Input Sourcing under Supply Chain Risk: Evidence from U.S. Manufacturing Firms

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Motivation

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- **Open questions:**
  - Measurement: how to measure supply chain risk at the firm level?
  - Theory: how to incorporate risk into a quantitative model of input trade?

This Paper

- **Measurement**
  - Specific type of supply chain risk: **volatility of ocean shipping times**
  - Use U.S. transaction-level import data to construct risk measure
  - Use variation induced by weather shocks along shipping routes

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  - Importers would accept up to 25% longer shipping times to avoid risk

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- Climate change may worsen weather risk going forward

Outline

1. Empirical Framework
2. Measurement
3. Delays and Firm Outcomes
4. Shipping Risk and Import Demand
5. Model

Literature

- **Risk for final goods trade:** Ramondo et al 2013, Fillat and Garetto 2015, Esposito 2022, Baley et al 2020
  $\longrightarrow$ We focus on risk for inputs trade
- **Models of input sourcing:** Halpern et al 2015, Antras et al 2017, Blaum et al 2018
  $\longrightarrow$ We add supply chain risk to an otherwise standard model
- **Management of supply chain risk:** Clark et al 2014, Gervais 2018, Huang 2019, Carreras-Valle 2021
  $\longrightarrow$ We perform systematic analysis in transaction-level data with weather risk
- **Supply chain disruptions:** Boehm et al. 2019, Carvalho et al 2021, Antras and Chor 2021
  $\longrightarrow$ We focus on how risk affects sourcing strategy
- **Shipping times:** Evans and Harrigan 2005, Hummels and Schaur 2013, Brancaccio et al 2019
  $\longrightarrow$ We focus on the uncertainty around **timeliness**

Empirical Framework

A Model of Shipping Times

- **Shipping time** = Time between departure abroad until the good has cleared customs in U.S.

- For shipment s, it could depend on:
  - Importer (f)
  - Foreign supplier (x)
  - Product (h)
  - Shipping route (r)
  - Time period (t)
  - Vessel (v)
  - Related party status (a)

- As well as
  - Shipping charges (C^s) $\longrightarrow$ higher charges could reduce shipping times
  - Weight (W^s) $\longrightarrow$ greater weight could increase shipping times

A Model of Shipping Times

- Thus:

$$\ln(T^s_{xhrtvfa}) = \left(\bar{\pi}_x + \bar{\alpha}_h + \bar{\gamma}_r + \bar{\theta}_t + \bar{\xi}_v + \bar{\delta}_f + \bar{\omega}_a\right)$$

- **bar** = deterministic components known by the importer

x = foreign supplier; h = product; r = route;
t = time (quarter-year); v = vessel; f = importer;
a = related party / arm's-length

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- Population variance given charges C^s and weight W^s:

$$\sigma^2_{xhrtvfa} = \mathbb{V}(\pi_x) + \mathbb{V}(\alpha_h) + \mathbb{V}(\gamma_r) + \mathbb{V}(\theta_t) + \mathbb{V}(\xi_v) + \mathbb{V}(\delta_f) + \mathbb{V}(\omega_a)$$

- All deterministic components drop out when computing sample variance

Removing Anticipated Components

- We will measure risk across some of these dimensions, e.g., (f, h, r)
  - Deterministic components $\left\{\bar{\theta}_t; \bar{\xi}_v; \bar{\pi}_x; \bar{\omega}_a\right\}$ will not be constant within (f, h, r)
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- Residualization step by regressing on fixed effects
  - Sample variance of residualized shipping time excludes deterministic components

$$\hat{t}_{xhrtvfa} = \ln(T^s_{xhrtvfa}) + \hat{\eta}\ln(C^s) - \hat{\rho}\ln(W^s) - \bar{\theta}_t - \bar{\xi}_v - \bar{\pi}_x - \bar{\omega}_a$$

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- Then compute the sample variance of $\hat{t}_{xhrtvfa}$
  - No need to residualize w.r.t. $\left\{\bar{\delta}_f, \bar{\alpha}_h, \bar{\gamma}_r\right\}$ since these are constant within (f, h, r)

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- Focus on variation in residualized shipping times due to weather

Empirical Measurement

Data

- **Longitudinal Firm Trade Transaction Database (LFTTD)**
  - Transaction-level data for all imports for 1992-2016
  - Standard: Importer, exporter, HS10 product, date of import and export abroad
  - Not used much so far: port of entry and departure, vessel identity
- **Longitudinal Business Database (LBD) / Census of Manufactures**
  - Employment, industry, sales, cost of materials and labor
- **Wave Watch III Model from U Hawaii / NOAA**
  - Height and direction of significant waves at hourly/three-hourly frequency for geo locations at 0.5 degree distances in the oceans for 2011-2016

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- **We focus on the manufacturing sector**

Summary Stats

Shipping Time Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Avg. Time	Std. Time	P5	P25	P50	P75	P95	Total Value ($Bill.)
Vessel	**16.38**	**23.54**	**3.49**	**10.00**	**13.46**	**20.48**	**33.32**	**4,250**

Source: LFTTD. Table summarizes the distribution of shipping times. Values are reported in billions of 2009 dollars.

Vessel shipments have high dispersion

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Train	4.42	6.256	0.00	0.00	0.00	8.48	16.86	1,450
Truck	0.05	0.36	0.00	0.00	0.00	0.00	0.00	2,210
Airplane	0.49	0.89	0.00	0.00	0.00	1.00	2.298	1,610
Other	11.94	74.70	0.00	0.00	0.00	2.47	24.18	1,020

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⇒**Focus on volatility of <u>vessel borne shipments</u>**

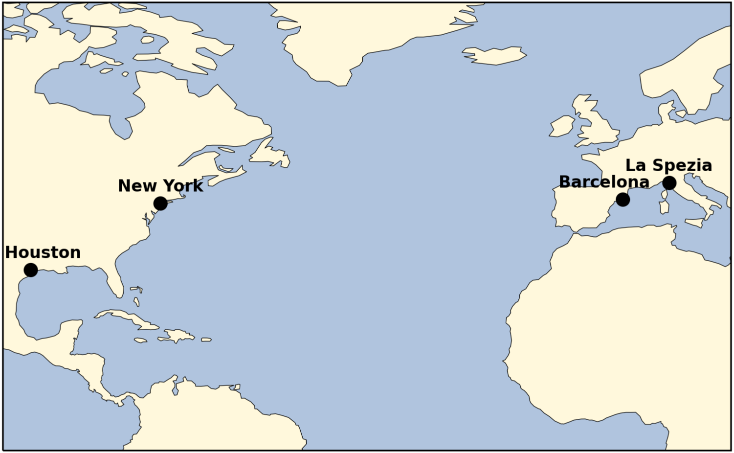
- will treat the other modes of transportation as riskless

Adding in the Weather Data

- Using LFTTD, compute route for each transaction from origin port to U.S. port Details

  - customs records include all intermediate stops if vessel loads cargo for the U.S.
  - e.g., La Spezia - Barcelona - New York - Houston

Adding in the Weather Data



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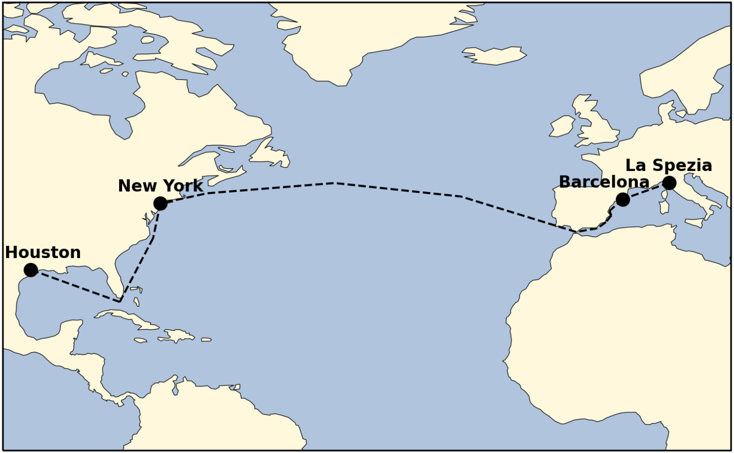

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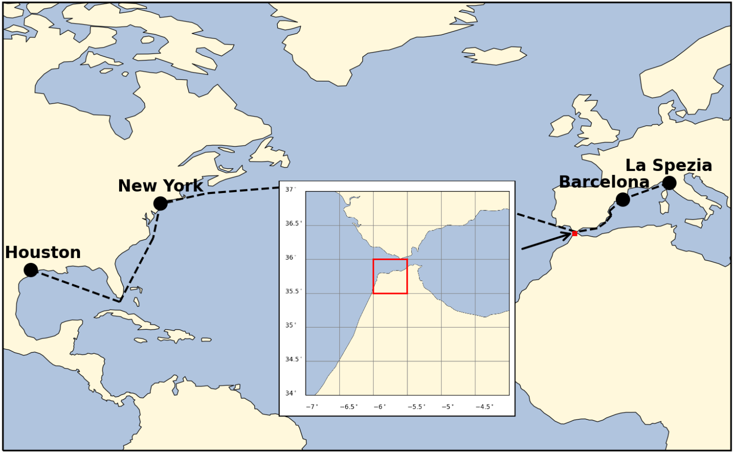

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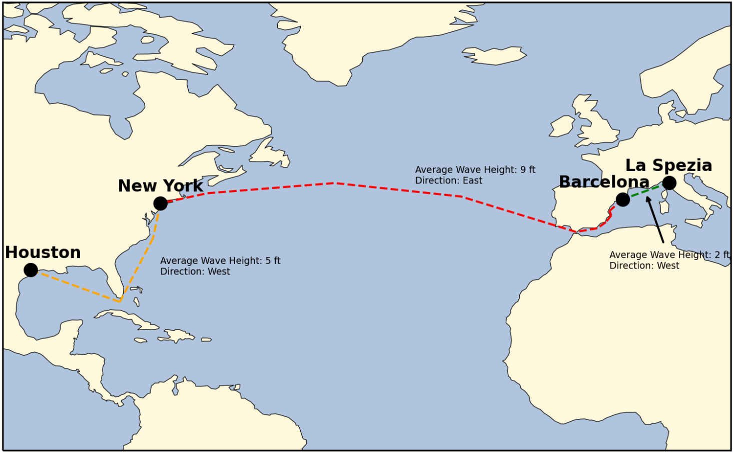

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- Compute average weather for each trip segment
  - e.g., if La Spezia (11/6) and Barcelona (11/11), average over these 6 days
- Compute average across all segments of a trip

Delays and Firm Outcomes

Shipping Time Risk

1. Do delayed shipments adversely affect importers?
2. Do importers actively manage shipping time risk?

Shipping Time Risk

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2. Do importers actively manage shipping time risk?

Constructing Shipping Delays

1. Construct residualized shipping time within product-route (h, r)

$$\hat{t}^{s}_{xhrtvfa} = \ln(T^{s}_{xhrtvfa}) + \hat{\eta}\ln(C^{s}) - \hat{\rho}\ln(W^{s}) - \bar{\theta}_t - \bar{\xi}_v - \bar{\delta}_f - \bar{\omega}_a - \bar{\pi}_x$$

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3. Set delay indicator $\mathbb{D}^s_{xhrtvfa} = 1$ if deviation is above 95th percentile

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3. Set delay indicator $\mathbb{D}^s_{xhrtvfa} = 1$ if deviation is above 95th percentile
4. Scale with total input costs (including domestic):

$$FracDelayed_{ft} = \frac{\sum_{x,h,r,v,a}[\mathbb{D}^s_{xhrtvfa} \cdot \text{Imp Value}_{xhrtvfa}]}{\text{Total Input costs}_{ft}}$$

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5. Instrument with weather in the IV regressions

Constructing the Weather Instrument

- Regress residualized times on weather conditions and route FE

$$\begin{aligned}\hat{t}^{s}_{xhrtvfa} &= \beta_1 \cdot \text{WaveHeight}^{s} + \beta_2 \cdot \text{Direction}^{s} \\ &\quad + \beta_3 \cdot \text{WaveHeight}^{s} \cdot \text{Direction}^{s} + \bar{\gamma}_r + \epsilon^{s}_{xhrtvfa}\end{aligned}$$

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- Use predicted variable and construct $FracDelayed^{weather}_{ft}$ as before

Table: Effects of Weather on Shipping Time

Dep. Var:	$\hat{t}^s_{xhrtvfa}$
Wave Height^s	-0.0330^{***}
	(0.0006)
Direction^s	-0.0002^{***}
	(0.0000)
Wave Height$^s \times$	0.00003^{***}
Direction^s	(0.0000)
Route FE	Y
Observations	5,774,000

- Higher waves increase vessel speed (consistent with Filtz et al., 2015)
- Tail wind marginally increases vessel speed

Effect of Delays on Firm Outcomes

- We estimate the following regression with firms' outcomes:

$$\ln(Y_{ft}) = \beta_1 \mathit{FracDelayed}_{ft} + \gamma_f + \rho_t + \epsilon_{ft}$$

  - Y_{ft} = sales, profits (sales − materials − labor costs), or number of employees

- Run OLS and instrumented with $\mathit{FracDelayed}_{ft}^{weather}$

Weather Delays Reduce Firm Performance

	(1)	(2)	(3)
		Weather IV	
Dependent Variable:	**ln(Sales)**	ln(Profits)	ln(Employees)
Frac Delayed	$-\mathbf{6.131}^{***}$	-3.307^{**}	-0.816^{*}
	$(-\mathbf{2.056})$	(-1.651)	(-0.420)
Importer FE	**Y**	Y	Y
Year FE	**Y**	Y	Y
F-Stat	**19.53**	19.53	19.53
Observations	$\mathbf{142,000}$	$142,000$	$142,000$

- Increasing $FracDelayed_{ft}$ by 1 std (0.024) lowers
  - **sales by 15%**
  - profits by 8%
  - workers by 2%

OLS Regressions

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OLS Regressions

Negative Effects Without Alternate Suppliers

	(1)	(2)	(3)
		Weather IV	
Dependent Variable:	ln(Sales)	ln(Profits)	ln(Employees)
Frac Delayed (Alt)	-4.024^{*}	-1.579	-0.396
	(-2.062)	(-1.359)	(-0.431)
Frac Delayed (NoAlt)	$-\mathbf{8.317}^{**}$	$-\mathbf{5.755}^{*}$	$-\mathbf{1.271}^{**}$
	(-3.403)	**(-3.344)**	**(-0.623)**
Importer FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	$142,000$	$142,000$	$142,000$

- Negative effects are significantly worse for products for which the firm does not have alternative suppliers

Shipping Risk and Import Demand

Shipping Time Risk

1. Do delayed shipments adversely affect importers?

2. **Do importers actively manage shipping time risk?**

Strategy:

- Compute risk for each supplier-product-route cell
- Do importers facing riskier supplier-product-routes in the past adjust sourcing today?

Computing Weather Risk

1. Construct residualized time within supplier-product-route (x, h, r)

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2. Regress $\hat{t}^{s}_{xhrtvfa}$ on weather conditions and route FE and get $\hat{t}^{s,weather}_{xhrtvfa}$

Computing Weather Risk

1. Construct residualized time within supplier-product-route (x, h, r)

$$\hat{t}^s_{xhrtvfa} = \ln(T^s_{xhrtvfa}) + \hat{\eta}\ln(C^s) - \hat{\rho}\ln(W^s) - \bar{\theta}_t - \bar{\xi}_v - \bar{\delta}_f - \bar{\omega}_a$$

2. Regress $\hat{t}^s_{xhrtvfa}$ on weather conditions and route FE and get $\hat{t}^{s,weather}_{xhrtvfa}$

3. Compute mean and standard deviation of $\hat{t}^{s,weather}_{xhrtvfa}$ for each (x, h, r) cell in each year using three-year rolling windows

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4. Aggregate to the importer-product-year level across all exporters and routes, using all imports over the past three years
   - Non-vessel transactions have zero risk

Risk Exposure and Import Demand

Main specification:

$$\ln(Y_{fht}) = \beta_1 \ln(\widehat{StdTime}^{weather}_{fht-3,t-1}) + \beta_2 X_{fht} + \gamma_h + \gamma_t + \gamma_f + \epsilon_{fht}$$

- Y_{fht}: Variable of interest, e.g., number of suppliers
- $\widehat{StdTime}^{weather}_{fht-3,t-1}$: weighted average of risk across all routes and suppliers
- X_{fht}: Weighted avg. shipping time across suppliers and routes in $t-3$ to $t-1$

  Unit value

  Sum of value shipped by suppliers in $t-3$ to $t-1$

  Sum of value imported in $t-3$ to $t-1$

Effect of Risk on Import Demand: Extensive Margin

	(1)	(2)	(3)	(4)
	Weather IV			
Dep. Var.:	**ln(Number of Suppliers)**	ln(Number of Routes)	ln(HHI over Suppliers)	ln(HHI over Supplier-Routes)
Std Time	**0.077***** **(−0.008)**	0.123*** (−0.009)	−0.052*** (−0.003)	−0.074*** (−0.003)
Importer FE	**Y**	Y	Y	Y
Product FE	**Y**	Y	Y	Y
Year FE	**Y**	Y	Y	Y
Controls	**Y**	Y	Y	Y
Observations	**72,500**	72,500	72,500	72,500

- Going from 25th to 75th percentile of risk distribution (0.61 log points) increases
  - **number of suppliers by 4.7%**
  - number of routes by 7.5%

OLS Regressions Inventories

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Std Time	0.077^{***}	$\mathbf{0.123}^{***}$	-0.052^{***}	-0.074^{***}
	(-0.008)	$(-\mathbf{0.009})$	(-0.003)	(-0.003)
Importer FE	Y	**Y**	Y	Y
Product FE	Y	**Y**	Y	Y
Year FE	Y	**Y**	Y	Y
Controls	Y	**Y**	Y	Y
Observations	72,500	**72,500**	72,500	72,500

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  - **number of routes by 7.5%**

OLS Regressions Inventories

Effect of Risk on Import Demand: Intensive Margin

	(1)	(2)
	Weather IV	
Dep. Var.:	**Value per Supplier-Year**	Value Imported per Year
Std Time	$-\mathbf{0.163}^{***}$	-0.086^{***}
	$(-\mathbf{0.011})$	(-0.012)
Importer FE	**Y**	Y
Product FE	**Y**	Y
Year FE	**Y**	Y
Controls	**Y**	Y
Observations	**72,500**	$72,500$

- Going from 25th to 75th percentile of risk distribution (0.61 log points) lowers
  - **value imported per supplier by 9.9%**
  - total value imported by 5.3%

OLS Regressions | Inventories | Using Air Shipments

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Std Time	-0.163^{***}	$-\mathbf{0.086}^{***}$
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Importer FE	Y	**Y**
Product FE	Y	**Y**
Year FE	Y	**Y**
Controls	Y	**Y**
Observations	$72,500$	$\mathbf{72,500}$

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OLS Regressions Inventories Using Air Shipments

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- Key departure from literature: shipping time and thus input qualities are stochastic.

Input Sourcing With Supply Chain Risk

- Assume production uses labor, domestic input, and a CES aggregator of foreign inputs:

$$\tilde{y} = \varphi l^{1-\gamma} \left((x_D)^{\frac{\varepsilon-1}{\varepsilon}} + \left(\sum_{i=1}^{N} (\alpha_i x_i)^{\frac{\kappa-1}{\kappa}} \right)^{\frac{\kappa}{\kappa-1}\frac{\varepsilon-1}{\varepsilon}} \right)^{\gamma \frac{\varepsilon}{\varepsilon-1}}$$

  where φ is productivity, N is number of foreign suppliers, α_i is the **stochastic** input quality

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$$\alpha_i = days_i^{-\tau}$$

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- Two stages of production
  1. Under uncertainty, firm chooses x, x_D and N
  2. After shipments arrive, firm chooses l

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- Find risk aversion ρ that matches the risk elasticities ($\rho = 9$)
- Implied Certainty Equivalent ranges between 16-20 days, on average 17
  - U.S. importers would choose, in order to avoid supply chain risk, to increase their shipping times from 16 to 16-20 days (up to 25%)

Conclusion

- We analyze a new measure of supply chain risk: the volatility of ocean shipping times
- We find that firms diversify risk across suppliers, routes and modes
  - Shipping delays $\Rightarrow$ Sales and employment $\downarrow$
  - Higher shipping time volatility $\Rightarrow$ Number suppliers $\uparrow$, imports $\downarrow$
- Incorporate risky delivery times into standard sourcing model
  - We need risk aversion to match the data
  - Importers would accept an increase in shipping times of up to 25% to avoid risk
  - Climate change may worsen the negative effects

Appendix

FRB New York Survey 2021 Return

QUESTION 9

What have you done and/or planned to do to mitigate the effects of supply disruptions?

Please check all that apply

	Business Leaders Survey	Empire State Manufacturing Survey
	Percentage of Respondents	Percentage of Respondents
Build extra inventories	43.1	58.1
Make do without some inputs	35.8	11.0
Switch to existing backup supplier(s)	25.8	41.2
Find new suppliers	42.4	58.8
Source more goods from U.S. as opposed to foreign suppliers	7.3	11.8
Acquire upstream suppliers	0.7	2.2
Other	12.6	10.3

FRB New York Survey 2021 Return

QUESTION 7

Which of these, if any, have contributed to the disruptions in 2020 and thus far in 2021?

Please check all that apply

	Business Leaders Survey		Empire State Manufacturing Survey	
	Thus Far in 2021	In 2020	Thus Far in 2021	In 2020
Shipping delays (at the ports)	29.1	36.4	34.6	42.7
Trucking delays	39.1	43.1	41.2	47.8
Rail delays	7.3	8.6	2.9	2.9
Air delays	11.3	11.9	10.3	17.7
Domestic suppliers shut down or have limited supplies	50.3	66.2	60.3	76.5
Foreign suppliers shut down or have limited supplies	30.5	46.4	30.9	44.9
Other	7.3	8.6	8.1	6.6

Summary Statistics

Table: Summary Statistics

	All	**Vessel Only**
Total Imports (\$*Bill*)	10,540	4,250
Unique Importers (f)	171,400	92,300
Unique Exporters (x)	815,000	407,400
Number of Transactions (millions)	109	35.8
Number of U.S. Ports of Entry (p_i)		302
Number of Foreign Ports (p_e)		1,795
Number of Origin-Destination Port Pairs		43,080
Unique Vessels (v)		401,700

Return

Factors Affecting Shipping Times

Dep. Var.: Log Shipping Times	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Q2	-0.028^{***}		0.321^{***}	0.362^{***}			
	(0.000)		(0.001)	(0.000)			
Q3	-0.029^{***}		0.490^{***}	0.558^{***}			
	(0.000)		(0.001)	(0.000)			
Q4	-0.020^{***}		0.801^{***}	0.894^{***}			
	(0.000)		(0.001)	(0.000)			
Related-Party		0.014^{**}					
		(0.000)					
Log Shipment Weight					0.008^{***}		0.010^{*}
					(0.000)		(0.00
Log Shipping Charges						0.004^{***}	-0.003
						(0.000)	(0.00
R^2	0.616	0.616	0.808	0.824	0.616	0.616	0.61
Route FE	Y	Y	Y	Y	Y	Y	Y
Observations (thousands)	35,480	35,480	1,017	2,844	35,480	35,480	35,48

- Significant heterogeneity in shipping times across buyers and vessels
- Shipping times are slower in the winter, for related-party transactions, and for heavier shipments

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Attributes of Importer-Product-Year Tuples

Table: Attributes of Importer-Product-Year Tuples

	All		Vessel Only	
	Mean	Standard Deviation	Mean	Standard Deviation
Suppliers per Importer-Product-Year	1.90	3.84	1.83	2.81
Suppliers per Importer-Product-Country-Year	1.39	1.56	1.39	1.39
Dep. Port-Entry Port Pairs per Importer-Product-Year			2.18	3.18
Dep. Port-Entry Port Pairs per Importer-Product-Country-Year			1.75	1.91
Vessels per Port Combination-Year			16.78	44.94

Source: LFTTD and authors' calculations. Table reports the mean and standard deviation across importer (f) by product (h) by year or importer (f) by product (h) by country (c) by year tuples during our 1992 to 2016 sample period.

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Effect of Extreme Shipping Delays

- Compute for each year the log deviation from the average shipping time for each importer-exporter-HS10-country-port of entry combination.
- Compute the value of transactions whose shipping time is larger than the 99th percentile of deviations in the data ("extreme delays").
- Aggregate this variable at the importer-year level and scale it by the importer's total production costs.

Weather Delays Reduce Firm Performance

	(1)	(2)	(3)
		OLS	
Dependent Variable:	Sales	Profits	Employees
Frac Delayed	-1.982^{***}	-0.869^{**}	-0.371^{**}
	(-0.387)	(-0.351)	(-0.173)
Importer FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	$142,000$	$142,000$	$142,000$

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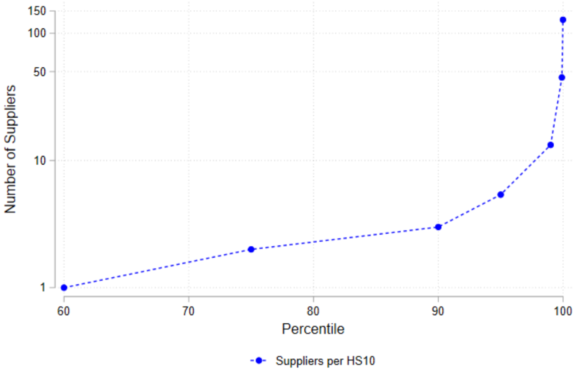
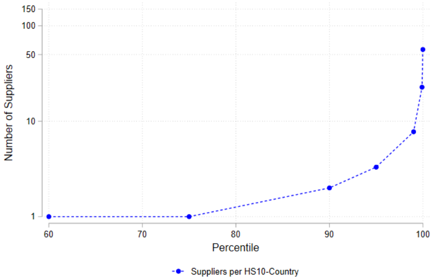
Importers Have Multiple Suppliers



- Average importer has 1.9 suppliers per product-year
  - But firms sourcing from more than one supplier account for 90% of imports
- Could part of the reason be risk diversification?

Importers within HS-Country Detailed Statistics

Importers Have Several Suppliers



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Effect of Risk on Import Demand: Extensive Margin

	(1)	(2)	(3)	(4)
Dep. Var.:	Number of Suppliers	Number of Routes	HHI over Suppliers	HHI over Supplier-Routes
Std Time	0.053^{***}	0.096^{***}	-0.036^{***}	-0.054^{***}
	(-0.004)	(-0.006)	(-0.002)	(-0.002)
Importer FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	$328,000$	$328,000$	$328,000$	$328,000$

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Effect of Risk on Import Demand: Intensive Margin

	(1)	(2)
Dep. Var.:	ln(Value per Supplier-Year)	ln(Value Imported per Year)
Std Time	-0.151^{***}	-0.098^{***}
	(-0.006)	(-0.007)
Importer FE	Y	Y
Product FE	Y	Y
Year FE	Y	Y
Controls	Y	Y
Observations	$328,000$	$328,000$

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Effect of Risk on Intensive Margin with Inventories

	(1)	(2)	(3)	(4)
Dep. Var.:	Number of Suppliers	Number of Routes	HHI over Suppliers	HHI over Supplier-Routes
Std Time	0.061^{***}	0.114^{***}	-0.039^{***}	-0.059^{***}
	(0.005)	(0.007)	(0.002)	(0.002)
Inventory-Sales Ratio	-0.018	-0.036^{**}	0.000	0.005
	(0.013)	(0.015)	(0.003)	(0.003)
Importer FE	Y	Y	Y	Y
Product FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	237,000	237,000	237,000	237,000

Back

Effect of Risk on Extensive Margin with Inventories

	(1)	(2)
Dep. Var.:	ln(Value per Supplier-Year)	ln(Value Imported per Year)
Std Time	-0.157^{***}	-0.095^{***}
	(0.008)	(0.008)
Inventory-Sales Ratio	-0.063	-0.082
	(0.048)	(0.060)
Importer FE	Y	Y
Product FE	Y	Y
Year FE	Y	Y
Controls	Y	Y
Observations	$237,000$	$237,000$

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Risk Diversification Using Air Shipments

- Firms could use air shipments as an alternative way to diversify risk
- Run regression:

$$Air_{fht} = \beta_1 \ln(\widehat{StdTime}^{weather}_{fht-3,t-1}) + \beta_2 X_{fht} + \gamma_h + \gamma_t + \epsilon_{fht}$$

- Air_{fht} = dummy if air shipments > 0
- $\widehat{StdTime}^{weather}_{fht-3,t-1}$ = risk measure (based on vessel shipments)
- X_{fht} = same controls as before

Risk Diversification by Air

Dep. Var.:	Air Shipments
Std Time	0.009***
	(0.001)
Importer FE	Y
Product FE	Y
Year FE	Y
Controls	Y
Observations	328,000

- Increasing log risk by 1 std (1.009) increases the likelihood of using air by 1 log point

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Construction of Route Measure

Transaction records are noisy, so we iteratively assign transactions to a “trip”, which begins with the loading of cargo at a foreign port and ends with unloading of cargo at U.S. port

1. Sort each vessel’s transactions by foreign departure date and assign to a single trip: “Trip 1”
2. Compare foreign departure date to earliest U.S. arrival. If departure date occurs later, assign to “Trip 2”
   2.1 Repeat until no further sub-trips can be formed
3. Occasionally, arrival dates are misreported. If most recent arrival date is *after* earliest departure date of next trip, recombine two trips into one
4. Resulting dataset contains only non-overlapping departure and arrival dates for every vessel

Return

Shipping Time Risk and Import Demand with Additional Controls

Table: Shipping Time Risk and Import Demand with Inventory-Sales Ratio Control

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	Number of Suppliers	Number of Routes	HHI over Suppliers	HHI over Supplier-Routes	Value per Supplier-Year	Value Imported per Year
Std Time	0.061^{***}	0.114^{***}	-0.039^{***}	-0.059^{***}	-0.157^{***}	-0.095^{***}
	(0.005)	(0.007)	(0.002)	(0.002)	(0.008)	(0.008)
Inventory-	-0.018	-0.036^{**}	0.000	0.005	-0.063	-0.082
Sales Ratio	(0.013)	(0.015)	(0.003)	(0.003)	(0.048)	(0.060)
Importer FE	Y	Y	Y	Y	Y	Y
Product FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	237,000	237,000	237,000	237,000	237,000	237,000

Return