon \\ &+ \int_{\epsilon^*}^{\gamma + z} \Big[-f^a\Big(-q^o + \frac{a\epsilon - f^a}{2b\epsilon}\Big) + \epsilon\Big[a - b\frac{a\epsilon - f^a}{2b\epsilon}\Big]\frac{(a\epsilon - f^a)}{2b\epsilon}\Big]\frac{1}{2z}d\epsilon. \end{aligned} \tag{7}$$

By ϵ^*, the bound of the integral is a function of the ocean quantity. A larger ocean quantity raises ϵ^* and reduces the "weight" of potential air shipment. Large ocean shipments reduce the flexibility to intervene on the market in the second period.

The optimal amount of ocean shipment maximizes the first-period expected profit function. Differentiate the expected profit (7) with respect to the ocean quantity and solve for the optimal ocean quantity $q^{o*}(\cdot)$ as a function of the risk parameter (z), the expected realization of the shock (γ), unit air and ocean freight rates (f^a and f^o), as well as the demand parameters (a and b).[8]

The exporter mixes ocean and air transport if the marginal revenue of an air

[8] For the analytical version of the optimal ocean quantity see appendix 5.1.2.

shipment evaluated at the optimal ocean quantity is greater than the marginal cost. To determine the realizations of ϵ that trigger an air shipment, substitute the optimal ocean quantity into ϵ^* to derive the *zero air shipment threshold*

$$u(z, \gamma, f^a, f^o) = \frac{f^a}{a - 2bq^{o*}(\cdot)}.^{9} \tag{8}$$

In optimum, the exporters optimal threshold is a function of the expected shock, the volatility parameter and freight rates. The exporter makes an air shipment if and only if the realization of the shock is strictly greater than $u(z, \gamma, f^a, f^o)$.

In the tradeoff between ocean and air shipping, the *zero air shipment threshold* links the first-period optimal ocean shipment to the second-period probability of an air shipment. Large first-period ocean shipments lower the second-period marginal revenue of air shipping for all realizations of ϵ. This raises the *zero air shipment threshold* and air shipment is less likely.

To derive the intuition for how ocean shipping determines the probability of air shipping, fix a level of demand volatility, z'. With equal probability, ϵ takes any value on its support $[\gamma - z', \gamma + z']$. Air shipment is optimal when ϵ falls into the interval $[u(\cdot), \gamma + z']$, determined by the *zero air shipment threshold* and the upper bound of the shock. Figure 1 shows this for a level of volatility determined by $z' = \frac{1}{2}, \gamma = 1$. Applying (8), a larger optimal ocean quantity leads to a higher *zero air shipment threshold.* This shrinks the range of ϵ that trigger an air shipment relative to the support. In other words, an increase in the optimal ocean quantity reduces the probability of air shipment.

[9] For the complete analytical version of $u(z, \gamma, f^a, f^o)$ see the appendix (5.1.3).

For a fixed level of demand volatility, a large first-period ocean shipment minimizes transport costs, but sacrifices flexibility to intervene on the market with an air shipment.

To examine the optimal transport mix, the average share of air shipment in the total quantity combines the probability of an air shipment with the air and ocean quantities. To derive the average air share conditional on the variance and the freight rates, apply the optimal rule for air shipping (5), the optimal threshold (8), the optimal ocean quantity $q^o(\cdot)$ and the distribution of ϵ. Now take the expectation over ϵ to obtain the share of air shipment averaged over all possible realizations of the shock,

$$E\left(\frac{q^a}{q^a+q^o}\middle| z, f^a, f^o, a, b, \gamma\right) = \int_{\frac{f^a}{a-2bq^o(\cdot)}}^{\gamma+z} \frac{\epsilon a - f^a - 2q^o(\cdot)\epsilon b}{\epsilon a - f^a} \frac{1}{2z} d\epsilon. \tag{9}$$

By simulation, figure 2 illustrates the main result. Higher demand volatility predicts a greater share of air shipment. The realization of the shock is only the trigger for an air shipment. The underlying fundamentals are the freight rates and the demand volatility.

The intuition for this result is as follows. To lower the loss in the event of a bad shock, high demand volatility urges a firm to decrease its ocean quantity and delay shipping until the uncertainty concludes. The lower ocean quantity raises the probability of an air shipment. After the uncertainty concludes, increased air transport works as a real option that the firm exercises at high realizations of the market price to re-optimize profits.

Figure 3 illustrates the three channels that deliver this intuition. First, for a sufficient level of demand volatility, $z > z^*$, the *zero air shipment threshold* decreases as the demand volatility increases. Applying 8, the decrease in the *zero air shipment threshold* must work through a decrease in the optimal ocean quantity. Second, according to the *optimal rule of air shipment*, (5), the lower ocean shipment implies a greater air shipment for all realizations of ϵ that induce an air shipment. Third, for a given $z > z^*$, a realization of ϵ prompts an air shipment, if it falls between the *zero air shipment threshold* and it's upper bound into the gray shaded area. As the demand volatility increases, the range of realizations of the shock where air shipment is optimal increases relative to the total spread of ϵ. This implies a higher probability of air shipment.

For an exporter subject to a level of demand volatility given by $z \leq z^*$, air shipment is never optimal. The gain from smoothing a small amount of risk does not cover the higher cost of air transport.[10]

2.3 Comparative Statics

Figure 4 shows that a higher air freight rate, lowers the share of air shipment for all levels of demand volatility. An increase in the air freight rate raises the cost of waiting for the realization of the demand. Consequently, firms use more ocean shipping, the *zero air shipment threshold* increases and the probability of an air shipment decreases. The higher air freight rate and ocean quantity lower the marginal revenue of air shipping. The optimal air quantity drops for all possible realizations of the shock. The increase in the ocean quantity and decrease in both, the probability of an air shipment and the air quantity reduce the average share of air shipment.

[10]If we place a constraint such that the cut-off level for air-shipment must be less than or equal to the upper bound of the distribution, firms pick q^o such that the cut-off level is equal to the upper bound of the distribution.

For a decrease in the ocean freight rate, figure 5 illustrates that the share of air shipment falls for all levels of demand volatility. The marginal cost of ocean shipping decreases and exporters ship a larger ocean quantity. This results in a higher *zero air shipment threshold*, a lower probability of air shipping and a decrease in the quantity that is air shipped. Combining these effects, for a decrease in the ocean freight rate, the exporter ships a lower share of its quantity via airplane.

3 Estimation

3.1 Specification

The theory states that high demand volatility urges a firm to ship a smaller ocean quantity. The lower ocean quantity increases the probability of a realization of the price that prompts an air shipment and raises the air shipment. The share of air shipment combines these effects. For given freight rates, high demand volatility predicts a larger share of air shipment. A higher air freight rate or lower ocean freight rate reduces the share of air shipment. To investigate these hypothesis, we use variation in US imports of merchandise across 10-digit industries i, source countries j, and years t.

The bridge between the theory and empirics is the measure of demand volatility. Define the demand volatility, (sdp_{ijt}), as the standard deviation of normalized monthly unit values within a given year t, by industry and source country.

We normalize the monthly unit values by their annual mean, because an increase in the price level raises the standard deviation of the unit value even if the underlying source of volatility remains the same.

Our baseline specification

$$\frac{q^a_{ijt}}{q^a_{ijt}+q^o_{ijt}} = S_{ijt} = \theta_t + \delta_0 sdp_{ijt} + ... + \delta_4 sdp_{ijt-4} + \delta_5 f^a_{ijt} + \delta_6 f^o_{ijt} + c_{ij} + v_{ijt}, \quad (10)$$

relates the share of air shipments to a distributed lag of demand volatility in addition to the air and ocean freight rates (f^a_{ijt}, f^o_{ijt}), a commodity-by-exporter fixed effect (c_{ij}) and an aggregate time effect (θ_t). All variables are in logs. In the theory, a firm knows the underlying volatility determined by z. In practice this is not the case. The fourth order distributed lag of demand volatility, $\delta_0 sdp_{ijt} + ... + \delta_4 sdp_{ijt-4}$, captures that firms must use their past experience. Consequently, this specification tests the hypothesis that high demand volatility in the past raises the current share of air shipment.

We augment this specification with additional industry-level determinants of the shipping mix. The unit values (p_{ijt}) capture the average realization of the price in a given period. The theory predicts high air shares for periods with high realizations of the price. The total number of shipments per year $(camo_{ijt})$ captures an alternative channel to measure demand volatility. Industries subject to demand volatility may experience high replenishing rates and ship at a high frequency (Evans & Harrigan 2005). This intuition predicts a positive relationship between the total number of shipments and the air share. The fixed effect captures other determinants of the shipping mix such as the average value of the good (Harrigan 2005), the dimensions of the good, or the transport infrastructure within the source country.

Determinants of the shipping mix that vary across source countries and time capture cross-country differences. The real interest rate ($rirate_{jt}$), captures inventory costs. Firms located in countries with a high inventory cost have an incentive to relocate their stock of goods to the destination market (Evans & Harrigan 2005). This makes air shipments less relevant. The pipeline cost ($pipe_{jt}$) captures the opportunity cost of locked up capital on lengthy ocean transit. This is an interaction term of the log average ocean transit time in days with the log of the source-country's real interest rate. An increase in the pipeline cost raises the cost of ocean transport relative to air shipment and raises the share of air shipments. The source country's GDP (gdp_{jt}) absorbs aggregate shocks in the source country. As a final macro determinant we account for the exchange rate volatility (de_{jt}). To smooth uncertainty, firms subject to exchange rate volatility could ship a large quantity with airplanes. On the other hand, a high exchange rate volatility identifies a more flexible exchange rate regime which can absorb shocks to the relative price.

Finally, we capture the industry's history of demand smoothing with the lag of the dependent variable. A high air share in the past reveals that the firm was subject to demand volatility. Since firms that were subject to demand volatility in the past shift into a faster transport mix, this results in a positive relationship between the current air share and its lags. In addition, past demand volatilities are a function of the firm's effort to smooth demand in the past. To account for these channels, we estimate the partial effect of the past demand volatility on the current air share, holding fixed the industry's history of the transportation mix.

3.2 Estimation Procedure

We estimate the specifications that do not include the lag of the air share, with a fixed effect procedure. To include the lag of the air share we augment (10) with the first lag of the dependent variable, drop the 4th lag of the demand volatility and first difference to obtain

$$\Delta S_{ijt} = \Delta S_{ijt-1} + \Delta\theta_t + \Delta\delta_0 sdp_{ijt} + ... + \Delta\delta_3 sdp_{ijt-3} + \Delta\delta_5 f^a_{ijt} + \Delta\delta_6 f^o_{ijt} + \Delta v_{ijt}. \quad (11)$$

Δ is the first difference operator. We employ lagged variables as instruments and estimate (11) by first difference two stage least squares (FD-2SLS).

Consistent fixed effect estimation requires that all the regressors are strictly exogenous conditional on the unobserved effect c_{ij} (Wooldridge 2002). If freight charges or demand volatilities are correlated with the characteristics of a commodity, it is likely that the share of air shipment in t is correlated with the freight rates or demand volatilities in other years, if we don't control for these characteristics via the fixed effect. With the commodity-by-exporter fixed effect, the assumption of strictly exogenous regressors is more likely to hold.

In the FD-2SLS estimation we take first differences to eliminate the country by commodity fixed effect. We instrument for the first lag of the difference in the air share, because the difference in the error term $(v_{ijt} - v_{ijt-1})$ will be correlated with the lag of the first difference of the air share $(S_{ijt-1} - S_{ijt-2})$. This results from 10, where the air share in $t-1$ is a function of the error in $t-1$. We instrument with higher order lags of the first difference of the air share. We estimate the coefficients by pooled instrumental variable two stage least squares. Successful identification in the FD-2SLS procedure relies on the assumption that the instruments do not belong into the original model but are correlated with the variables for which they instrument. In the first difference estimation, this results in the assumption that the error term in a given period t can be correlated with the endogenous regressors in the current or future periods but not with their past.

3.3 Data

We construct the firm level information from monthly import data to the US from the US Census, "Imports of Merchandise" CD-ROMs from 1990 to 2004. The data reports the value (V), weight (W), freight and insurance charges (F) and the total number of shipments ($camo$) by transport mode ($m = a(ir), o(cean)$) for US imports with detail by commodity groups (i) at the 10-digit Harmonized System[11], source country (j), and district of entry (k). The US customs appraises the value of the imports based on the price actually paid or payable for merchandise when sold for exportation to the United States. The import charges are the sums of all freight, insurance and other charges incurred in bringing the merchandise from alongside the carrier at the export port and placing it alongside the carrier at the first port of entry in the United States. We constrain our empirical work to the mainland United States and exclude Canada as well as Mexico from the exporter list. A large portion of imports from these countries is by road, and we don't have information on whether the shipment was a rush to fill in demand at high speed, or just a usual transit.

[11] Roughly 15000 categories.

The identification requires cross-commodity, time and cross-country variation. We aggregate the data over the districts of entry to obtain imports for the United States. We use monthly observations to generate regressors within each year and exploit annual variation to identify the coefficients.

Identification of the tradeoff between demand volatility and the transport mix requires information about how firms change their transport mix. This information is contained in the share of air shipments at the margin of the data where firms mix air and ocean transport. This restricts our empirical work to the portion of commodity-exporter combinations where we observe a mix of air and ocean shipment. Figure 6 shows that at annual aggregates, 30 percent of the observations for the US imports of merchandise mix air and ocean transport. Note that our identification strategy requires industries to mix air and ocean shipment in multiple consecutive years. This limits the amount of usable data within the observations that mix air and ocean transport.

The selection of the sample would raise concerns if we were to produce a coefficient from the selected sample that we want to apply over the whole universe of import data. Our estimation identifies the trade-off within the sample where we observe information about the trade-off, and the estimated coefficients apply to that particular sample. Nevertheless, if we find that the incentive to smooth demand volatility matters on the margin, then the choice of the transport mode has implications for pass through and the location of production over the whole sample.

To construct the demand volatility, calculate the monthly unit values by dividing the total import value by the total weight in a given month. Now normalize each monthly unit value by the annual mean of the unit values and define demand volatility (sdp_{ijt}) as the standard deviation of the normalized unit values within a given year. Construct the annual unit value (p_{ijt}) as the total value of imports per weight in a given year and calculate the share of the quantity that is transported by airplane ($\frac{q^a_{ijt}}{q^a_{ijt}+q^o_{ijt}}$) as the weight of a given commodity that is imported by air to the total weight. To obtain the freight rates for air and ocean transport (f^a, f^o), divide the total annual freight charge separated by transport mode by their respective total import weight. For details on the construction of the demand volatility, freight rates and the air share please see the data appendix.

We calculate the observed exchange rate volatility (de_{jt}) as the standard deviation of monthly changes in the exchange rate within a year, instead of using a model of exchange rate risk (e.g. Meese & Rogoff (1983), Cheung, Chinn & Pascual (2005)). Empirical applications with respect to exchange rate risk usually focus on a few countries with well-behaved exchange rate series (e.g. United States-Great Britain, United States - Australia). We have a much broader range of countries and want to include the exchange rate volatility as a control and not as the main object of interest. For this reason, the application of models that propose to identify exchange rate risk are beyond the scope of this paper.

For a small amount of observations (7,000 observations or about 4 percent of the data) the air freight rate is lower than the ocean freight rate. This violates one of our main assumptions, so we drop the observations from the sample.

We employ GDP in constant US dollars and real interest rates from the World Bank's World Development Indicators and exchange rate data from the International Financial Statistics. The average time it takes a vessel to arrive in the United States is generated from a master schedule of shipping for 1999 taken from www.shipguide.com.

Table 1 contains the variable descriptions, and table 2 reports summary statistics for the variables.

3.4 Results

Table 3 summarizes the results of the fixed effect estimation. The first column shows the results of the baseline specification. Columns two and three add the micro and macro level determinants.

Over all of these three specifications, the elasticity of the air share with respect to a 1 percent increase in the lagged demand volatilities ranges from about 7 percent at the first lag to about 2 percent at the third lag. At the fourth lag the demand volatility shows no significance. Through all three specifications, an increase in the air freight rate lowers the air share. In contrast, an increase in the ocean freight rate raises the air share. The demand volatilities and freight rates predict the share of air shipment as suggested by the theory.

Column two shows the estimates including the unit value and total number of shipments. As suggested by the theory, the unit value has a large positive effect on the air share. The total number of shipments has a moderate positive effect, which is consistent with the interpretation that the total number of shipments is a measure of demand volatility.

As we introduce the unit value and total number of shipments into the specification, the estimates on the lagged price volatilities and freight rates drop slightly in absolute size. This bias is consistent with a positive relationship between the value of the good and the freight rates.

High-value goods are more expensive to transport and more likely shipped by airplane. The information contained in the price raises the explanatory power according to the R^2.

Column three shows that the macro variables enter the relation as expected. Exporters located in a country with a high GDP ship a lower quantity by airplane. This is consistent with the intuition that aggregate demand shocks in the exporter's country divert shipments to the exporter's domestic market. Firms located in countries with high interest rates rely less on air shipment. High interest rates imply greater inventory costs, and firms relocate their inventory to the destination market. Firms located in countries subject to high pipeline costs ship a larger share of their quantity by air. Pipeline costs raise the cost of ocean transport relative to air transport and firms substitute into air shipping. Industries operating in markets with high exchange-rate volatility ship a lower share of their quantity by airplane.

Table 4 shows the results from the FD-2SLS estimation. The magnitudes and signs of the coefficients are similar to the fixed effect estimation. The FD-2SLS estimation confirms that an increase in the past demand volatility results in a higher air share in the current period. The specification in column one accommodates the first lag of the dependent variable. The specification in column two includes the first and second lags of the dependent variable. The specifications instrument for the lagged first difference of the dependent variable. The instruments are the second and third order lags of the first difference of the dependent variable. In both specifications (1 and 2), the estimate on the lagged dependent variable shows that industries with a history of demand smoothing are likely to smooth uncertainty today. This is consistent with the interpretation that firms with high air shares in the past are subject to high demand volatility. In column two, the second lag of the dependent variable shows no significance. Contrary to the fixed effect estimation, GDP on the source market does not determine the air share significantly. This is consistent with the assumptions in the theory that demand shocks on the source market don't matter.

In summary, the pattern of the coefficients in the estimation confirms the intuition derived in the theory. All else equal, the elasticity of the air share with respect to lagged demand volatility is positive and significant back to the third lag. As predicted in the theory, the elasticity of the air share with respect to the air freight rate is negative, and the elasticity of the air share with respect to the ocean freight rate is positive.

3.5 Robustness Exercises

We apply three types of robustness checks. First, to determine robustness with respect to concerns of endogenous regressors, we re-estimate the FD-2SLS and sequentially instrument for additional variables. Table 5 reports the results. In addition to the first lag of the dependent variable the specifications instrument for the unit value (Column one), the unit value and the current period demand volatility (Column two) and the unit value, current demand volatility and first lag of the demand volatility (Column three). As before, the instruments consist of higher order lags of the instrumented variables.[12]

As we instrument for the unit value in column one, the size of the coefficient on the unit value decreases but remains positive and significant. This is consistent with a bias that is generated by omitted demand shocks that are correlated with the price. As we instrument for the current period demand volatility in column two, the coefficients on the lagged demand volatilities increase and remain significant.

[12]The details of the instruments are reported in the tables.

As we instrument for the current- and past-period demand volatility in column three, the coefficients on the lagged demand volatilities increase again but just miss the 10 percent margin of significance. We conclude that if there is a bias, then it is likely working against us and we underestimate the coefficients on the lags of the demand volatility. The potential bias results from the reverse causality of the air share to the demand volatility. Firms that ship a lot by air also smooth demand, and we observe lower demand volatilities with high air shares in the data.

As a second robustness check we calculate demand volatilities exclusively from information on ocean shipments, ($sdpo_{ijt}$). This robustness check eliminates concerns that the feedback from air shipments to the calculated demand volatilities results in mismeasurement and might bias the estimates to our favor. Table 6 reports the results. The estimates confirm the pattern of the estimation results from the previous specifications.

As a third robustness check, we calculate demand volatilities from the unit values without the normalization by the annual mean, $sdpuv_{ijt}$. This demonstrates robustness with respect to the specification of the measure of demand volatility. Table 7 reports the results. The estimates confirm the pattern of the estimation results from the previous specifications.

4 Conclusion

As predicted by the theory, our data show that firms subject to demand volatility ship a larger share of their quantity by airplane. The elasticity of the air share is about 7 percent with respect to the first lag of the demand volatility and decreases slowly to about 2 percent with respect to the third lag of demand volatility. Fast transport hedges demand volatility.

Also as predicted by the theory, higher air freight rates lower the share of air shipment and higher ocean freight rates raise the share of air shipment. Favorable realizations of the price lead to a faster transport mix employing a larger share of air shipment. These estimates are robust to respecification, accounting for the firm's past history of the transport mix, pipeline costs, inventory costs, exchange rate volatility, total number of shipments and aggregate demand shocks on the export market.

The empirics reveal a reverse causation from the price volatility to the transportation cost by the firm's choice of the optimal transportation mix. This result is evidence for a quantity response in the arbitrage of price shocks. The channel has implications for studies of market integration that rely on relative price differentials because the larger the underlying, uncertainty the higher the cost of arbitrage. This finding suggests the need to examine the significance of the transport mechanism for the integration of markets and the cost of arbitrage.

Furthermore, this paper extends the field by building on (Aizenman 2004). Specifically, the empirics show that volatility on the market predicts transportation decisions. This supports the argument that the pass through of shocks across borders depends on whether the pricing decision is made before or after the realization of the shock. The identified tradeoff between demand volatility and the transportation mix suggests an avenue of research that examines the impact of this mechanism on the pass through of shocks into market prices. Aizenman shows that this mechanism has welfare consequences which are especially relevant to emerging economies.

The mechanism identified in the empirics relates to the question of the source of a firm's willingness to pay for air transport. A firm that does not consider air transport would make an ocean shipment that maximizes expected profit. Its fortune depends on the outcome of the shock. Air shipment allows the firm to lower the ocean quantity, which limits the loss for a bad realization of the price. In addition, it presents a firm with the opportunity to re-optimize profits in the event of a favorable realization of the price. In an environment with high demand volatility, the option to air ship therefore creates value which explains a firm's willingness to pay for fast transport. We leave it for future research to price the option to identify how much of the willingness to pay the option to air ship explains. Identifying the underlying sources for the willingness to pay is important, since it has implications for the pattern of trade and the location of production.

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5 Appendix

5.1 Data Appendix

We construct freight rates, price volatility, the share of air shipped quantity in the total imports and the total number of shipments from monthly import data of the United States. The data reports the value (V), weight (W), freight and insurance charges (F) and the total number of shipments *camo* by transport mode ($m = a(ir), o(cean)$) for US imports with detail by commodity groups (i) at the 10-digit Harmonized System[13], exporter (j), and district of entry (k).

We assume that there is a constant multiplier ω_{ij} that converts the units into weight, where $\omega_{ij} = 1$ if the relevant unit is in kilograms, and calculate the air share for the import of commodity i, from country j in time t as $S_{ijt} = \frac{q^a_{ijt}}{q^a_{ijt}+q^o_{ijt}} = \frac{q^a_{ijt}}{q^a_{ijt}+q^o_{ijt}} \times \frac{\omega_{ij}}{\omega_{ij}} = \frac{W^a_{ijt}}{W^a_{ijt}+W^o_{ijt}}$.

Define the unit value as the value of a given import divided by its weight, $uv = V/W$. To calculate the demand volatility, we normalize the monthly unit values. We divide each monthly unit value with the mean unit value within a given year. This is the same as dividing the price per unit by the mean price calculated within a year. To obtain the unit price from the value per kilogram for a given month x, calculate $p_{ijx} = uv_{ijx}\omega_{ij}$ and construct the normalized price as $p^n_{ijx} = \frac{uv_{ijx}\omega_{ijt}}{\sum_{t\in T} uv_{ijx}\omega_{ijt}/T}$, where T is the set of all months x within the year where we observe an import of commodity i from country j. We calculate the per unit price volatility (sdp_{ijt}) as the standard deviation of p^n_{ijx} within each year.

Freight rates are based on weight and we calculate the freight rates as, $f^m_{ijt} = \frac{F^m_{ijt}}{W^m_{ijt}}$.

[13] Roughly 15000 categories.

We define the price for a given commodity in a given year as the total value imported within the year divided by the weight of the import, $p_{ijt} = \frac{V_{ijt}}{W_{ijt}}$. Note that the freight rates and the price are in US$ per kilogram. However, in the fixed effect as well as in the first difference estimation this units will cancel out.

5.1.1 Analytical First Order Condition of the First-Period Expected Profit Function (equation 7)

$$\frac{\partial E(\Pi)}{\partial q^o} = \frac{-1}{4}\frac{a^2\gamma^2 - 2a^2\gamma z + a^2 z^2 + 8a\gamma z q^o b}{z(a-2q^o b)} - \frac{4a\gamma^2 q^o b + 2f^a a\gamma + 2f^a az + 4az^2 bq^o}{z(a-2q^o b)}$$
$$+ \frac{4af^o z - 8f^o zbq^o}{z(a-2q^o b)} + \frac{4f^a zbq^o + 4f^a q^o b\gamma + 4z^2b^2(q^o)^2}{z(a-2q^o b)}$$
$$- \frac{8\gamma zb^2(q^o)^2}{z(a-2q^o b)} + \frac{4\gamma^2 b^2 (q^o)^2 + (f^a)^2}{z(a-2q^o b)} \tag{12}$$

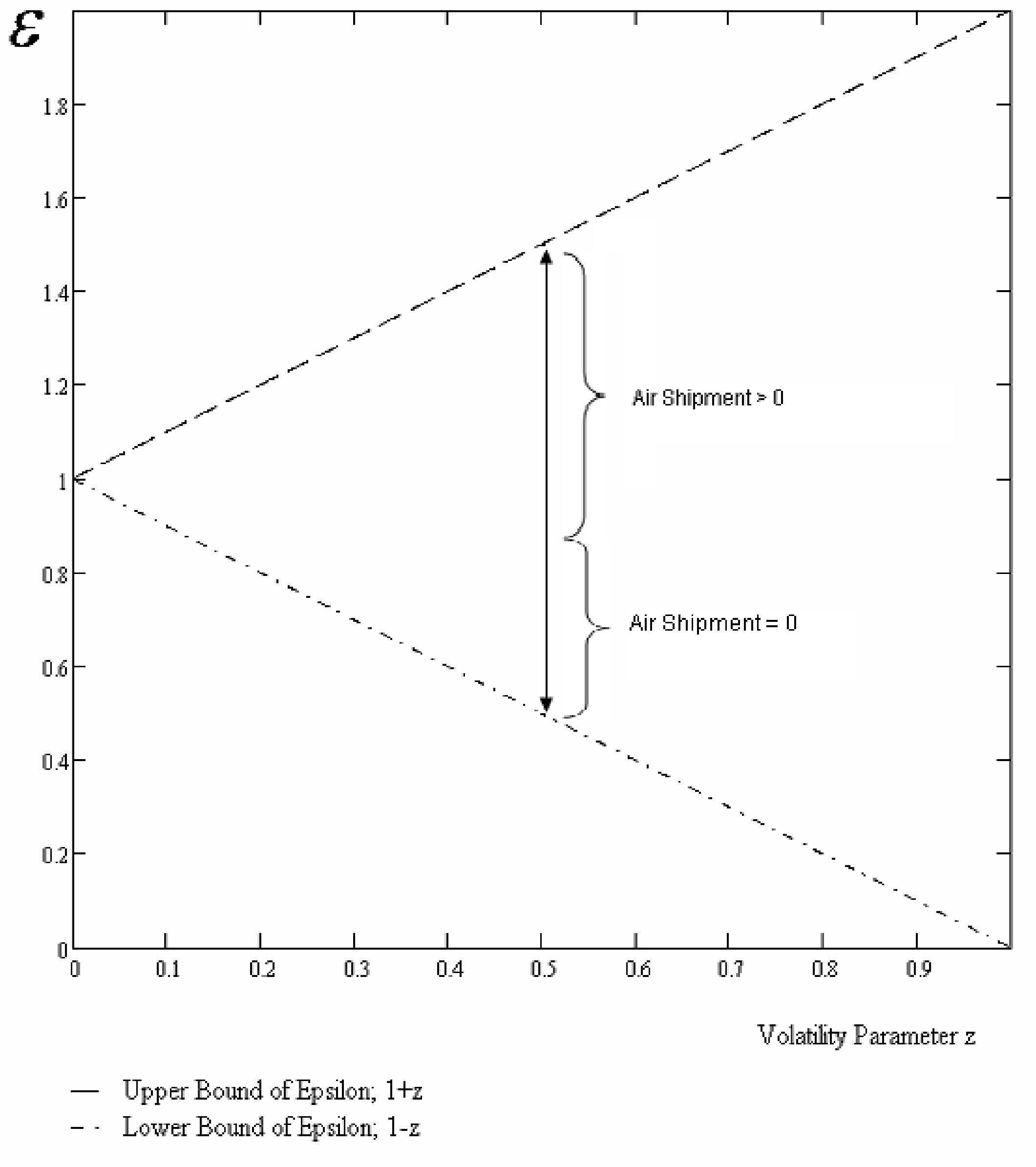
5.1.2 Analytical Optimal Ocean Quantity

$$q^o = \frac{1}{2b(4z^2 - 8\gamma z + 4\gamma^2)} \times \Big[-8\gamma za + 4\gamma^2 a + 8f^o z - 4f^a z$$
$$+ 4az^2 - 4c\gamma + 8\sqrt{-f^a z^2 f^o + (f^o)^2 z^2 - (f^o z)^2 - f^o f^a z\gamma + (f^a)^2) z\gamma}\Big] \tag{13}$$

5.1.3 The Analytical Optimal Threshold for Air Shipping

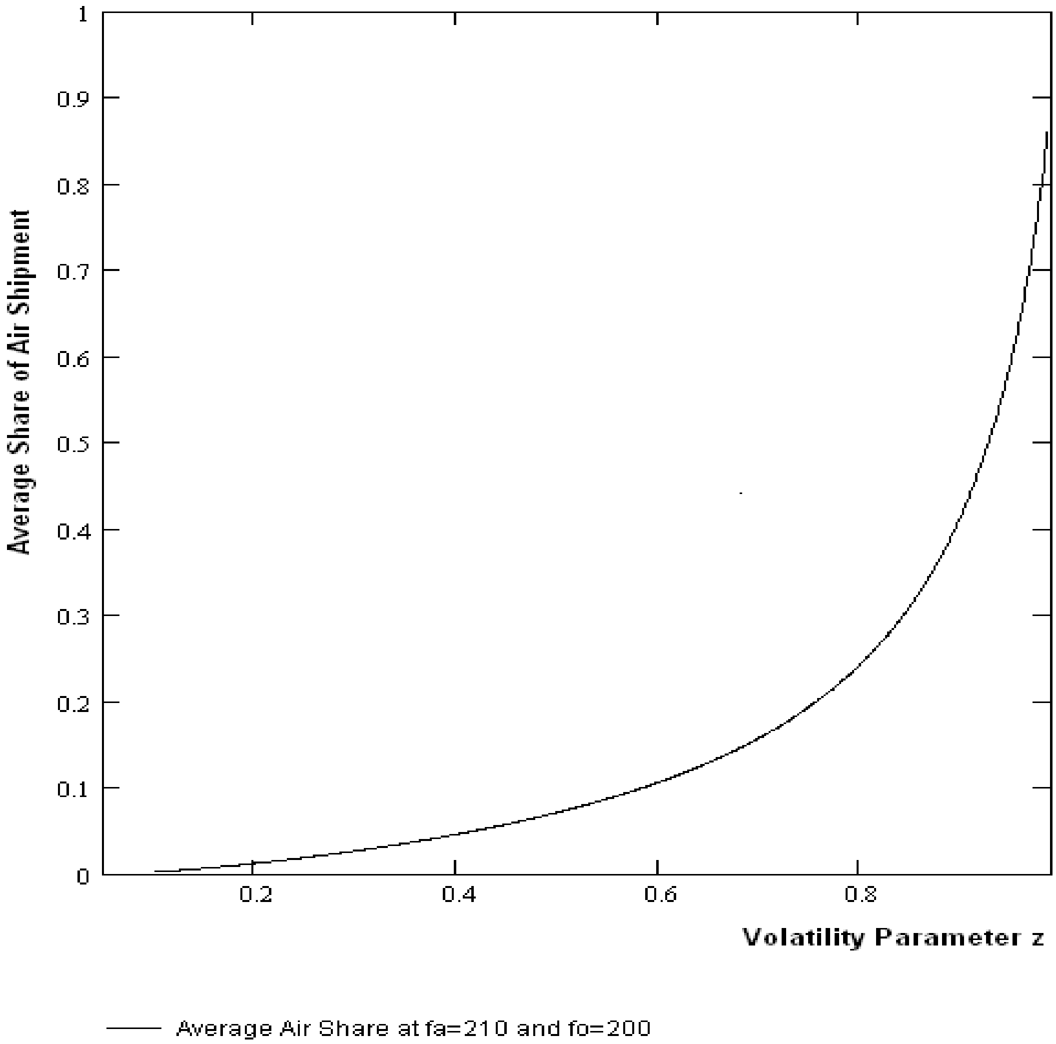
$$u(z,\gamma,f^a,f^o) = f^a \frac{(\gamma - z)^2}{-2f^o z + f^a z + f^a\gamma - 2\sqrt{-(f^a - f^o)z(-f^a\gamma + f^o z)}}. \tag{14}$$

Figure 1: The Distribution of Epsilon for a Fixed Volatility $z = 0.5$



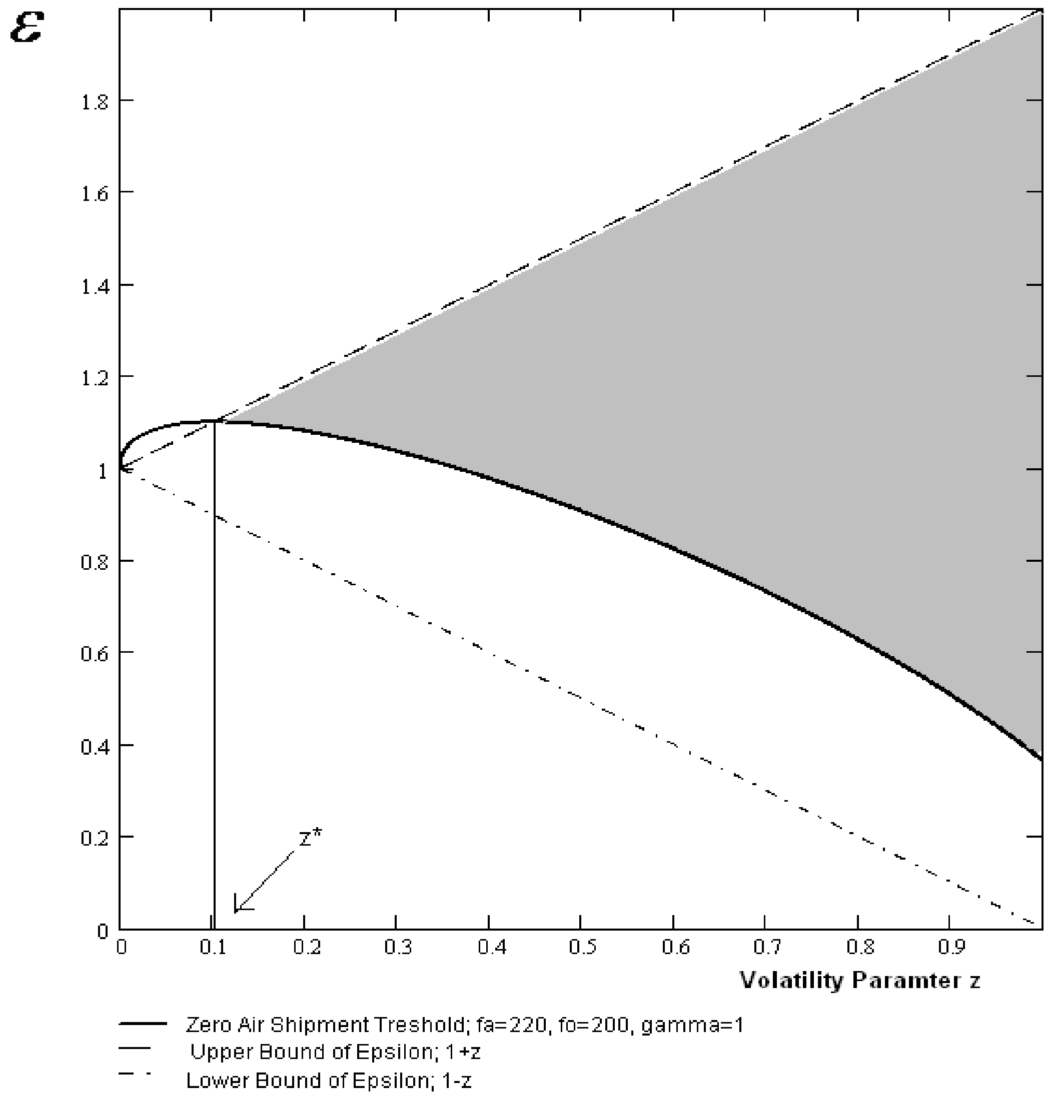
As z increases, the spread between the upper and lower bound increases, which is the same as to say that the demand volatility increases in z. Set $\gamma = 1$ and fix the volatility to $z = 0.5$. ϵ takes any value on the double arrow with equal probability. If ϵ falls into the interval $(u(\cdot), 1.5)$, air shipments are positive and zero otherwise.

Figure 2: The Air Share Increases as the Demand Volatility Increases



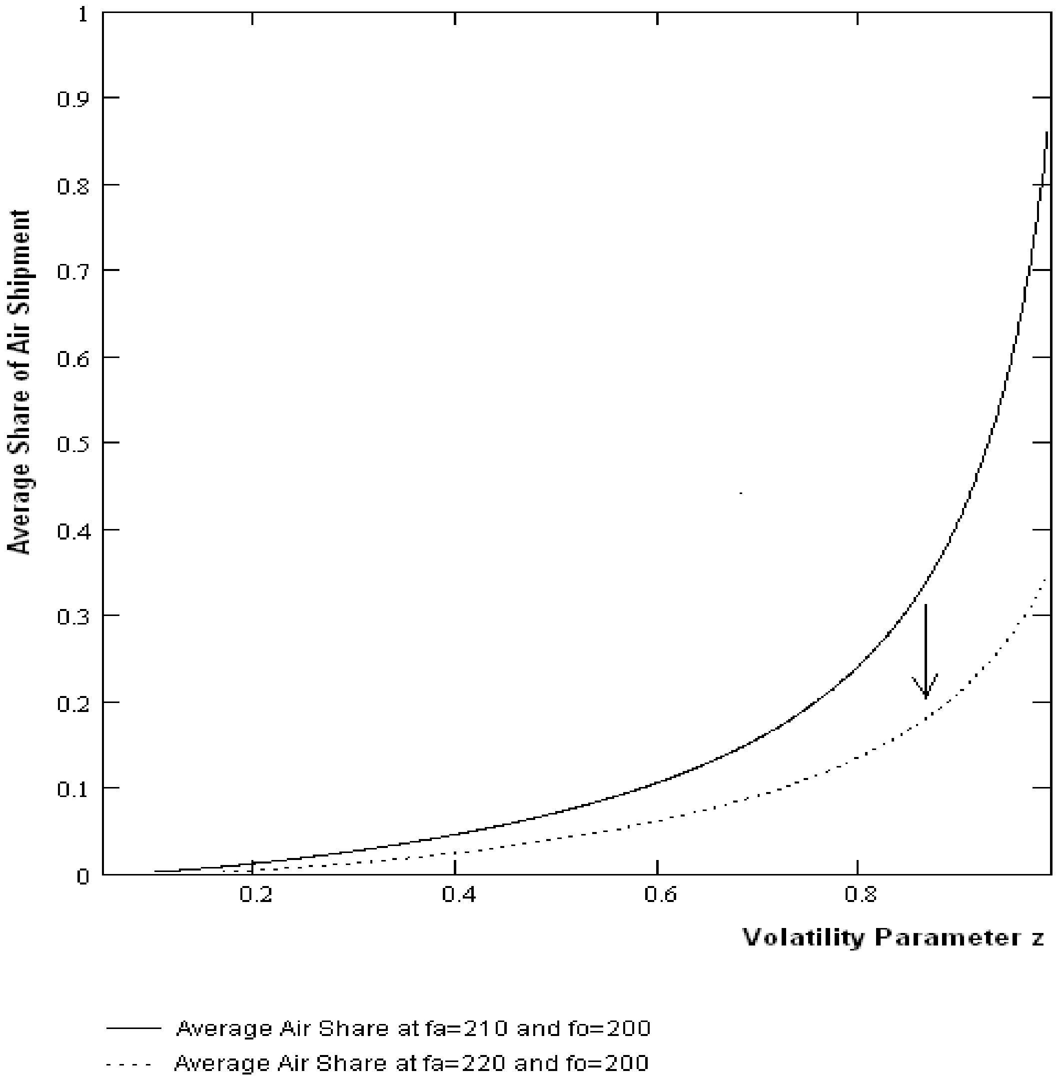
The average share of quantity that is shipped by airplane increases with the demand volatility. The parameter values are $a = 1000$, $b = 1, f^a = 210, f^o = 200, \gamma = 1$. The optimal ocean quantity is the unique solution to the first-period expected profit function (7). Calculate the average air share according to (9).

Figure 3: The Zero Air Shipment Threshold as a Function of the Volatility Parameter z



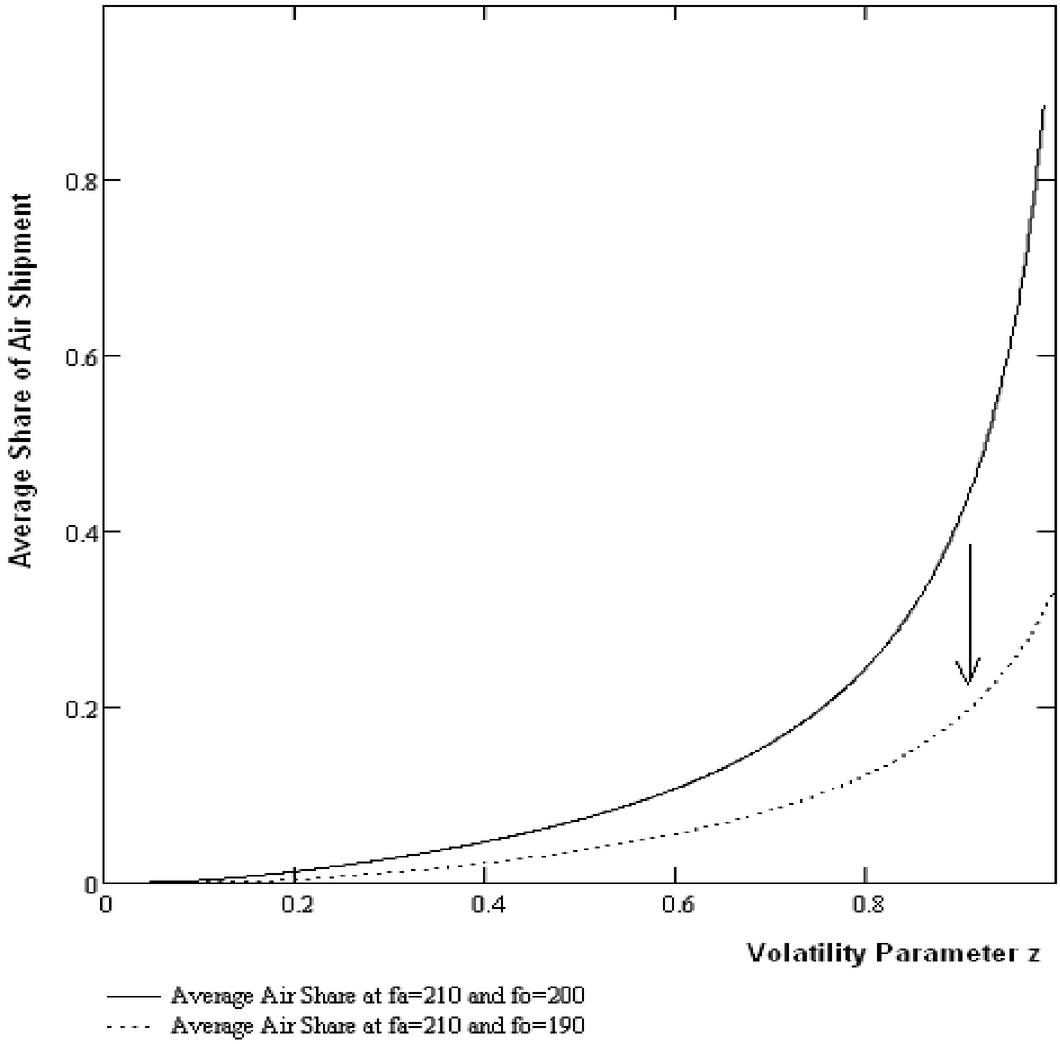
Note: As z increases, the spread of realizations of ϵ increases and the demand volatility increases. Fix any given $z > z^*$, ϵ takes any value between the upper and lower bound with equal probability. For $z > z^*$ the zero air shipment threshold decreases as the volatility increases with z. Air shipment is optimal whenever the realization of ϵ falls into the gray shaded area. For $z \leq z^*$ firms employ ocean shipping only. The demand parameters are $a = 1000$, $b = 1$.

Figure 4: An Increase in the Air Freight Rate Lowers the Air Share



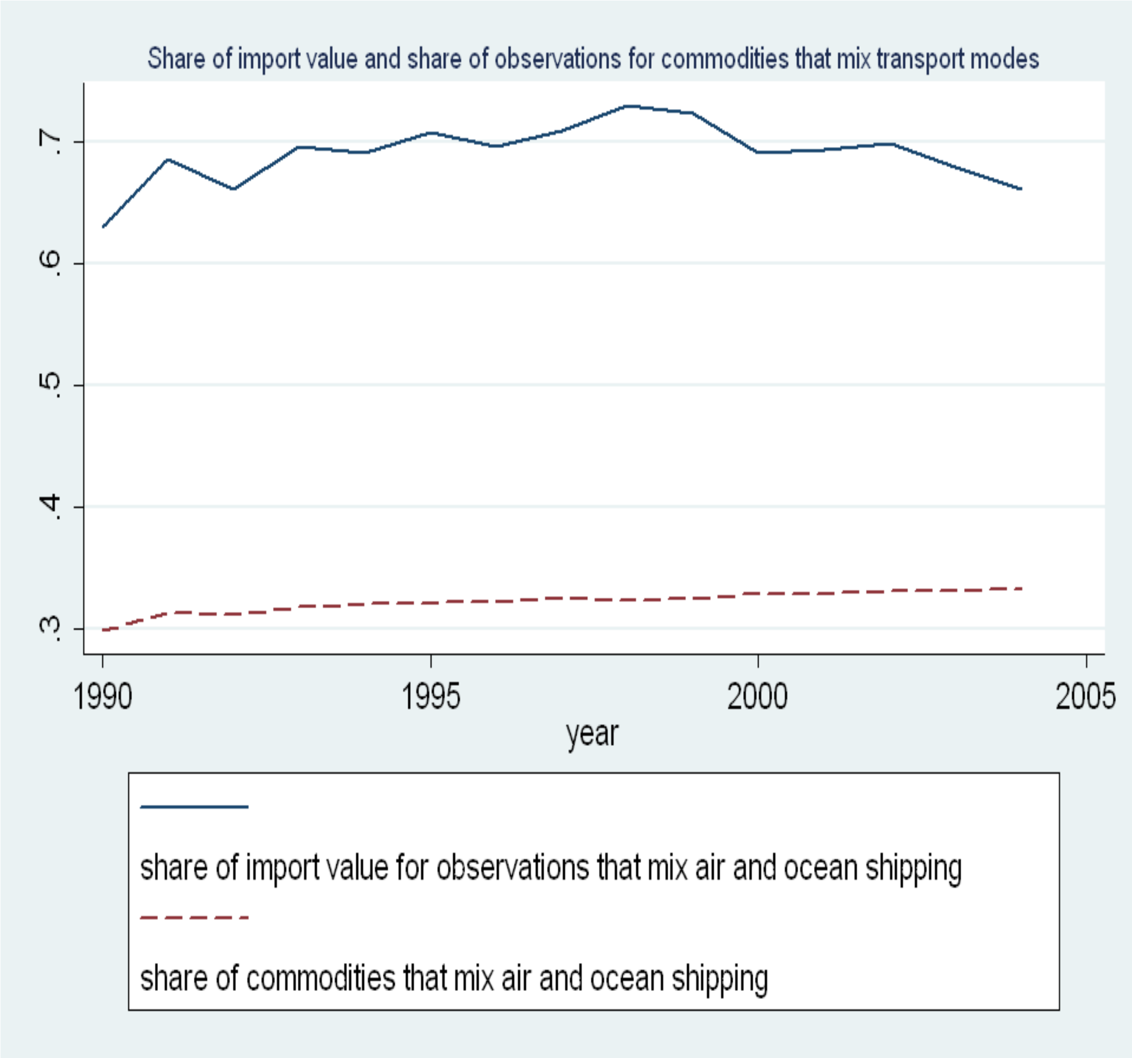
For an increase in the air freight rate, the air share is lower for all levels of demand volatility.

Figure 5: A Decrease in the Ocean Freight Rate Lowers the Air Share



For a decrease in the ocean freight rate, the air share is lower for all levels of demand volatility.

Figure 6: Share of Import Value and Share of Observations of Commodity-by-Country Pairs that Mix Transport Modes in the US Imports of Merchandise



Note: At annual aggregates, for all imports of merchandise to the United States, roughly 30% of the observations employ air and ocean shipping. These observations account for roughly 70% of the US import value of merchandise.

Table 1: Variable Description

Variable	**Description**
S_{ijt}	Quantity shipped by air over the total quantity
f^a_{ijt}	Air freight rate in US$
f^o_{ijt}	Ocean freight rate in US$
sdp_{ijt}	Price volatility; calculated by the normlized standard deviation of the unit values
p_{ijt}	Unit value in US$
$padj_{ijt}$	Unit value adjusted by the annual mean
$camo_{ijt}$	Total shipments per year
$rirate_{jt}$	Real interest rate
$avday_j$	Average number of days of vessel transport from each exporter to the US
$pipe_{jt}$	Interaction of log of $rirate_{jt}$ and log of $avday_j$
gdp_{jt}	Gross Domestic Product in constant (mil.) 2000 US$
de_{jt}	Standard deviation of the monthly growth rate of the US$ exchange rate w.r.t. country j within each year

Table 2: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N	Source	Units
S_{ijt}	0.25	0.28	0	1	209954	Information	
f^a_{ijt}	3.4	21.84	0.01	9464[a]	209954	from	US$/kg
f^o_{ijt}	0.51	0.9	0	170.95	209954	US	US$/kg
sdp_{ijt}	0.53	0.49	0	3.46	209954	Imports	
p_{ijt}	109.04	5781.99	0	1832498.13[b]	209954	of	US$/kg
$camo_{ijt}$	363.72	1382.21	2	111007.02[c]	209954	Merchandise	
$rirate_{jt}$	6.3	6.96	0.09	84.05	209954	World Dev. Indicators	%
gdp_{jt}	1346308.39	1557440.83	199.08	4932886	209954	World Dev. Indicators	(mil.) 2000 US$
$avday_j$	22.07	5.36	9.18	46.07	209954	www.shipguide.com	
de_{jt}	0.02	0.02	0	0.26	209954	constructed from IFS	

[a]The HS Categoy for this value is “Salt of Inorganic Acid/peroxoacid, exc azide, nesoi” from the United Kingdom.

[b]The HS Categoy for this value is 9102111030 in 1995. It shows high unit values in 1998 (1135102.8) and 2003 (801474.63).

[c]The HS catgory for this value is “Wooden furniture, nesoi” in 2003, which also shows a large total number of shipments in 2002 (88895) and 2001 (55179).

Table 3: Fixed Effects Estimation: Baseline specification

	FE (1)	FE (2)	FE (3)
sdp_{ijt}	.033	.091	.091
	(.006)***	(.005)***	(.005)***
sdp_{ijt-1}	.074	.074	.074
	(.005)***	(.005)***	(.005)***
sdp_{ijt-2}	.038	.031	.031
	(.005)***	(.005)***	(.005)***
sdp_{ijt-3}	.027	.021	.021
	(.005)***	(.005)***	(.005)***
sdp_{ijt-4}	.019	.008	.007
	(.005)***	(.005)	(.005)
f^a_{ijt}	-.654	-.719	-.719
	(.008)***	(.007)***	(.007)***
f^o_{ijt}	.450	.130	.129
	(.007)***	(.006)***	(.006)***
p_{ijt}		1.035	1.034
		(.008)***	(.008)***
$camo_{ijt}$		.025	.028
		(.006)***	(.006)***
gdp_{jt}			-.168
			(.046)***
$rirate_{jt}$			-.154
			(.075)**
$pipe_{jt}$			.049
			(.024)**
de_{jt}			-.018
			(.004)***
N	209954	209954	209954
R^2	.264	.264	.265
F	701.705	1648.586	1367.743

Note: FE(1)-FE(4): Fixed effect estimation with robust standard errors. Dependent variable in all specifications: log air share, S_{ijt}. All variables are in logs. All specifications include a year fixed effect. The standard errors are reported in parentheses.

Table 4: First Difference - 2SLS Estimation: Specification including the lagged dependent variable

	FD-2SLS (1)	FD-2SLS (2)
ΔS_{ijt-1}	.109† (.008)***	.089† (.014)***
ΔS_{ijt-2}		-.008 (.006)
Δsdp_{ijt}	.069 (.006)***	.070 (.006)***
Δsdp_{ijt-1}	.064 (.007)***	.065 (.007)***
Δsdp_{ijt-2}	.016 (.007)**	.019 (.006)***
Δsdp_{ijt-3}	.010 (.007)	.014 (.006)**
Δf^{a}_{ijt}	-.719 (.008)***	-.713 (.009)***
Δf^{o}_{ijt}	.113 (.006)***	.112 (.006)***
Δp_{ijt}	1.030 (.009)***	1.023 (.010)***
$\Delta camo_{ijt}$	.074 (.009)***	.074 (.009)***
Δgdp_{jt}	.057 (.111)	.052 (.110)
$\Delta rirate_{jt}$	-.430 (.091)***	-.422 (.090)***
$\Delta pipe_{jt}$	.140 (.029)***	.138 (.029)***
Δde_{jt}	-.030 (.005)***	-.030 (.005)***
N	160547	160547
F	1052.364	1075.33

Note: FD-2SLS(1-2) First difference 2 stage least squares estimation with robust standard errors. Dependent variable: First difference of the log air share, S_{ijt}. Δ : First difference operator. All variables are in logs. † : Instrumented variables. We report the first stage R^2 in the order as the instrumented variables appear in the table from top to bottom. Column(1) instruments using ΔS_{ijt-2} ($R^2 = 0.19$). Column(2) instruments using ΔS_{ijt-3} ($R^2 = 0.23$). All specifications include a year fixed effect. The standard errors are reported in parentheses.

Table 5: Robustness Checks (First Difference - 2SLS): Instrumenting for the price and price Volatility

	FD-2SLS (1)	FD-2SLS (2)	FD-2SLS (3)
ΔS_{ijt-1}	$.112^{\dagger}$ (.008)***	$.112^{\dagger}$ (.008)***	$.112^{\dagger}$ (.008)***
Δsdp_{ijt}	.044 (.01)***	$.068^{\dagger}$ (.033)**	$-.097^{\dagger}$ (.329)
Δsdp_{ijt-1}	.064 (.007)***	.077 (.017)***	$.111^{\dagger}$ (.071)
Δsdp_{ijt-2}	.018 (.007)**	.026 (.011)**	.039 (.028)
Δsdp_{ijt-3}	.013 (.006)	.017 (.007)**	0.022 (.013)*
Δf^{a}_{ijt}	-.697 (.01)***	-.698 (.011)***	-.693 (.015)***
Δf^{o}_{ijt}	.244 (.04)***	.243 (.043)***	.236 (.045)***
Δp_{ijt}	$.588^{\dagger}$ (.14)***	$.592^{\dagger}$ (.144)***	$.572^{\dagger}$ (.151)***
$\Delta camo_{ijt}$	.062 (.009)***	.067 (.012)***	.035 (.063)
Δgdp_{jt}	.009 (.11)	.018 (.114)	-.001 (.121)
$\Delta rirate_{jt}$	-.401 (.092)***	-.401 (.092)***	-.405 (.093)***
$\Delta pipe_{jt}$	.132 (.03)***	.132 (.03)***	.134 (.03)***
Δde_{jt}	-.031 (.005)***	-.031 (.005)***	-.031 (.005)***
N	160547	160547	160547
F	517.34	517.69	511.06

Note: FD-2SLS(1-2) First difference 2 stage least squares estimation with robust standard errors. Dependent variable: First difference of the log air share, S_{ijt}. Δ : First difference operator. All variables are in logs. $\dagger$: Instrumented variables. We report the first stage R^2 in the order as the instrumented variables appear in the table from top to bottom. Column(1) instruments using ΔS_{ijt-2}, ΔS_{ijt-3}, Δp_{ijt-2}. The first stageR^2 are 0.23 and 0.18. Column(2) instruments using ΔS_{ijt-2}, ΔS_{ijt-3}, Δp_{ijt-2}, Δsdp_{ijt-4}, sdp_{ijt-2}. The first stage R^2 are 0.23, 0.3 and 0.17. Column(3) instruments using ΔS_{ijt-2}, ΔS_{ijt-3}, Δp_{ijt-2}, Δsdp_{ijt-4}, sdp_{ijt-2}. The first stage R^2 are .23,.03, .28 and .17. All specifications include a year fixed effect. The standard errors are reported in parentheses.

Table 6: Robustness Checks (First Difference - 2SLS): Employing only information on ocean shipments in the price volatility

	FD-2SLS (1)
ΔS_{ijt-1}	$.112^{\dagger}$ $(.008)^{***}$
$\Delta sdpo_{ijt}$	$.1^{\dagger}$ $(.022)^{***}$
$\Delta sdpo_{ijt-1}$	.08 $(.013)^{***}$
$\Delta sdpo_{ijt-2}$	.034 $(.009)^{***}$
$\Delta sdpo_{ijt-3}$	.024 $(.006)^{***}$
Δf^{a}_{ijt}	-.695 $(.01)^{***}$
Δf^{o}_{ijt}	.272 $(.058)^{***}$
Δp_{ijt}	$.617^{\dagger}$ $(.164)^{***}$
$\Delta camo_{ijt}$	.1 $(.01)^{***}$
Δgdp_{jt}	-.019 (.116)
$\Delta rirate_{jt}$	-.353 $(.098)^{***}$
$\Delta pipe_{jt}$	.117 $(.031)^{***}$
Δde_{jt}	-.03 $(.005)^{***}$
N	139649
F	486.64

Note: FD-2SLS(1) First difference 2 stage least squares estimation with robust standard errors. Dependent variable: First difference of the log air share, S_{ijt}. Δ : First difference operator. All variables are in logs. † : Instrumented variables. We report the first stage R^2 in the order as the instrumented variables appear in the table from top to bottom. Column(1) instruments using ΔS_{ijt-2}, ΔS_{ijt-3}, Δp_{ijt-2}, $\Delta sdpo_{ijt-4}$, $sdpo_{ijt-2}$. The first stage R^2 are 0.23, 0.3 and 0.2. All specifications include a year fixed effect. The standard errors are reported in parentheses.

Table 7: Robustness Checks (First Difference - 2SLS): Calculating the price volatility from unit values without the normalization

	FD-2SLS (1)
ΔS_{ijt-1}	$.114^{\dagger}$ $(.008)^{***}$
$\Delta sdpuv_{ijt}$	$.09^{\dagger}$ $(.037)^{**}$
$\Delta sdpuv_{ijt-1}$	.057 $(.02)^{***}$
$\Delta sdpuv_{ijt-2}$	.019 (.012)
$\Delta sdpuv_{ijt-3}$	$.014^{**}$ (.007)
Δf^{a}_{ijt}	-.703 $(.011)^{***}$
Δf^{o}_{ijt}	.257 $(.047)^{***}$
Δp_{ijt}	$.533^{\dagger}$ $(.153)^{***}$
$\Delta camo_{ijt}$	.082 $(.015)^{***}$
Δgdp_{jt}	.049 (.111)
$\Delta rirate_{jt}$	-.404 $(.093)^{***}$
$\Delta pipe_{jt}$	.133 $(.03)^{***}$
Δde_{jt}	-.031 $(.005)^{***}$
N	160547
F	503.94

Note: FD-2SLS(1) First difference 2 stage least squares estimation with robust standard errors. Dependent variable: First difference of the log air share, S_{ijt}. Δ : First difference operator. All variables are in logs. † : Instrumented variables. We report the first stage R^2 in the order as the instrumented variables appear in the table from top to bottom. Column(1) instruments using ΔS_{ijt-2}, ΔS_{ijt-3}, Δp_{ijt-2}, $\Delta sdpuv_{ijt-4}$, $sdpuv_{ijt-2}$. The first stage R^2 are 0.23, 0.26 and 0.2. All specifications include a year fixed effect. The standard errors are reported in parentheses.