I Feel The Need For Speed

The Value of Fast and Reliable Transit During Supply Chain Distruption

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March 6, 2025

Abstract

Supply chain disruptions have become increasingly frequent and severe, raising concerns about the resilience of global trade networks. This paper quantifies how U.S. importers adjust their transportation choices in response to fluctuations in freight costs and transit time reliability. Using detailed quote and shipment data from Flexport, we estimate importers' price sensitivity and their willingness to pay for faster and more predictable transit times. Our findings indicate that a 10% increase in shipping costs leads to a 2.6–11.3% decline in demand, while importers are willing to pay 0.56% of their cargo value per day saved in transit and 0.42% per day of reduced transit time variability. These results highlight the significant economic penalties associated with shipping delays and uncertainty. We further show that sectoral differences exist, with electronics importers prioritizing transit speed and apparel importers valuing predictability. Our findings have direct implications for trade policy, infrastructure investment, and supply chain risk management, providing a framework for evaluating the cost-benefit trade-offs of initiatives aimed at improving supply chain resilience.

Keywords: Transportation, International Trade

JEL Codes: R40, F13

1 Introduction

In recent years, supply chain disruptions have become more frequent, severe, and unpredictable, posing significant challenges for global trade. The COVID-19 pandemic highlighted the fragility of international logistics networks, with widespread delays, soaring freight rates, and bottlenecks at major ports disrupting the flow of goods worldwide. However, even before the pandemic, disruptions caused by trade tensions, extreme weather events, and geopolitical instability had already begun to reshape the global shipping landscape. Understanding how importers react to such disruptions—and quantifying the economic impact of delays and rising costs—has become an urgent priority for both policymakers and businesses.

This paper aims to address this critical issue by estimating U.S. importers' sensitivity to freight prices and their willingness to pay for faster, more reliable transit times. Using confidential quote and shipment data from Flexport, we analyze how importers adjust their transportation mode choices in response to fluctuations in freight rates and transit times, particularly during the COVID-19 crisis. Our study provides novel empirical evidence on how firms adapt their logistics strategies under extreme uncertainty, offering valuable insights for evaluating infrastructure investments and policy interventions aimed at improving supply chain resilience.

We begin by posing the following research question: How do importers adjust their shipping choices in response to price changes and transit time uncertainty, and what is the implicit cost of supply chain disruptions? While previous studies have examined trade elasticities and the impact of transportation costs on trade flows, relatively little work has quantified how firms respond to unpredictable delays in real-world shipping markets. Our study contributes to this literature by providing estimates of the economic penalties firms face due to longer and more volatile transit times, and by linking these penalties to firms' transportation decisions.

To answer this question, we use detailed transaction-level data on freight quotes and actual shipments, capturing the choices available to importers and the mode they ultimately select. Our analysis focuses on three primary transportation modes: full-container-load (FCL) ocean freight, less-than-container-load (LCL) ocean freight, and air freight. Each mode involves different trade-offs between cost, speed, and reliability. Importers typically prefer FCL due to its lower per-unit cost, but during periods of severe congestion, they may shift toward LCL or air freight to mitigate delays. [[The key challenge in our empirical strategy is to isolate the causal effect of price and transit time changes on mode choice while accounting for broader supply chain dynamics]].

Our main findings reveal several important patterns. First, we estimate that a 10% increase in shipping price leads to a 2.6–11.3% reduction in demand from U.S. importers in the apparel and electronics sectors. This estimate aligns with previous elasticity estimates in the trade literature and highlights that freight costs are a significant determinant of firms' sourcing decisions. Second, we find that importers are willing to pay an additional 0.56% of their cargo value for each day saved in transit, suggesting that time is a crucial factor in supply chain management. Third, importers are also sensitive to transit time variability: they are willing to pay an additional 0.42% of their cargo value to reduce transit time uncertainty by one day, indicating that firms place a premium on predictability, not just speed.

These results have significant implications for shipping firms, policymakers, and businesses reliant on international supply chains. This underscores the economic benefits of investing in infrastructure and logistics improvements that enhance both speed and reliability. Our findings also highlight the importance of sector-specific preferences: importers in the electronics industry prioritize faster shipping times, while apparel importers value transit time predictability more. These differences have critical implications for optimizing logistics strategies based on industry needs.

Beyond quantifying these effects, our paper contributes to broader policy discussions on supply chain resilience. The disruptions observed during the pandemic have led to renewed calls for investments in port infrastructure, better coordination in global logistics, and diversification of sourcing strategies. By providing a rigorous quantification of the costs associated with delays and volatility, our study helps inform cost-benefit analyses of infrastructure projects aimed at mitigating these risks. For instance, policymakers can use our estimates to evaluate whether investments in port expansion, automation, or alternative shipping routes would generate economic returns that outweigh their costs.

Our methodology builds upon a well-established empirical framework used in international trade and transportation economics. We estimate a multinomial logit model of transportation mode choice, where importers choose between air, FCL, and LCL shipping based on expected profitability. The key explanatory variables include freight rates, transit times, and transit time volatility. By leveraging high-frequency data on shipments, we capture short-run fluctuations in importers' decisions and identify causal relationships between changes in logistics conditions and mode selection.

One key advantage of our approach is that it allows us to separately identify the effects of speed and predictability. While previous studies have focused primarily on the impact of average transit time, we show that transit time volatility has an independent effect on firms' transportation choices. Our findings suggest that policies aimed at reducing supply chain unpredictability—such as improved congestion management or better demand forecasting—may be as valuable as investments in speed alone.

The remainder of the paper is organized as follows. Section 2 describes our data, highlighting key patterns in freight rates, transit times, and importers' shifting preferences. Section 3 presents our empirical framework, outlining the multinomial logit model used to estimate importers' sensitivity to price and time. Section 4 discusses the main estimation results, including elasticity estimates and sector-specific differences in transportation preferences. Section 5 explores policy implications and robustness checks, considering alternative specifications and potential sources of bias. Section 6 concludes with a discussion of the broader implications for supply chain resilience and future research directions.

Related Literature Our paper contributes to the literature studying the effect of delay on international trade. Hummels and Schaur (2013) analyze firms' choices between fast, costly air cargo and slower, cheaper ocean shipping. They estimate that each additional day in transit is equivalent to an ad-valorem tariff of 0.6% to 2.1%, with time-sensitive sectors like parts and components trade being most affected. Our estimates on the value of transit speed is very consistent with their estimates, but we also uncover the value importers put on the predictability of the transit time. Carreras-Valle and Ferrari (2025) document a decline in the distance traveled by U.S. manufacturing imports since 2018, driven by a shift away from China. They propose that rising delivery risks and delays have led firms to hold higher inventories, increasing costs. Their model estimates that from 2018 to 2024, delivery delays rose by 21 days, reducing output by 2.6% and raising prices by 0.4%. Our paper estimate the effect of increase in delivery time and risk using another margin of transportation choices. Esposito et al. (2024) analyze the impact of weather-induced shipping time volatility on U.S. manufacturing imports using transaction-level data and oceanic wave conditions. They find that a one standard deviation increase in shipping delay risk reduces import values by 5.1%, as firms diversify across more routes and suppliers but lower overall imports. Using multi-modal variation, we estimate that a one-day increase in transit time volatility will, on average, reduce the trade flow by around 2%.[1]

In sum, our paper provides one of the first empirical estimates of how U.S. importers adjust their transportation choices in response to supply chain disruptions, quantifying the economic cost of delays and volatility. Our findings are relevant for businesses seeking to optimize their logistics strategies, policymakers designing interventions to improve supply chain resilience, and researchers studying the evolving nature of global trade. Given the increasing frequency of disruptions—ranging from pandemics to geopolitical conflicts—our results offer timely and actionable insights into how firms navigate an uncertain shipping environment.

[1] This is calculated by multiplying our estimated trade elasticity (5.166) by the value of one day in transit time standard deviation (0.42%).

2 Data and Stylized Facts

2.1 Data

This analysis primarily relies on quote and shipment data to estimate importer preferences. The quote data provides information on the options offered to importers and their selected transportation modes for each shipment, while the shipment data details shipping prices and transit times for each leg. From this information, we constructed a dataset capturing the average transit times, transit time variability, and shipping prices over time for all major port-pair routes.

Our sample is limited to importers in the apparel and electronics sectors. We focus on these sectors because importers in these industries frequently use all three transportation modes, given that their cargo is more flexible and adaptable across shipping options. Our data sample is from 2019 to 2022.

2.2 Institutional Details and Stylized Facts

To estimate the demand for global container shipping services, we analyze importers' choices of transportation modes, allowing us to infer their sensitivity to price and preference for transit speed. Importers, particularly those handling fungible goods, often employ a mix of transportation modes to accommodate varying logistical requirements and mitigate risks associated with supply chain disruptions. By studying these choices, we gain insights into how importers balance trade-offs between cost, speed, and reliability in their shipping decisions.

Our study focuses on cross-continent shipments, where importers in our dataset predominantly choose among three primary modes of transportation:

1. **Ocean Full-Container Load (FCL) Freight**

   Importers opting for FCL shipping secure an entire container—typically 20-foot (TEU), 40-foot, or 45-foot—for their exclusive use.[2] This mode is generally favored by businesses with sufficient cargo volume to fill an entire container, as it offers cost efficiency on a per-unit basis and reduces handling risks compared to shared shipments.

2. **Ocean Less-Than-Container Load (LCL) Freight**

   For importers who do not require a full container, LCL freight allows them to share container space with other shippers. In this mode, cargo is first consolidated at a Container Freight Station (CFS) near the port of origin and later deconsolidated at another CFS upon arrival before being transferred to inland transportation. These additional handling steps result in longer transit times and typically lead to higher per-TEU freight costs compared to FCL shipments. Despite these drawbacks, LCL is often the preferred option for businesses with smaller shipment volumes that do not justify the cost of an entire container.

3. **Air Freight**

   Air freight provides the fastest, yet most expensive, shipping option. Importers dealing with time-sensitive or high-value cargo frequently opt for air transport to minimize delays. While significantly more costly than ocean freight, air shipping is crucial for industries where rapid delivery is essential, such as perishables, high-end electronics, or critical manufacturing components.

These three transportation options offer importers a range of choices to optimize the trade-off between transit time and shipping costs based on their specific logistical needs. However, these choices are not static. During periods of supply chain disruptions—whether triggered by demand fluctuations or supply constraints—relative freight costs and transit times change, prompting importers to reassess and adapt their shipping strategies. Understanding these shifts is critical to capturing the dynamic nature of demand in the global container shipping market.

[2] The standardized unit in container shipping is the Twenty-foot Equivalent Unit (TEU), which corresponds to a 20-foot container. However, the most commonly used container size is 40 feet.

To examine these dynamics, we first analyze how freight rates and transit times evolved across different shipping modes during the COVID-19 pandemic and identify the key factors driving these changes. We then investigate how importers adjusted their freight mode portfolios in response to these shifts.

Diverging Trends in Freight Rates and Transit Times Across Shipping Modes

To quantify the changes in freight rates and transit times induced by supply chain disruptions, we employ the following regression specifications:

$$f_{odt} = \bar{f}_t + \gamma_o + \gamma_d + \epsilon_{odt} \tag{1}$$

$$\tau_{odt} = \bar{\tau}_t + \gamma_o + \gamma_d + \epsilon_{odt} \tag{2}$$

where γ_o and γ_d are fixed effects for origin and destination gateways. Gateways represent an intermediate level of aggregation used by carriers and freight forwarders to construct detailed origin-destination pairs—more granular than regions or subregions but more aggregated than individual ports. For example, the origin gateways divide China's ports into China-East (Shanghai, Ningbo-Zhoushan), China-South (Yantian, Xiamen, Hong Kong), and China-North (Tianjin, Qingdao, Dalian).[3] The terms $\bar{f}_t$ and $\bar{\tau}_t$ represent time-varying average freight rates and transit times, respectively, capturing overall market trends.

The log freight rate is depicted in the upper panel of Figure 1, while the lower panel illustrates the evolution of average transit time and its standard deviation. A notable trend during the pandemic is the widening freight rate differential between air and ocean shipping. This phenomenon is partly explained by the fact that approximately 50% of global air freight cargo is transported in the belly holds of passenger aircraft, while the remainder is carried by dedicated freighters. At the onset of the pandemic (see the sharp spike in air freight

[3] We provide a full list of origin-destination gateways and illustrate their coverage using a heat map in Figure 5 in Appendix B.

rates in April 2020 in Figure 1), the drastic reduction in passenger air travel significantly constrained belly-hold cargo capacity, exacerbating shortages. Simultaneously, heightened demand for air freight—driven by ocean shipping congestion—further intensified air freight price pressures.

As shown in the lower left panel of Figure 1, the average transit time for both ocean FCL and LCL shipments nearly doubled during the pandemic's peak, whereas air freight transit times increased by less than 10 days. More strikingly, despite similar increases in *mean* transit times for FCL and LCL, the *volatility* of transit time diverged. Specifically, the standard deviation of FCL transit times surged by 12-13 days, whereas that of LCL increased by only 5-6 days (see the lower right panel of Figure 1). This suggests that while both FCL and LCL shipments experienced longer delivery times, FCL shipping became significantly less predictable, undermining its reliability in terms of transit speed.

The availability of detailed leg-level transit time data from Flexport allows us to decompose total transit time into ordering time and in-transit time to identify the sources of increased transit time variability. We define total transit time as $\tau_{odt} = \tau^o_{odt} + \tau^t_{odt}$, where ordering time ($\tau^o_{odt}$) captures the duration between cargo readiness and pickup, while in-transit time (τ^t_{odt}) represents the actual shipping duration. Ordering time reflects container availability, whereas in-transit time reflects congestion effects.

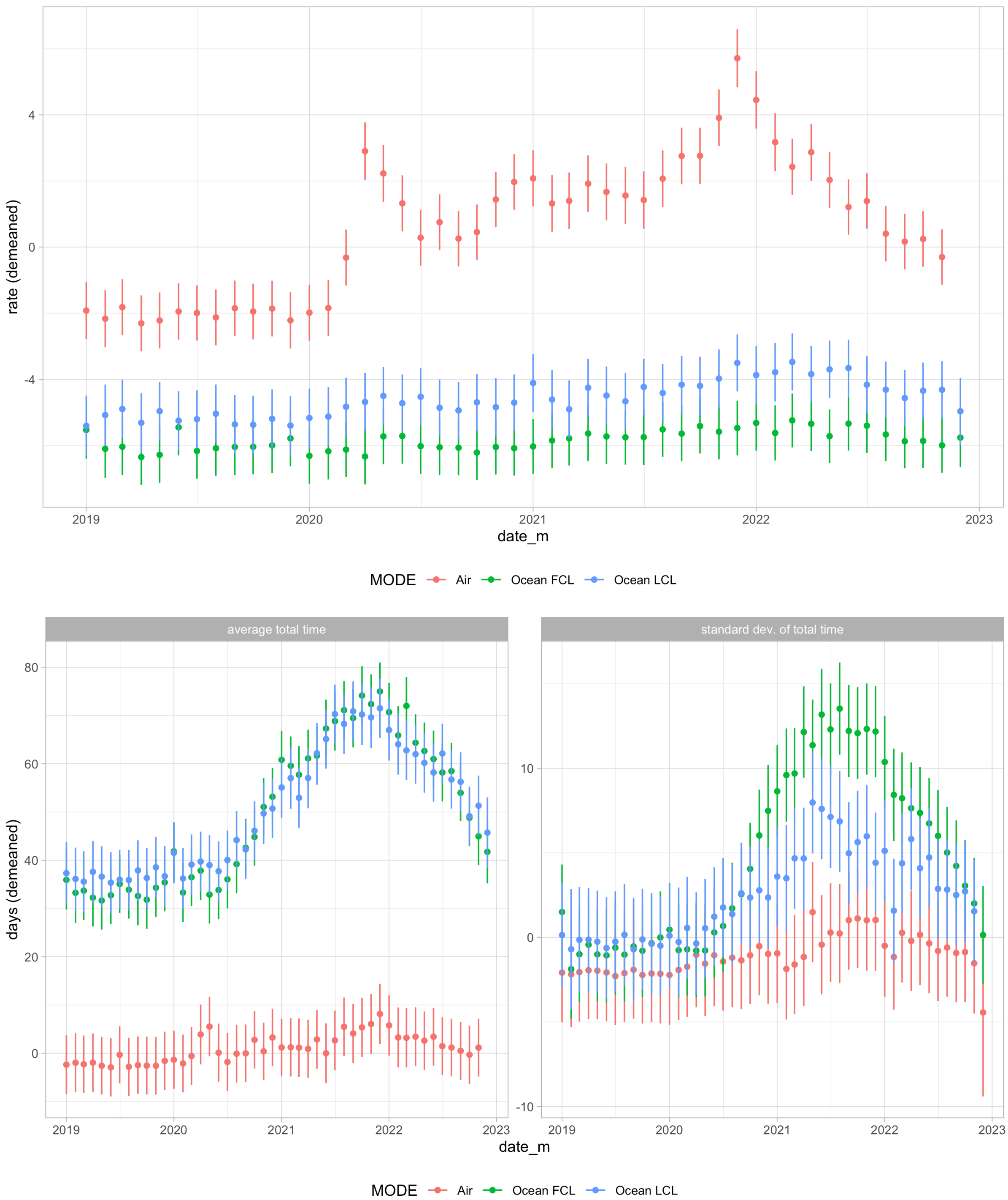
We estimate the time-varying averages of these components using:

$$\{\tau^o_{odt}, \tau^t_{odt}\} = \{\bar{\tau}^o_t, \bar{\tau}^t_t\} + \gamma_o + \gamma_d + \epsilon_{odt} \tag{3}$$

As illustrated in the upper panel of Figure 2, both the mean and standard deviation of FCL ordering times surged during the pandemic's peak. The average waiting time for an empty container rose from 2-3 days pre-pandemic to nearly 20 days by mid-2021, driven by severe container shortages at origin ports.[4] As a result, securing an empty container

[4]During the pandemic, major destination ports, such as Los Angeles and Long Beach, experienced extreme congestion due to supply chain bottlenecks, leading to delays in returning empty containers to exporting countries. This backlog was further exacerbated by a shortage of truck chassis, which are essential for

Figure 1: Diverging Freight Rates and Total Transit Times Across Transportation Modes



Note: Freight rates were regressed on time and origin-destination fixed effects. Dots and error bars represent point estimates and 95% confidence intervals for time fixed effects, illustrating average transit time trends across port pairs.

became both more time-consuming and unpredictable. Notably, despite LCL's inherently longer transit times due to consolidation at CFS facilities, its overall transit time volatility remained lower than that of FCL shipments.

Examining Importers' Shifts in Transportation Mode During Freight Market Disruptions

To analyze how importers adjusted their transportation mode in response to disruptions in the freight market, we first calculate the share of cargo—by weight—transported via different modes in the apparel and electronics sectors within our dataset. As illustrated in Figure 3, the share of Flexport's clients using air freight increased notably as supply chain disruptions intensified in the second half of 2021. Interestingly, the share of shipments utilizing LCL freight also saw a significant increase, rising from approximately 1.5% in 2019 to over 7% during July and August of 2021.

However, it is important to acknowledge certain caveats when interpreting these results. First, our dataset is not necessarily representative of the entire population of importers, as it is limited to Flexport's clients. Second, the observed changes in mode share reflect both intensive margin and extensive margin adjustments.[5] To address this concern, we construct a balanced panel that includes only continuing clients, and we find that the same patterns hold (see Figure 6 in Appendix B).

To further explore the impact of freight rate and transit time changes on mode choice at the individual firm level, we conduct a case study of the cashmere and hoisery shipments in the apparel sector. Specifically, we examine cashmere shipments from Hong Kong to New York and hosiery shipments from Shanghai to Los Angeles for this importer. The upper panel of Figure 4 presents the distribution of shipments for cashmere, while the lower panel displays shipments for hosiery.

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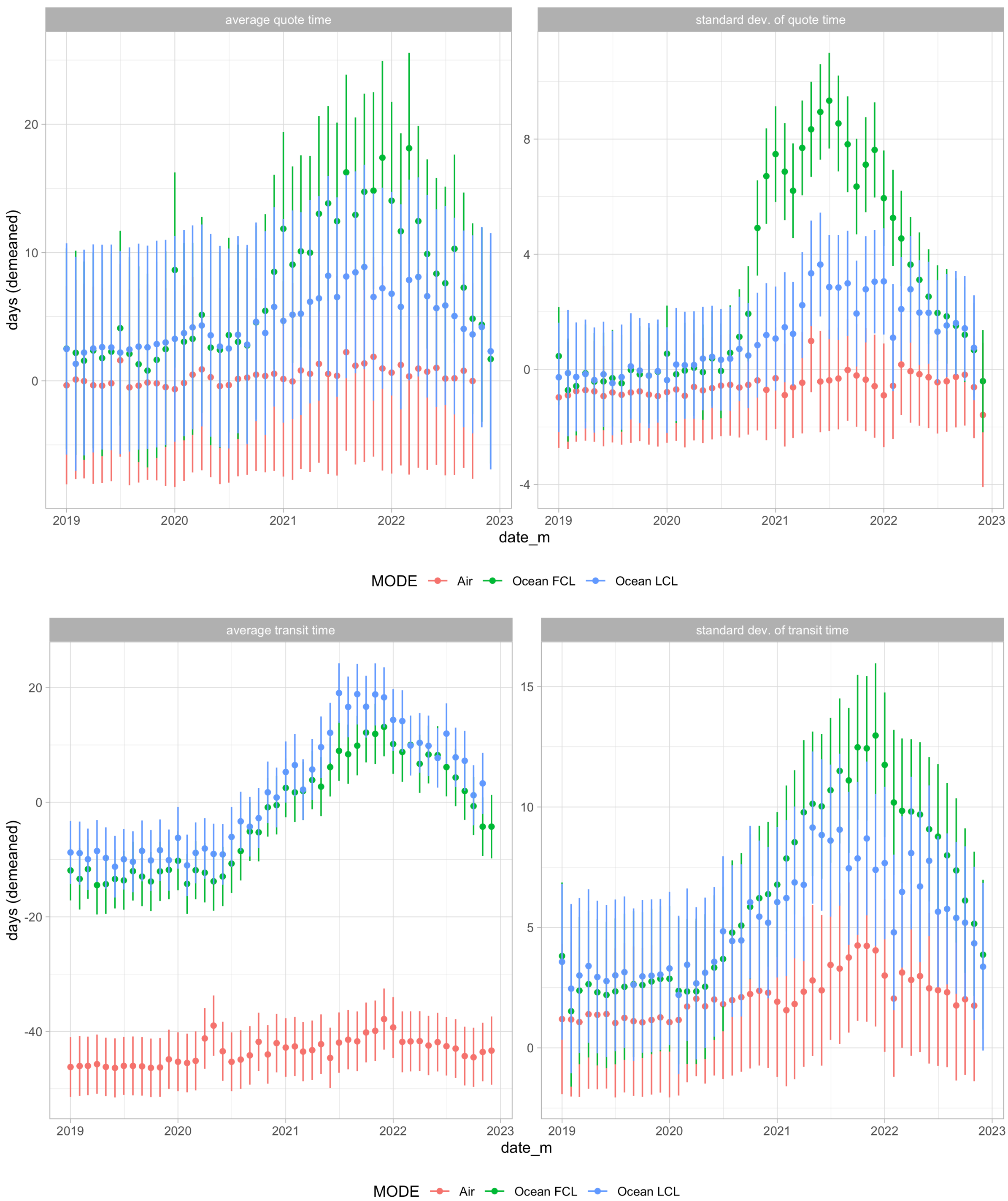
transporting containers inland, further delaying repositioning efforts.

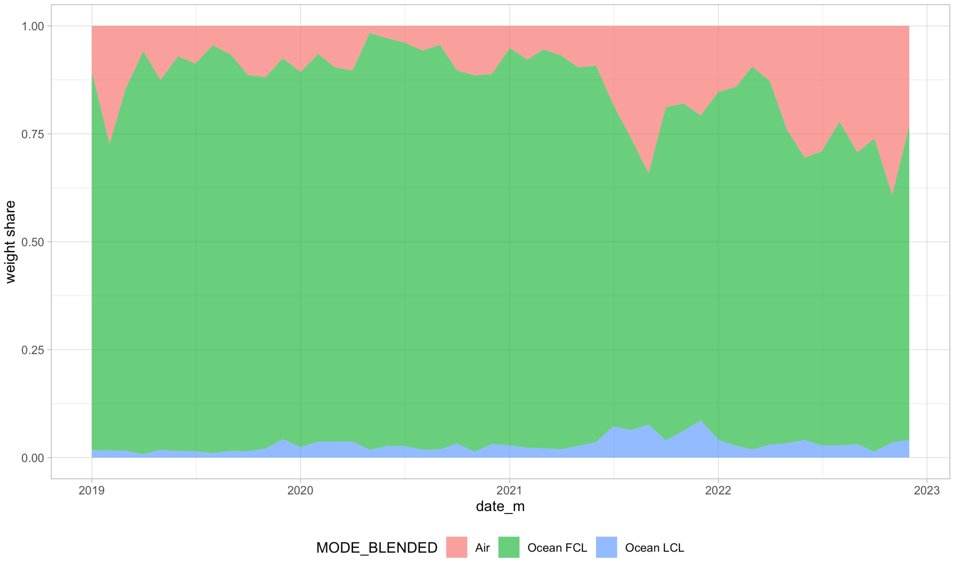
[5]Intensive margin changes refer to shifts in mode choice among existing clients, whereas extensive margin changes reflect shifts driven by new clients entering or exiting the dataset over time.

Figure 2: Decomposing Total Transit Time



Note: The upper panel shows mean and standard deviation of ordering time, while the lower panel shows the same for in-transit time. All transit times were regressed on time and origin-destination fixed effects.

Figure 3: Share of cargo transported by various modes



Note: The figure illustrates the evolution of transportation mode shares for cargo in the apparel and electronics sectors, highlighting shifts in response to supply chain disruptions.

Starting in the second half of 2021, as FCL freight faced significantly longer lead times due to congestion and equipment shortages, we observe a clear shift away from FCL towards LCL and air freight. This shift suggests that when ocean FCL shipments become unreliable, importers turn to alternative modes that, while costlier, provide greater predictability.

Beyond illustrating the broad shift in freight mode, this case study provides granular insights into how importers strategically adjust their transportation portfolios to mitigate disruptions. Prior to the pandemic, this retailer primarily relied on the cheapest option—ocean FCL freight—while complementing it with small air shipments for time-sensitive fashion products. However, given the pronounced seasonality of cashmere demand (see upper panel of Figure 4), ensuring timely and predictable delivery became a priority. Consequently, we observe that the retailer disaggregated bulk shipments into smaller portions, opting for a combination of LCL and air freight to enhance flexibility and mitigate unpredictability in transit times.

Furthermore, our analysis suggests that importers are more likely to switch to air freight when the unit value of their cargo is higher (see Figure 7 in Appendix B). This finding aligns with economic intuition, as higher-value goods justify higher transportation costs to avoid stockouts and lost sales.

3 Empirical Framework

Following Hummels and Schaur (2013), we assume the representative consumer's demand for shipment/product i is[6]:

$$q_{it} = E_t \left(\frac{p_{it}}{\exp(-\gamma_1 \tau_t^m) \exp(-\gamma_2 \sigma(\tau_t^m))} \right)^{-\sigma} \tag{4}$$

where E_t is representative consumer's real-expenditure for this specific product category, σ is the elasticity of substitution across different products, which is also the price elasticity of demand for shipment/product i: q_{it} assuming CES demand for representative consumer and monopolistic competition.

p_{it} is the final price of the product of cargo/shipment i. And under the assumption of monopolistic competition across retailers, $p_{it} = \frac{\sigma}{\sigma-1}(z_{it} + f_{iodt}^m)$ where z_{it} is cargo value/cost, and f_{iodt}^m is the shipping price using mode m. Notice that we assume an *additive* transportation cost, where the freight rate f_{iodt} is not proportional to the cargo value but only to the cargo weight/volume.[7] This is a more realistic assumption compared to the multiplicative transportation cost used in some of the previous literature. [[Hummels Skiba, Helpman]]

Finally τ_t^m and $\sigma(\tau_t^m)$ are the mean and standard deviation of transit time for mode m, respectively. We highlight the parameters of interest in red: σ is the price elasticity of demand, γ_1 represents the value of one day less in transit, and γ_2 represents the value of

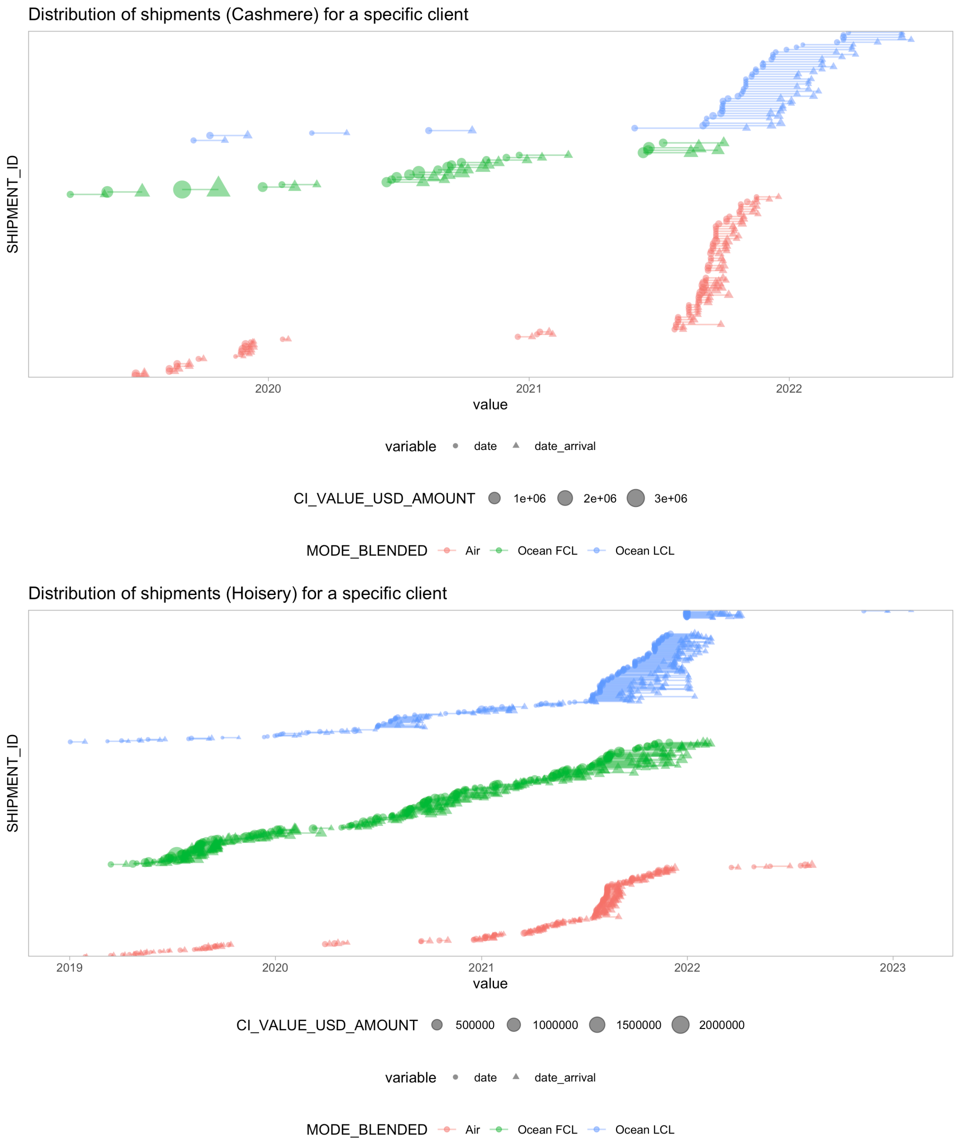
[6] This is generated from an underlying assumption of CES demand for consumer:

$$U_t = (\sum_i (q_{it})^{\theta})^{\frac{1}{\theta}}$$

where $\theta = \frac{\sigma-1}{\sigma}$

[7] We have standardize all the volume measures into chargeable weight for an apple-to-apple comparison between air and ocean freight.

Figure 4: Case Study: Mode Shift in Cashmere and Hosiery Shipments



Note: The upper panel illustrates cashmere shipments from Hong Kong to New York, and the lower panel shows hosiery shipments from Shanghai to Los Angeles. Each dot (departure) and triangle (arrival) represents a cashmere shipment, with size proportional to cargo value. Colors denote mode: green for ocean FCL, blue for ocean LCL, and red for air. The shift in 2021 indicates a preference for faster and more predictable transit.

reduced transit time variability. Similar to the strategy used in Hummels and Schaur (2013), we model the transit time and the variation of it as a product-quality term. To illustrate, for a 1% increase in the price of the goods, the demand for it will decrease by σ%. For one day increase in the transit time, the demand will reduce by $\sigma\gamma_1$%, and for one day increase in the standard deviation of transit time, the demand will reduce by $\sigma\gamma_2$%.

Then the profit function will be

$$\pi_{it} = \frac{\sigma^{-\sigma}}{(\sigma-1)^{1-\sigma}} E_t \cdot (z_{it} + f^m_{iodt}) \cdot \left(\frac{z_{it} + f^m_{iodt}}{\exp(-\gamma_1 \tau^m_t)\exp(-\gamma_2 \sigma(\tau^m_t))} \right)^{-\sigma} \tag{5}$$

The log profit function we use to estimate the multinomial logit model is:

$$\ln \pi_{iodt} = \ln C + (1-\sigma)\ln(z_{it} + f^m_{iodt}) - \sigma\gamma_1 \tau^m_t - \sigma\gamma_2 \sigma(\tau^m_t) \tag{6}$$

where C is a constant.[8]

We employ a multinomial logit model to estimate parameters for price sensitivity and transit time value. The probability that a importer chooses transportation mode $m \in \{\text{air, fcl, lcl}\}$ for shipment i is given by:

$$Pr[m|i] = \frac{\exp(\ln \pi_{it}(m))}{\sum_{m\in\{\text{air, fcl, lcl}\}} \exp(\ln \pi_{it}(m))}$$

where $\pi_{it}(m)$ represents the profit from shipment i using mode m. Note that we do not include the outside option in our estimation for two reasons. First, in our data sample, we believe the quotes that are not accepted is not representative of all the quote that importers requested. For details, please see Appendix A on data issues. Second, the constant term $\ln C$ is not an object of interest in our estimation. This implies that the elasticity we estimated is the price elasticity of demand faced by importers who have already decided to import.

[8] $C = (1-\sigma)\ln(\frac{\sigma}{\sigma-1}) + \ln E_t$

3.1 Identification

To see how each parameter is identified, we can compare the log-profit for the same shipment i across different modes. The following equation defines the difference in log profit between two transportation modes m_1 and m_2:

$$\begin{aligned}
\ln \pi_{iodt}^{m_1} - \ln \pi_{iodt}^{m_2} =& (1-\sigma)(\ln(z_{it} + f_{iodt}^{m_1}) - \ln(z_{it} + f_{iodt}^{m_2})) \\
& - \sigma\gamma_1(\tau_t^{m_1} - \tau_t^{m_2}) \\
& - \sigma\gamma_2(\sigma(\tau_t^{m_1}) - \sigma(\tau_t^{m_2}))
\end{aligned}$$

In order to identify all three parameters: $(\sigma, \gamma_1, \gamma_2)$, we need to have at least choices of three different transportation modes, which also need to vary in their freight price, transit time, and the volatility of transit time. As we mentioned in previous section, ocean FCL, LCL and air freight all differ in their freight price, first and second moment of transit time. Especially FCL's significantly higher volatility in ordering time for a full container provides variation necessary to separately identify γ_2. Also, given the panel structure of the freight rate and transit time data, the diverging trend across three modes of transportation provides the necessary variation to identify all three parameters.

3.2 Discussion

Model Specification A concern for our empirical framework is the model specification. We assume a logarithm utility for the importer which is special case of CRRA utility with $\gamma = 1$ implying a moderately risk averse representative importer. We also impose a quite strong assumption on how the first and second moment of transit time is impacting the profit of the shipment by including them as $\exp(-\gamma_1\tau)$ and $\exp(-\gamma_2\sigma_\tau)$ respectively. Another assumption embedded in our previous model specification is that price volatility will result in disutility regardless whether the transit time is unexpectedly longer or shorter than the industry average. Alternatively we could assume that only delays would lead to profit loss for importers, by specifically modeling the risk aversion. Now we assume the profit function of the importers only depends on the first moment of transit time:

$$\pi_{it} = \frac{\sigma^{-\sigma}}{(\sigma-1)^{1-\sigma}} E_t \cdot (z_{it} + f_{iodt}^m) \cdot \left(\frac{z_{it} + f_{iodt}^m}{\exp(-\gamma_1 \tau_t^m)} \right)^{-\sigma} \tag{7}$$

If we continue assume a log-utility for importers. Then the expected utility is

$$\mathbb{E}[\ln(\pi_{it})] = \mu_{\ln\pi} + \frac{1}{2}\sigma^2_{\ln\pi}$$

where $\ln(\pi) \sim \mathcal{N}(\mu_{\ln\pi}, \sigma^2_{\ln\pi})$. And the mean of log-profit is determined as: $\mu_{\ln\pi} = \ln C + (1-\sigma)\ln(z_{it} + f_{iodt}) - \sigma\gamma_1\mu_\tau$, while the variance of log-profit is determined as: $\sigma^2_{\ln\pi} = \sigma^2\gamma_1^2\sigma_\tau^2$. Therefore, Equation 7 becomes:

$$\mathbb{E}[\ln(\pi_{it})] = \ln C + (1-\sigma)\ln(z_{it} + f_{iodt}) - \sigma\gamma_1\mu_\tau + \frac{1}{2}\sigma^2\gamma_1^2\sigma_\tau^2 \tag{8}$$

Equation 8 provides a testable specification in the data as $\ln(z_{it} + f_{iodt}), \mu_\tau, \sigma_\tau^2$ are all measurable. This specification also serves as a test of the model in Equation 7. Because our multinomial logit model would recover the coefficient in front of μ_τ, σ_τ^2, and Equation 8 provides a defined relationship between these two coefficient. If we let $\beta_1 = -\sigma\gamma_1$ and $\beta_2 = \frac{1}{2}(1-\gamma^a)\sigma^2\gamma_1^2$ where $1-\gamma^a$ could be interpreted as a proxy for risk aversions, if the estimated coefficients satisfies $\frac{\hat{\beta}_2}{\hat{\beta}_1^2} = -\frac{1}{2}$, then we can confirm model in Equation 7 is correct. If, however, $\hat{\beta}_2 < \frac{1}{2}\hat{\beta}_1^2$, then the second moment of transit delay will have a larger impact on importer's utility than those implied by the log-utility in Equation 7. This could be rationalized by a higher risk aversion. For details, please see Appendix C.

4 Estimation and Results

4.1 Construct Choice Set

Because of data quality issue mentioned in Appendix A, we only use the quote that has been accepted as the main data sample where we base our estimation on. Therefore, we need to construct the choice set for each shipment we observed in the data. To construct the choice set, we first created a rate-time panel data of average per-unit freight rate, average and standard deviation of transit time for all origin-destination gateway in each month. For each shipment, we only observe the information for the mode that is chosen. We populate the alternative mode choice for each shipment by assuming the freight rate and transit time it *would have* if it chose other freight type is the same in the rate-time panel data for a certain origin-destination-month pair. For more details, please refer to Appendix D.

4.2 Estimation Results

We use the pseudo Poisson maximum likelihood estimation method to estimate our multinomial logit model. As Equation 6 shows, the coefficients directly estimated from the model are $(1-\sigma, -\sigma\gamma_1, -\sigma\gamma_2)$. We show the detailed regression results in Table 4 in Appendix D. Then we summarized the results of parameters in Table 1. We use the delta method to calculate the standard error for $\gamma_1, \gamma_2, \gamma^a$.

Table 1: Estimation Results

	(1)	(2)	(3)
σ	5.166	5.044	5.063
	(0.114)	(0.110)	(0.111)
γ_1	0.006	0.006	0.006
	(0.000)	(0.000)	(0.000)
γ_2	0.004		
	(0.000)		
γ^a			1.210
			(0.001)

As we can see from Table 1, the price elasticity of demand is around 5 across different model specifications. This agrees with the trade elasticity estimates in the literature, and sits in the middle of the range. (Please see a summary of the trade elasticity estimated in the literature in Table 2). Note, however, that the trade elasticity is not the same as the price elasticity of demand for the container shipping service. The price elasticity of shipping demand is a fraction of the trade elasticity, where the proportion is the ratio of freight cost to total cost:

$$\sigma^{\text{shipping}} = \frac{f}{f+z}\sigma$$

If we use the freight to total cost ratio in 2021, then the interquartile range of price elasticity of shipping demand ranges from 0.26 to 1.13. This implies that for a 10% increase in freight price, the import demand of US importers will decrease by 2.6-11.3%, or around 7.8% on average. This also implies that, under the assumption of a constant trade elasticity, the US importers will be more price-sensitive when freight is high. For details on the dynamics of freight to total cost ratio, please see Figure 8 in Appendix D.

Table 2: Summary of Trade Elasticity Estimates in the Literature

Study	Estimates	Notes
Simonovska and Waugh (2014)	4.0	Novel estimator using disaggregated price and trade data.
Christoph E. Boehm and Pandalai-Nayar (2020)	0.76 to 2.0	Short-run and long-run elasticities estimated via local projections.
Ahmad and Riker (2020)	1.22 to 5.52	Uses industry-specific profit margin data from the U.S. Economic Census.
Soderbery (2015)	2.5 to 5.1	Meta-analysis of 3,524 estimates of Armington elasticity.
Imbs and Mejean (2015)	4.4 (median)	Uses disaggregated sectoral data across countries.
Broda and Weinstein (2006)	3.6 (median)	Import demand elasticities at the 3-digit industry level.
Eaton and Kortum (2002)	8.3	Ricardian model of international trade, estimated from price and trade data.
Head and Ries (2001)	5.0	OECD bilateral trade flow analysis.
Feenstra (1994)	3.0	U.S. automobile imports, estimating substitution between domestic and foreign varieties.
Michael P. Gallaway and Rivera (2003)	1.6 (median)	U.S. Armington elasticities for 309 industries using a CES framework.

Also we can see that US importers are willing to pay an additional 0.56% of their cargo value for each day saved in transit. This implies that one more day in the transit is equivalent to a 0.6% ad-valorem tariff. This is consistent with the 0.6-2% estimates in Hummels and Schaur (2013). The average 30 days delay during the peak of Pandemic will translate into a substantial 18% of ad-valorem tariff on the cargo. What's new in our paper is that we also measured importers' preference for more predictable transit time- US importers are willing to pay an additional 0.42% of they cargo value for each day of reduced transit time variability. This implies that if the standard deviation of transit time increased by 10%, it's equivalent to a 4.2% tariff on the cargo. This is one of the first papers that quantify the impact of transit time volatility (See Esposito et al. (2024), Carreras-Valle (Carreras-Valle), Carreras-Valle and Ferrari (2025)). Also our estimates of the proxy for risk aversion generates a $\gamma^a = 1.21$ which is significantly larger than 1, therefore implying the importers are more risk averse than that suggested by the log-utility.

4.3 Robustness Check

Sectoral Heterogeneity We first explore the heterogeneity in importers' preference for freight cost and transit speed across different sectors. We found that, in our sample, importers in apparel sector care more about the second moment of transit speed while the importers in electronics cares more about the average speed. This difference between the two sector is also implied by the much higher risk aversion proxy estimated.

Table 3: Estimation Results by Sector

HS2 Code: 61/62 - Apparel		
Coefficient	Estimates	Standard Error
σ	5.319	0.223
γ_1	0.003	0.000
γ_2	0.007	0.000
γ^a	3.472	0.000
HS2 Code: 85 - Electronics		
Coefficient	Estimates	Standard Error
σ	4.940	0.127
γ_1	0.006	0.000
γ_2	0.003	0.000
γ^a	0.914	0.042

5 Conclusion

The increasing frequency and severity of supply chain disruptions underscore the need for a deeper understanding of how importers respond to changing freight costs and transit conditions. Our study provides new empirical evidence on how U.S. importers adjust their transportation choices in response to shifts in freight rates and transit time reliability. Using detailed quote and shipment data, we estimate the price elasticity of shipping demand and quantify firms' willingness to pay for both faster and more predictable transit times. Our findings suggest that a 10% increase in shipping prices reduces demand by 2.6–11.3%, while importers are willing to pay an additional 0.56% of cargo value per day saved in transit and 0.42% per day of reduced transit time variability. These results highlight that both cost and predictability play critical roles in firms' logistics decisions.

These findings have direct implications for policymakers and businesses considering investments in supply chain resilience. Given the substantial costs associated with delays and uncertainty, our results suggest that targeted investments in port infrastructure, congestion management, and alternative shipping routes could yield significant economic benefits. Moreover, sector-specific differences in preferences—where electronics importers prioritize speed while apparel importers value predictability—indicate that tailored solutions may be necessary to address industry-specific supply chain challenges. As global trade continues to evolve amid geopolitical tensions, climate risks, and potential future pandemics, our research provides a valuable framework for assessing the economic impact of disruptions and informing strategies to build more robust, efficient, and responsive supply chains.

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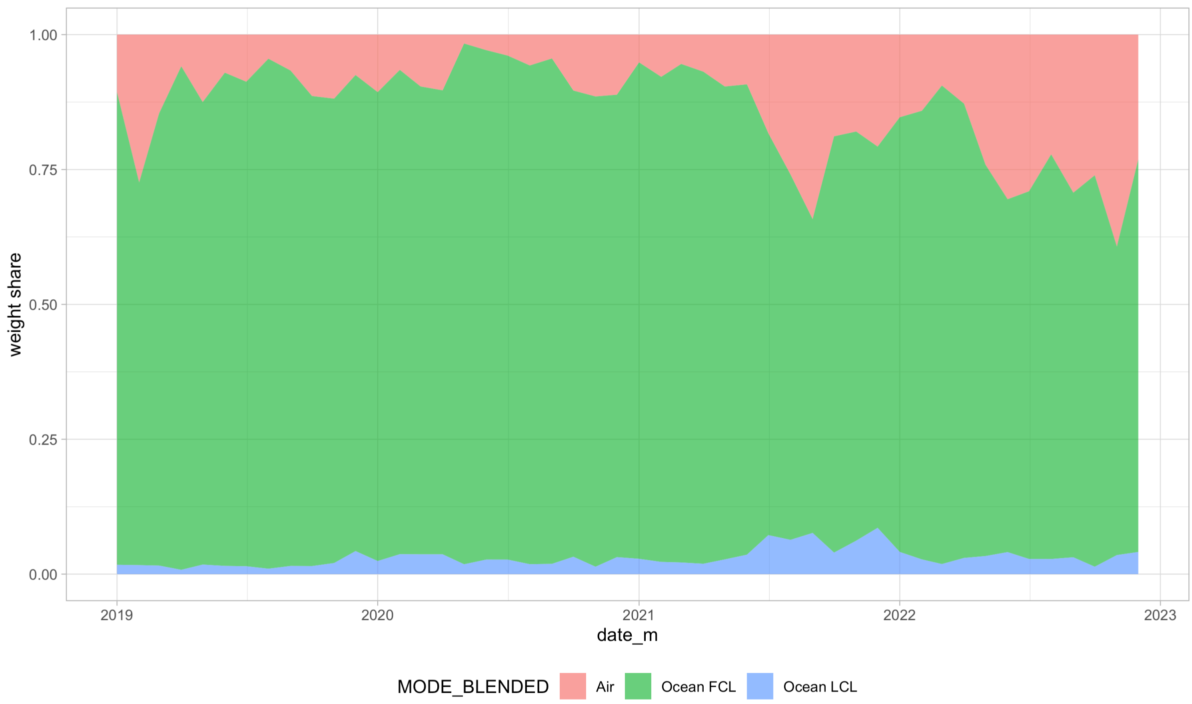
A More Details on Data

A.1 Data Issues

A.2 Measure of Transit Time

B More Details on Stylized Facts

Figure 6: Share of cargo transported by various modes: continuing clients



Note:

Figure 5: Coverage of gateway origin-destination pairs

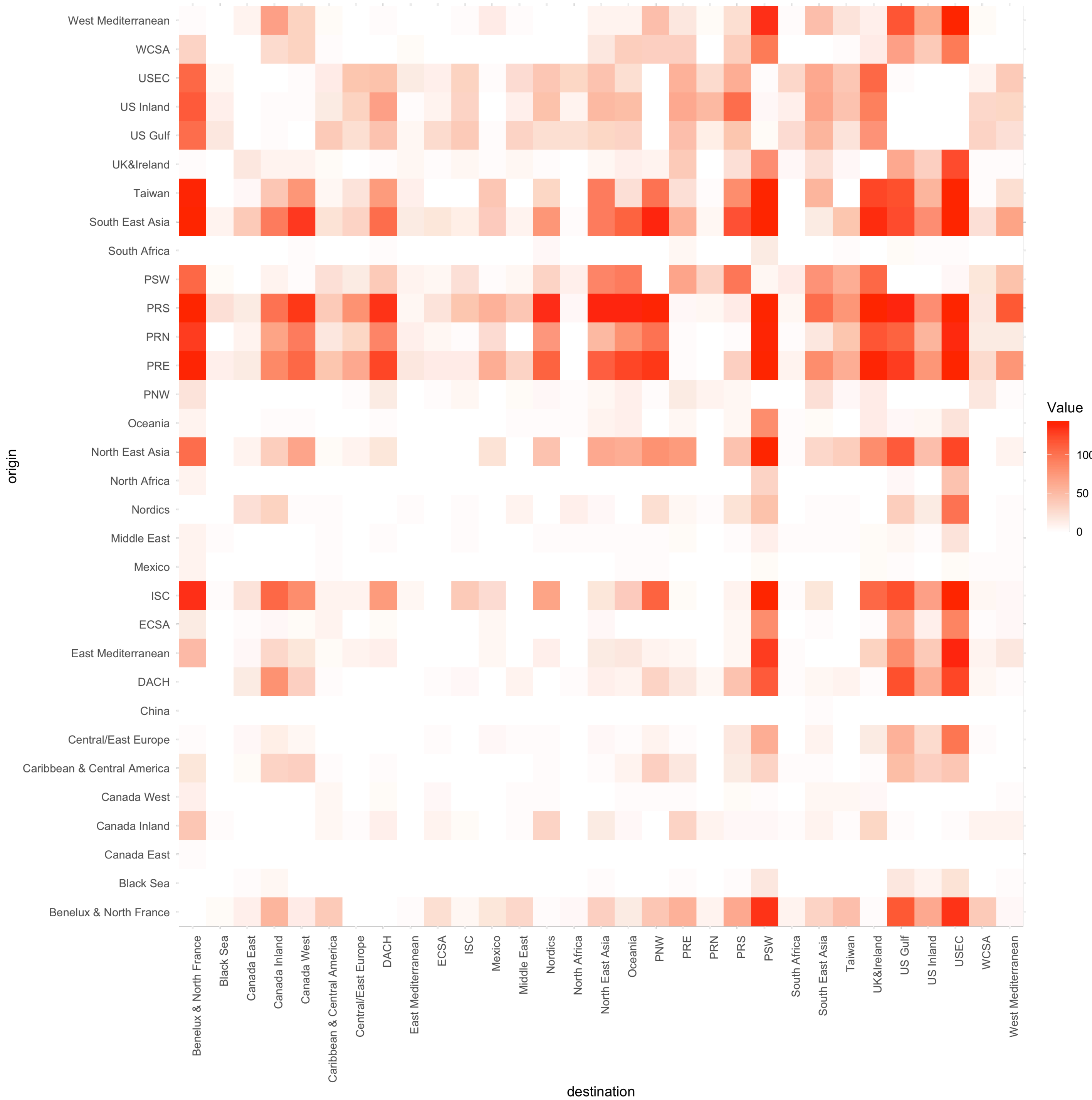
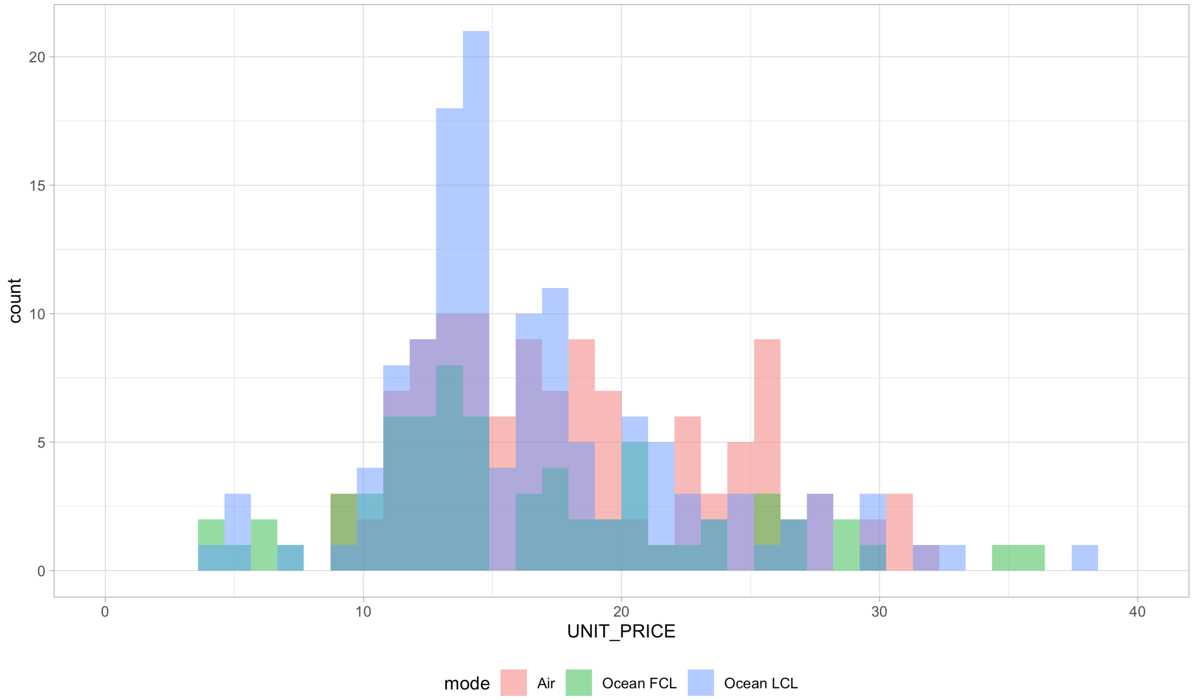


Figure 7: Distribution of the unit price across freight mode during 2022



Note:

C More Details on Empirical Framework

If we assume the utility of importers is a CRRA utility function with respect to the profit:

$$U_{it} = \frac{\pi_{it}^{1-\gamma}}{1-\gamma}$$

Under the assumption that the profit π_{it} follows a log-Normal distribution[9], then the expected utility of shipment i is

$$\mathbb{E}(U_{it}) = \frac{1}{1-\gamma}\exp\left((1-\gamma)\mu_\pi + \frac{(1-\gamma)^2}{2}\sigma_\pi^2\right)$$

Given the non-linearity of this functional form, it's hard to directly estimate using the

[9]This is based on the assumption that $\tau \sim Normal(\mu_\tau, \sigma_\tau^2)$.

Table 4: Benchmark Regression Results

Dependent Variable:	CHOICE		
Model:	(1)	(2)	(3)
Variables			
cost	-4.166***	-4.044***	-4.064***
	(0.1144)	(0.1102)	(0.1113)
time_tot_med	-0.0290***	-0.0320***	-0.0317***
	(0.0006)	(0.0005)	(0.0005)
time_tot_sd	-0.0219***		
	(0.0021)		
time_tot_sd square			-0.0001**
			(4.22×10^{-5})
Fixed-effects			
SHIPMENT_ID	Yes	Yes	Yes
Fit statistics			
Observations	70,278	70,278	70,278
Squared Correlation	0.16670	0.16281	0.16309
Pseudo R^2	0.07097	0.06960	0.06966
BIC	352,990.3	353,114.0	353,118.9

Clustered (SHIPMENT_ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

multinomial logit framework. However, one could use the maximum-likelihood function approach to estimate $(\sigma, \gamma_1, \gamma)$ where γ measures the risk aversion. We will leave this estimation to future work.

D More Details on Estimation

Table 5: Regression: Apparel

Dependent Variable:		CHOICE	
Model:	(1)	(2)	(3)
Variables			
cost	-4.319***	-4.072***	-4.176***
	(0.2225)	(0.2092)	(0.2169)
time_tot_med	-0.0179***	-0.0234***	-0.0212***
	(0.0012)	(0.0011)	(0.0011)
time_tot_sd	-0.0394***		
	(0.0038)		
time_tot_sd square			-0.0006***
			(9.26×10^{-5})
Fixed-effects			
SHIPMENT_ID	Yes	Yes	Yes
Fit statistics			
Observations	15,826	15,826	15,826
Squared Correlation	0.08276	0.06920	0.07433
Pseudo R^2	0.03839	0.03205	0.03448
BIC	72,349.8	72,480.6	72,436.3

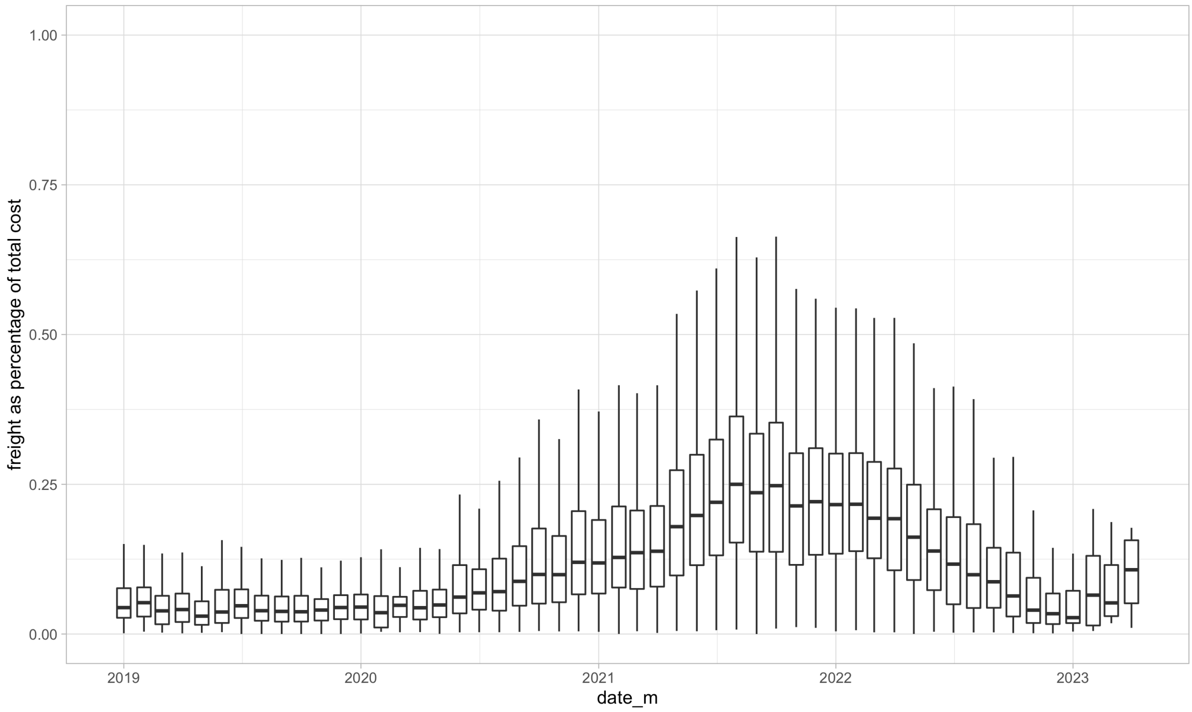
Clustered (SHIPMENT_ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Regression: Electronic

Dependent Variable:		CHOICE	
Model:	(1)	(2)	(3)
Variables			
cost	-3.940***	-3.867***	-3.858***
	(0.1270)	(0.1236)	(0.1239)
time_tot_med	-0.0322***	-0.0342***	-0.0343***
	(0.0007)	(0.0006)	(0.0006)
time_tot_sd	-0.0143***		
	(0.0025)		
time_tot_sd square			5.06×10^{-5}
			(4.87×10^{-5})
Fixed-effects			
SHIPMENT_ID	Yes	Yes	Yes
Fit statistics			
Observations	54,452	54,452	54,452
Squared Correlation	0.20110	0.19930	0.19922
Pseudo R^2	0.08553	0.08501	0.08503
BIC	267,780.3	267,808.4	267,818.3

Clustered (SHIPMENT_ID) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figure 8: Freight Price to Cargo Value Ratio



Note: This figure plots the ratio of freight rates to total import cost (freight + cargo value), calculated as $\frac{f}{f+z}$.