The Price of Delays: Supply Chain Disruptions and Pricing Dynamics

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"Trade, value chains and financial linkages in the global economy"

Motivation

- Supply-chain disruptions surged in 2020–23, as we experienced record inflation.

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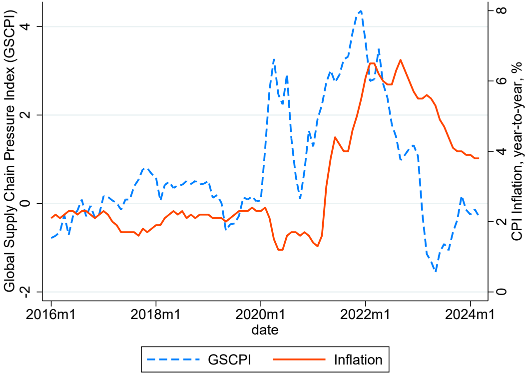

Figure: GSCPI vs. core CPI ex-food & energy

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- Our contribution:
  - Merge firm-level shipment data & consumer prices.
  - Estimate delay vs. cost pass-through & competitor amplification.
  - Simulate contribution of various shocks to realized price dynamics during COVID.

This Paper

- Simple inventory–pricing model with stochastic delays & strategic interactions.
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  - Identification using shift–share exposures and IV.
- Accounting exercise solving for perturbed new equilibrium given cost and delay shocks.

Theory: Pricing with Availability

Overview:

- Simple model: firm sets price with flow demand and stochastic deliveries.
  - Markups adjusted by demand elasticity (σ) and availability wedge (κ/s).
- Extensions: strategic interactions across firms.
  - Rival prices and availability enter via simple indices.

Setup

- Downstream firm sources a ready-made good.
- Chooses log price p ($P = e^p$). Marginal cost c ($MC = e^c$).
- Flow demand: $\lambda(p) = \Lambda e^{-\sigma p}$, decreasing in p.
- Replenishment: random delivery times $\sim \text{Exp}(\mu)$ (mean $1/\mu$).
- Base–stock target $\tau \in \mathbb{N}$.
- Lost-sales setting: unmet demand is not backlogged.

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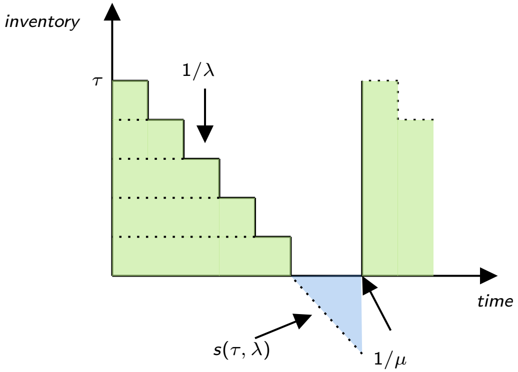
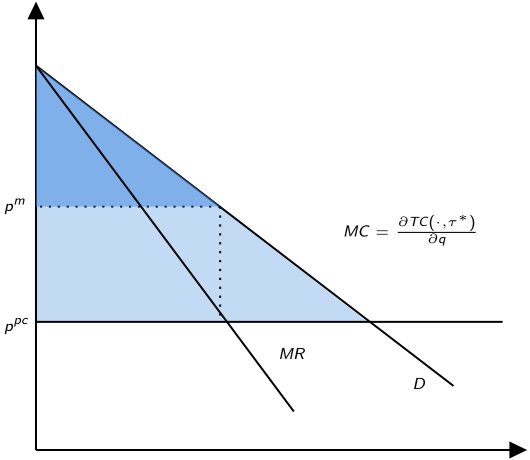


Monopolist Price

- **Objective (baseline):**

$$\max_{p} \; \Pi(p) = (P - MC)\,\lambda(p)$$

$$\lambda(p) = \Lambda e^{-\sigma p}, \quad P = e^{p}, \; MC = e^{c}$$



Monopolist Pricing

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$$\max_{p} \; \Pi(p) = (P - MC)\,\lambda(p)$$

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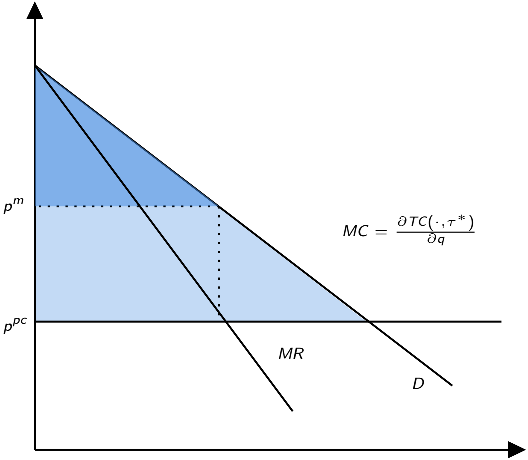
- **Optimal price (Lerner rule):**

$$\frac{P^{*} - MC}{P^{*}} = \frac{1}{\sigma} \quad \Longleftrightarrow \quad p^{*} = c + \ln\left(\frac{\sigma}{\sigma - 1}\right).$$



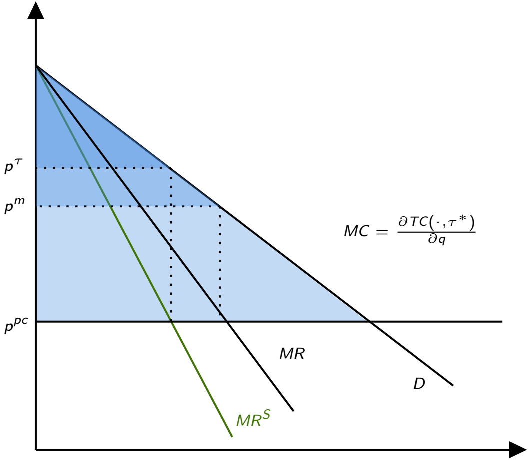
Monopolist Pricing: With deliveries (availability)

- **Objective (with availability):**

$$\max_{p} \; \Pi(p) = (P - MC)\,\lambda(p)\,s(\tau, \lambda, \mu)$$

$$s = 1 - r^{\tau}, \qquad r = \frac{\lambda}{\lambda + \mu}$$

- **Availability:**
  - $\partial s / \partial \lambda < 0$ (higher demand $\Rightarrow$ more congestion).
  - $\partial s / \partial \mu > 0$ (faster delivery $\Rightarrow$ better availability).



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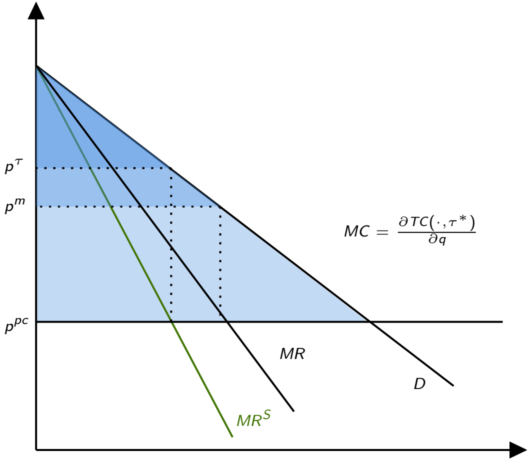
$$\lambda(p) = \Lambda e^{-\sigma p}, \quad r = \tfrac{\lambda}{\lambda+\mu}, \quad s = 1 - r^{\tau}.$$

- **Optimal price (generalized Lerner):**

Inventory choice

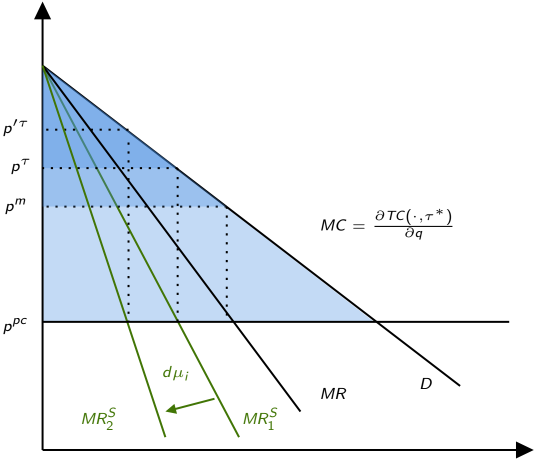
$$\frac{P^* - MC}{P^*} = \frac{1}{\sigma\big(1 + \kappa/s\big)}, \qquad \kappa \equiv \lambda\, \partial_\lambda s < 0.$$

- Interpretation: tighter availability ($s \downarrow$) lowers effective elasticity and raises markups.



Monopolist Price: Comparative Statics

- **Slower delivery ($\mu \downarrow$):**
  - Lower availability s (more stockouts).
  - Markups rise; optimal price p^* increases.
  - Higher value of holding inventory $\Rightarrow$ larger τ^*.
- **Limits:**
  - $\mu \to \infty$: frictionless monopoly, markup $\frac{1}{\sigma}$.
  - $\mu \to 0$: scarcity so severe that further slowdowns barely affect p^*.



From Theory to Empirics: Derivation

- Starting from the firm's **generalized Lerner rule** with availability:

$$\frac{P^* - MC}{P^*} = \frac{1}{\sigma(1 + \kappa/s)}.$$

- Linearizing around an operating point gives a simple decomposition of price changes:

$$dp = \alpha\, dmc + \beta_s\, d\ln s + \varepsilon,$$

  where

$$\alpha = \tfrac{1}{1+\Gamma} \in (0,1), \qquad \beta_s = \tfrac{\Lambda}{1+\Gamma} < 0.$$

- **Intuition:**
  - Cost shocks shift mc and pass through at rate α.
  - Availability shocks ($d\ln s$) affect markups: when stock is scarce, s falls and prices rise.
  - Both channels are dampened by the scarcity feedback Γ.

From Theory to Empirics: Measurement

- **Availability in the data:** Stockouts are not observed directly. We proxy $d \ln s$ with delivery shortfalls S_{it}:

$$\Delta \ln s_{it} \approx -\phi_i S_{it}, \quad \phi_i = \eta_{sI} \times \eta_{IM}.$$

  ($\eta_{sI} > 0$: sensitivity of availability to inventories; η_{IM}: import dependence of inventories.)

- **Cost shocks:** $\Delta mc_{it} \approx \theta_{Mi} \Delta \ln P_t^M + \theta_{Fi} \Delta \ln F_t$.

- **Resulting estimating equation:**

$$\Delta p_{it} = \alpha \left(\theta_{Mi} \Delta \ln P_t^M + \theta_{Fi} \Delta \ln F_t \right) - \beta_s \phi_i S_{it} + FE + \varepsilon_{it}.$$

- **Takeaway:** observed price changes can be decomposed into (i) cost pass-through, and (ii) availability-driven markup adjustment.

Data: new dataset linking prices and shipments

1. **Price** dynamics from Consumer Panel
2. **Shortfalls** from BoL data
3. **Marginal costs:** Freight and import unit cost from Census

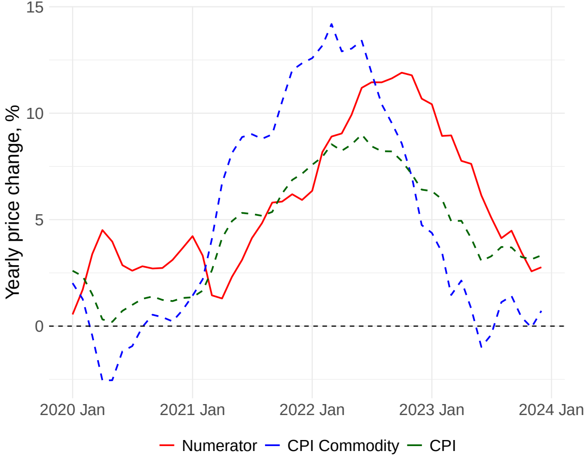
1. New Dataset on Consumption and Prices

Consumer panel (**Numerator**) data: Sum Stats: Stores Sum Stats: Expenditures Sum Stats: Sectors Validation: Flour

- **Source:** Digitized purchase receipts during the 2019-2023 period. App
- **Content:** 1bn receipts digitized, 2.5m users, *400k static users*, 36,680 stores, 120m items, sales, prices.
- **Structure:** Firm/manufacturer, Brand (85k), Parent Brand (64k), Category (3.8k), Department (280), Sector (23).
- Here, **product** = firm × brand × category.
- Construct median product-level price from various receipts in a month.
  - Since no unit prices (lbs, pack size, etc), calculate within-product price changes (and aggregate when needed).

1. New Dataset on Consumption and Prices

Figure: Numerator price growth vs CPI



Notes: The solid red line illustrates the 12-month aggregate price changes derived from Numerator data. We compute median product-level price changes within each category and then aggregate these category-level changes using product category sales weights.

2. US Shipments Data

Bill of lading (**Panjiva**) data:

- **Source:** Legal document between shipper and carrier with detailed shipment info.
- **Content:** Over a billion individual shipments from 17 different sourcing countries from 2007-2023. (issues with redaction, see Flaaen et al. 2023) Panjiva vs. Census
- **Structure:** HS6 code classification from OCR of Bill of Lading.
- **Variables:** quantity, consignee name + location, shipper name + location, HS category, port of entry + shipper. No values (impute w Census).

Delivery Shortfall Measures

Monthly firm-HS-code-level delivery shortfall: percent deviation of the k-weeks moving average of imports $D_{f,j,t}$ from their 2019 counterpart. f- firm, j- HS2 code, t- month.

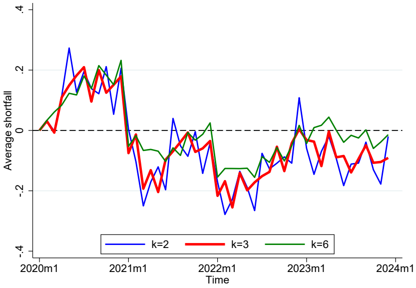
$$DeliveryShortfall_{f,j,t(k)} = 2\frac{\sum_{m=t-k}^{t} D_{f,j,m} - \sum_{m=t-k,2019}^{t,2019} D_{f,j,m}}{\sum_{m=t-k}^{t} D_{f,j,m} + \sum_{m=t-k,2019}^{t,2019} D_{f,j,m}}.$$

Firm-level delivery shortfall:

$$DeliveryShortfall_{f,t(k)} = \sum_{j} s_{fj}^{2019} DeliveryShortfall_{f,j,t(k)}.$$

US Shipments Data

Figure: Average Delivery Shortfall Over Time



Notes: Weighted firm-level shortfalls over time. Panjiva sample. Weights are firm-level total annual imports.

Combining Panjiva and Numerator Datasets

Merged Data

- Merge: Panjiva consignees $\longleftrightarrow$ Numerator manufacturers/brands
  - Firm–month shortfalls + price changes
  - Covers 43% product-month obs (50% of sales) Sourcing partners

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Stylized Facts: 2020-2023

→ Large heterogeneity in delivery shortfalls and price growth across:
  - Product groups/sectors. here
  - Firms. here

→ Price increases larger for bigger firms. here

→ Price increases smaller for firms with more diversified supply chains. here

3. Marginal Cost Shocks

Marginal cost components ΔMC:

- Import unit cost ($\Delta UnitCost$)
- Freight cost ($\Delta FreightCost$)

3. Marginal Cost Shocks: Import Unit Costs

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- Import unit cost across HS2
  - Unit costs from US Trade Online (Census)
- Freight cost at US Ports

Unit Cost Exposure

$$\Delta \text{UnitCostExp}_{f,t} = \sum_h \omega_{h,f,2019} \, \Delta \text{UnitCost}_{h,t}$$

$\omega_{h,f,2019}$	Firm f's 2019 HS2 import share
$\Delta \text{UnitCost}_{h,t}$	12-mo log change in HS-level unit cost

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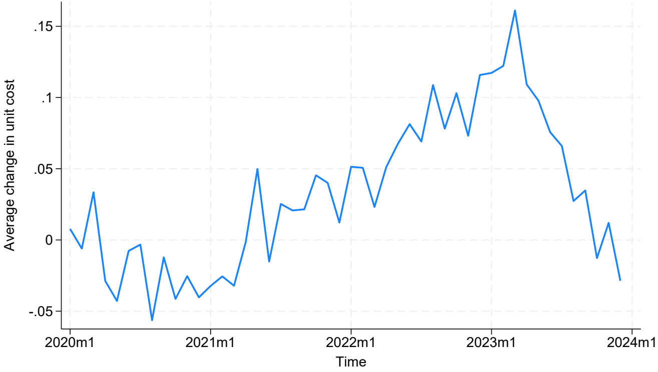

Figure: Marginal Cost Changes: Unit Values

Notes: Weighted average of firm-level change in unit value ratio over time. Panjiva firms. Weights are firm-level annual total imports.

3. Marginal Cost Shocks: Freight Costs

Marginal cost components ΔMC:

- Import unit cost across HS2
- Freight cost at US Ports
  - CIF value/Custom value (Census)

Freight Cost Exposure

$$\Delta \text{FreightCostExp}_{f,t} = \sum_p \omega_{p,f,2019} \, \Delta \text{FreightCost}_{p,t}$$

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$\Delta \text{FreightCost}_{p,t}$	12-mo log change in port-level freight cost

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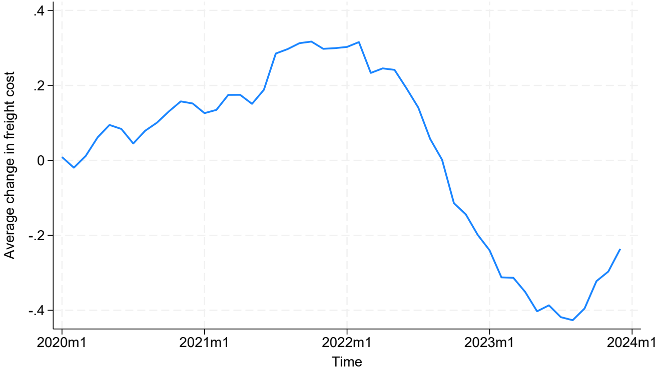

Figure: Marginal Cost Changes: Average Freight Cost Ratios

Notes: Weighted average of firm-level freight cost ratio over time. Panjiva firms. Weights are firm-level annual total imports.

Empirics: estimating pass-throughs

Estimating Equation: Own Pass-Through

$$\Delta \text{Price}_{p,f,t} = \phi_s \underbrace{\textit{Shortfall}_{f,t(k)}}_{\substack{\text{own}\\ \text{availability}}} + \phi_M \underbrace{\Delta \textit{UnitC}_{f,t}}_{\substack{\text{own}\\ \text{import cost}}} + \phi_F \underbrace{\Delta \textit{FreightC}_{f,t}}_{\substack{\text{own}\\ \text{freight cost}}} + \theta_f + \theta_{j(p),q(t)} + \epsilon_{p,f,t}$$

- $\textit{Shortfall}_{f,t(k)}$: k-month cumulative import shortfall vs. 2019 baseline.
- $\Delta \textit{UnitC}_{f,t}, \Delta \textit{FreightC}_{f,t}$: firm exposures to import and freight cost changes.
- θ_f: firm FE .
- $\theta_{j(p),q(t)}$: product–category $\times$ quarter FE
- ϕ_s: availability channel (> 0).
- ϕ_M, ϕ_F: cost pass-through ($= \alpha\theta_M,\ \alpha\theta_F$).

(*Read as elasticities:* cost exposures and shortfalls are scaled so coefficients are pass-through elasticities.)

Identification. Delivery Shortfalls

OLS: bias:

- Endogeneity: Demand shocks $\uparrow$ both ΔPrice and *Shortfall*
    - Firms adjust shipments in anticipation of price moves (simultaneity)
- Aggregate demand shocks: product-market-time f.e.
- Firm-level demand shocks: IV.

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IV for Shortfall:

1. Shortfall exposure;
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Firm Shortfalls Exposure

Delivery shortfall exposure combines external HS2-code shocks with firm's 2019 import shares:

$$\text{Exposure}_{f,t(k)} = \sum_{h \in S^{HS2}} \omega_{h,f,2019} \times \mathit{Shortfall}_{h,t(k)_{-f}}$$

$h \in S^{HS2}$	HS2 codes
$\mathit{Shortfall}_{h,t(k)_{-f}}$	Leave-out delivery shortfall for code h
$\omega_{h,f,2019}$	Firm f's 2019 HS2 import share

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   Collected from vessel-location data (Fuchs and Wong, 2025) Details

Port Dwell Time Exposure

$$\text{DwellExp}_{f,t} = \sum_p \omega_{p,f,2019} \times \Delta\text{DwellTime}_{p,t}$$

$\Delta\text{DwellTime}_{p,t}$ Change in log port-level dwell time (residualized)

$\omega_{p,f,2019}$ Firm f's 2019 port share

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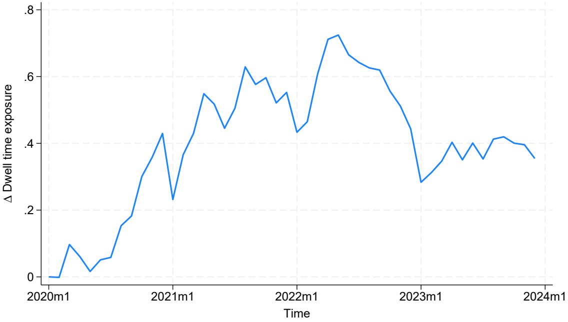

Figure: Average Dwell Time Exposure Over Time

Notes: Weighted firm-level dwell time exposure over time. Panjiva sample. Weights are firm-level total annual imports.

1. Estimating Pass-Through. Own Disruptions

1. *Significant pass-through from delivery shortfalls and cost shocks to prices.*

Table: Price Effects of Own Supply Chain Disruptions. Baseline Pass-Through Estimates

	ΔP (OLS)	ΔP (OLS-Shift Share)	ΔP (IV)	ΔP (IV)	ΔP (IV)
Shortfall	0.006	0.108***	0.211***	0.241***	0.267***
	(0.0047)	(0.0378)	(0.0770)	(0.0795)	(0.0853)
$\Delta UnitC$	0.151**	0.152**	0.146**	0.037	0.032
	(0.0607)	(0.0607)	(0.0613)	(0.0670)	(0.0671)
$\Delta FreightC$	0.097**	0.104**	0.154***	0.028	0.033
	(0.0437)	(0.0438)	(0.0496)	(0.0585)	(0.0591)
Lag Shortfall				-0.050	-0.041
				(0.0761)	(0.0745)
Lag $\Delta UnitC$				0.214***	0.218***
				(0.0674)	(0.0673)
Lag $\Delta FreightC$				0.230***	0.231***
				(0.0552)	(0.0552)
Firm FE	✓	✓	✓	✓	✓
Cat-Quarter FE	✓	✓	✓	✓	✓
Observations	969539	969539	968175	939819	939819
Weak IV F-stat			371.986	124.526	118.615

Notes: The table reports regressions of 12-month price changes on measures of own supply chain disruptions, estimated using product-month-level Numerator–Panjiva matched data for 2020–2023. Column (1) uses the *Shortfall* measure in OLS; Column (2) uses the *Shortfall Exposure* measure instead; the remaining columns report IV estimates using *Shortfall Exposure* and *Dwell Time Exposure* as instruments. Column (5) additionally includes an import

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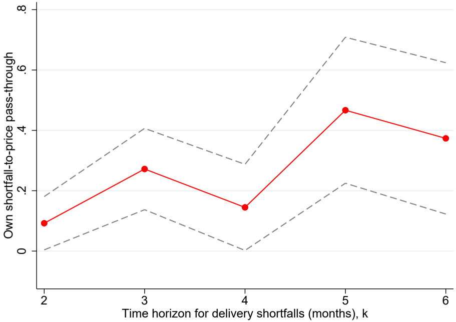
Horizons of delivery shortfalls

$$\Delta \ln \text{ Price }_{p,f,t} = \beta_k \ \widehat{\text{DeliveryShortfall}}_{f,t(k)} + ...,$$

for various *k*-weeks moving averages.



Notes: Coefficients from the separate regressions of 12-month price changes at the product level on firm-level delivery delays in moving averages at different horizons. Robust se clustered at the category-quarter level.

Generalizing with Strategic Interactions

- **Extension:** Firms set prices considering both own costs/availability and rivals' conditions (cf. Amiti–Itskhoki–Konings 2019).
- **Best response:** Each firm's optimal price is a fixed point:

$$\tilde{p}_{it} = mc_{it} + \mathcal{M}_i(\tilde{p}_{it}, \tilde{\tau}_{it}, \boldsymbol{p}_{-it}, \boldsymbol{\tau}_{-it}; \boldsymbol{\xi}_t).$$

- **Implication:** Markups depend on own demand & availability plus sectoral price and availability indices shaped by rivals.

Price Change Decomposition with Rivals

(Equilibrium) Price Change with Strategic Interactions

$$\Delta p_{it} = \underbrace{\tfrac{1}{1+\Gamma_{it}}}_{\alpha}\,\Delta mc_{it} + \underbrace{\tfrac{\Lambda_{it}}{1+\Gamma_{it}}}_{\beta}\,\Delta\tau_{it} + \underbrace{\tfrac{\Gamma_{-it}}{1+\Gamma_{it}}\,\bar{\alpha}_{-it}}_{\gamma^{mc}}\,\Delta mc_{-it} + \underbrace{\left(\tfrac{\Lambda_{-it}}{1+\Gamma_{it}} + \tfrac{\Gamma_{-it}}{1+\Gamma_{it}}\,\bar{\beta}_{-it}\right)}_{\delta^{\tau}}\,\Delta\tau_{-it} + \varepsilon_{it}$$

- **Own effects:** $\alpha =$ pass-through of own costs; $\beta =$ effect of own availability.
- **Rival effects:** $\gamma^{mc} =$ spillover from rivals' cost shocks; $\delta^{\tau} =$ spillover from rivals' availability (direct + via rivals' pricing).

- Competitor indices:

$$\Delta mc_{-it},\ \Delta\tau_{-it}$$

  are share-weighted averages of rivals in the same market.

Estimating Pass-Through: Strategic Interactions

$$\Delta\text{Price}_{p,f,t} = \underbrace{\phi_s\, \textit{Shortfall}_{f,t(k)}}_{\text{own shortfall}} + \underbrace{\phi_M\, \Delta \textit{UnitC}_{f,t} + \phi_F\, \Delta \textit{FreightC}_{f,t}}_{\text{own cost}}$$

$$+ \underbrace{\psi_s\, \textit{Shortfall}_{-f,\,j(p),\,t(k)}}_{\text{rivals' shortfall}} + \underbrace{\psi_M\, \Delta \textit{UnitC}_{-f,\,j(p),\,t} + \psi_F\, \Delta \textit{FreightC}_{-f,\,j(p),\,t}}_{\text{rivals' cost}}$$

$$+ \theta_f + \theta_{j(p),q(t)} + \epsilon_{p,f,t}$$

- **Rival indices** $X_{-f,\,j,\,t}$: leave–one–out, revenue–share–weighted averages within market j:

$$X_{-f,\,j,\,t} = \sum_{g \neq f} \omega_{fg,t}\, X_{g,t}, \quad \omega_{fg,t} = \frac{S_{gjt}}{1 - S_{fjt}}.$$

- Own variables as in baseline; k-month shortfall is cumulative vs. 2019.

- **Mapping:** ϕ_s (availability), ϕ_M, ϕ_F (own cost pass-through); ψ_s (rivals' availability spillover), ψ_M, ψ_F (rivals' cost spillover).
- **Fixed effects:** θ_f (firm), $\theta_{j(p),q(t)}$ (category×quarter).
- **Read as elasticities:** cost exposures and shortfalls are scaled so coefficients are pass-through elasticities.

2. Estimating Pass-Through. Strategic interactions

2. *Competitors' shortfalls important for own prices (incl. for unaffected firms).*

	Importing firms			*All firms*
	OLS	OLS-Shift Share	IV	IV
Shortfall	0.005	0.112***	0.221***	0.322***
	(0.0048)	(0.0379)	(0.0768)	(0.0591)
$\Delta UnitC$	0.155**	0.157***	0.151**	0.270***
	(0.0608)	(0.0608)	(0.0613)	(0.0549)
$\Delta FreightC$	0.098**	0.105**	0.159***	0.066**
	(0.0438)	(0.0439)	(0.0498)	(0.0331)
Shortfall, compet	-0.003	-0.007	0.122***	0.133***
	(0.0132)	(0.0130)	(0.0464)	(0.0286)
$\Delta UnitC$, compet	0.351**	0.349**	0.346**	0.366***
	(0.1626)	(0.1625)	(0.1637)	(0.1314)
$\Delta FreightC$, compet	0.194*	0.212**	0.234**	0.069
	(0.1037)	(0.1039)	(0.1053)	(0.0806)
Firm FE	✓	✓	✓	✓
Cat-Quarter FE	✓	✓	✓	✓
Observations	962815	962815	961451	1671773
Weak IV F-stat			387.074	705.376

Notes: The table reports regressions of 12-month price changes on measures of own and competitor's supply chain disruptions, estimated using product-month-level data. Columns (1)-(3) use Numerator–Panjiva matched data for 2020–2023, while column (4) also adds non-importing firms that do not ever match to Panjiva. Column (1) uses the *Shortfall* measure in OLS; Column (2) uses the *Shortfall Exposure* measure instead; the remaining columns report IV estimates using *Shortfall Exposure* and *Dwell Time Exposure* as instruments for *Shortfall*. All specifications include import dummy and firm- and product category–quarter fixed effects. Standard errors, clustered at the product category–quarter level, are reported in parentheses. ***, **, *: significance at the 1%, 5%, 10% levels, respectively.

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Aggregate implications

Quantification Methodology

Equilibrium Pricing Rule

$$\Delta \mathbf{p} = (I - \gamma W)^{-1} \left[\alpha \, \Delta \mathbf{mc} \; - \; \beta \, \Delta \boldsymbol{\tau} \; + \; \delta \, W \, \Delta \boldsymbol{\tau} \right]$$

where $W_{ij} = S_j / (1 - S_i)$ captures competitor shares.

Quantification Methodology

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- **Step 1:** Gather monthly firm-level $\{ \, \Delta mc_i, \, \Delta \tau_i, \, S_i$, CPI weights$\}$.
- **Step 2:** Compute $\Delta \hat{\mathbf{p}} = (I - \gamma W)^{-1} [\alpha \, \Delta mc - \beta \, \Delta \tau + \delta \, W \, \Delta \tau]$.

Quantification Methodology

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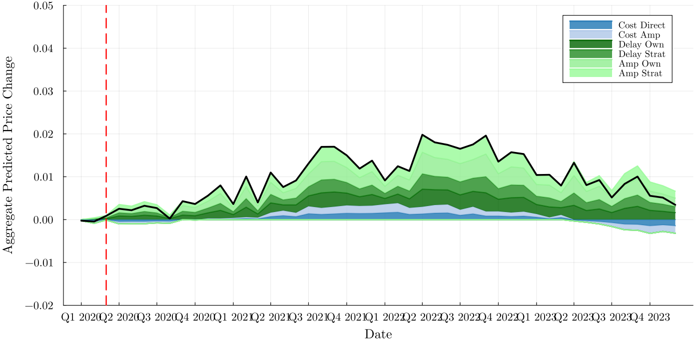
- **Step 2:** Compute $\Delta\hat{\mathbf{p}} = (I - \gamma W)^{-1}[\alpha\, \Delta mc - \beta\, \Delta\tau + \delta\, W\, \Delta\tau]$.
- **Step 3:** Decompose each $\Delta\hat{p}_i$:

$$\Delta p = \underbrace{\alpha \Delta mc}_{\text{Cost direct}} + \underbrace{(X - I)\, \alpha \Delta mc}_{\text{Cost amplification}} + \underbrace{\left[-\beta \Delta\tau + \delta W \Delta\tau\right]}_{\text{Delay direct (own+strategic)}} + \underbrace{\left[X - I\right]\left[-\beta \Delta\tau + \delta W \Delta\tau\right]}_{\text{Delay amplification}} \tag{1}$$

The role of supply chain disruptions in COVID inflation surge

Supply chain disruptions contributed to the recent inflation surge: 95% in 2020; 15% in 2021; 4% in 2022.



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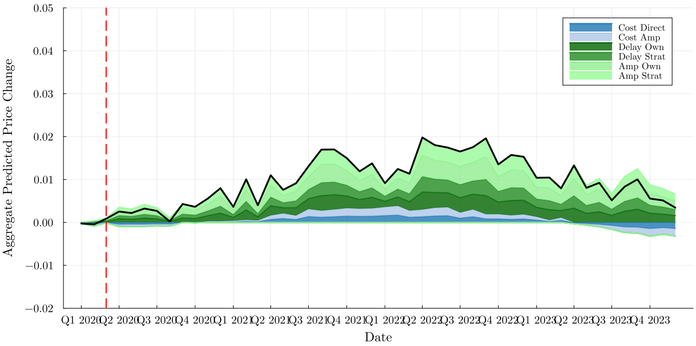

Delay channel:

- Most of the effect in 2020 (lockdowns, SC bottlenecks);
- Some after reopening (port congestion during high demand).

Cost channel:

- Mostly, contributed in the 2021-2022 period.

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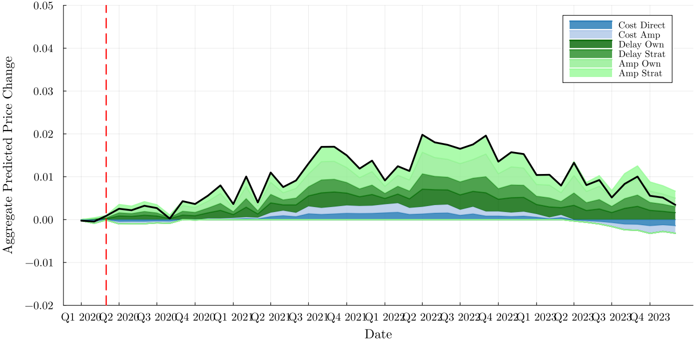

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- Most of the effect in 2020 (lockdowns, SC bottlenecks);
- Some after reopening (port congestion during high demand).

Cost channel:

- Mostly, contributed in the 2021-2022 period.

Strategic amplification doubled the direct incidence on firms.

Conclusions

- New micro evidence: firm-level delivery shortfalls and import & freight costs raise consumer prices.
- **Model link:** simple inventory–pricing framework with stochastic replenishment $\rightarrow$ generalized Lerner rule and availability channel.
- **Spillovers:** competitors' disruptions also raise prices by shifting sectoral costs and availability. **Main Findings**
  - Own shocks: costs pass through at rate α; shortfalls increase markups ($\phi_s > 0$).
  - Rival shocks: higher competitor costs and tighter availability spill over to raise firm prices.

Appendix

Inventory Choice (backup)

back

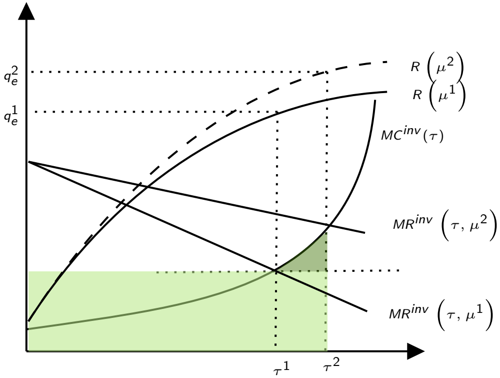
- **Inventory decision:** choose base–stock τ to balance

$$\max_{\tau} \,(P - MC)\,\lambda(p)\,s(\tau,\lambda,\mu) - h\,\mathbb{E}[I(\tau,\lambda,\mu)].$$

- **Condition:**

$$(P^* - MC)\,\lambda\,r^{\tau^*}(1-r) = h\,(1-r^{\tau^*+1}), \quad r = \frac{\lambda}{\lambda+\mu}.$$

- **Comparative statics (see figure):** slower deliveries $(\mu\downarrow) \Rightarrow$ higher τ^*; faster deliveries $(\mu\uparrow) \Rightarrow$ lower τ^*.



Identification: All Instruments

2SLS Specification

$$\Delta \text{Price}_{p,f,t} = \beta\, \widehat{\mathit{Shortfall}}_{f,t(k)} + \gamma\, \widehat{\Delta MC}_{f,t} + \delta\, \widehat{\mathit{Shortfall}}_{-f,t(k)} + \zeta\, \widehat{\Delta MC}_{-f,t} + \alpha_f + \alpha_{j(p),q(t)} + \epsilon_{p,f,t}$$

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Shortfall IVs

- Shortfall shift–share exposure: $\sum_h Shortfall_{h,t(k)_{-f}}\, \omega_{h,f,2019}$
- Dwell time exposure: $\sum_p \Delta DwellTime_{p,t}\, \omega_{p,f,2019}$
- $Shortfall_{-f,t(k)} \rightarrow$ $$\sum_{j \neq f} \frac{S_j}{1 - S_f} \left(\sum_h Shortfall_{h,t(k)_{-j}} \omega_{h,j,2019} \right)$$

Identification: All Instruments

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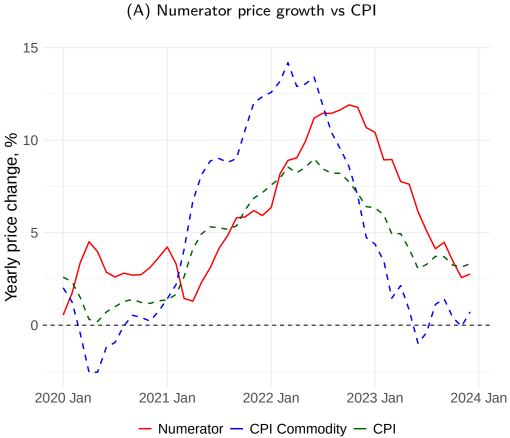
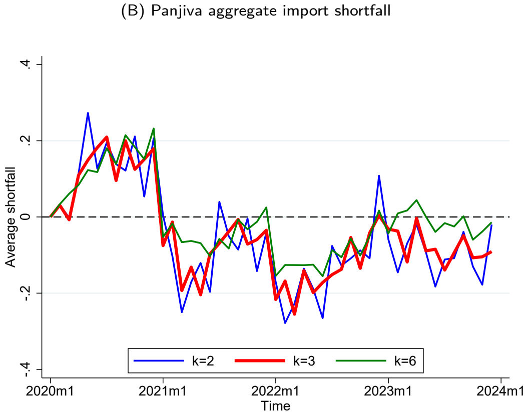
ΔMC

- Unit cost exposure: $\sum_h \Delta UnitCost_{h,t}\, \omega_{h,f,2019}$
- Freight cost exposure: $\sum_p \Delta FreightCost_{p,t}\, \omega_{p,f,2019}$
- $\Delta MC_{-f,t} \rightarrow$ $\sum_{j \neq f} \frac{S_j}{1 - S_f} \left(\sum_h \Delta UnitCost_{h,t}\, \omega_{h,j,2019} \right)$
- Scale all variables with input import share (Census).

Fact 1: Shortfall in imports and increase in prices

Back



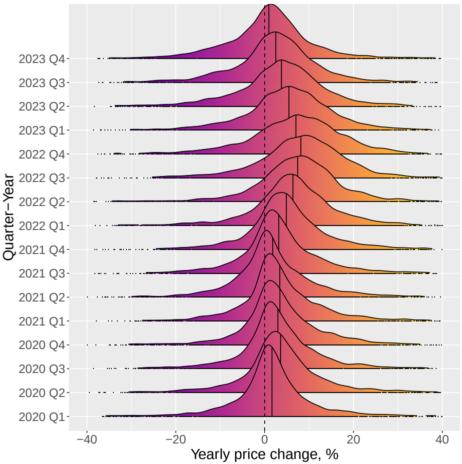


Notes: (A) Laspeyres index for static user: weighted with expenditure shares and demo weights, 1 percent trimmed micro sample (Numerator, own calculations) (B) Import shortfalls constructed as mean level deviations in the same month compared to 2019 baseline, weighted by quantity-weights constructed from US Trade online (Census, Panjiva, own calculations). PanjivavsCensus (sample)

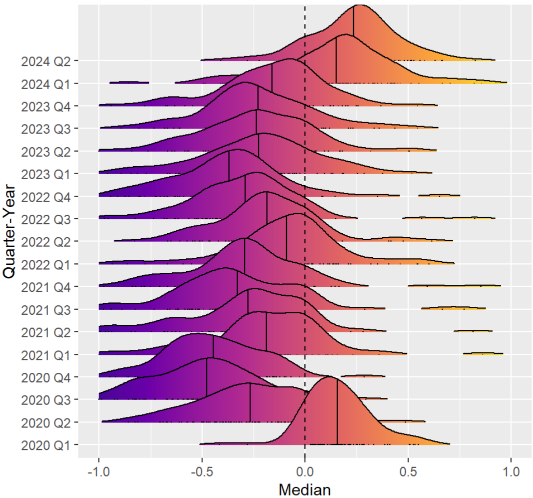
Fact 2: Heterogeneity across product groups over time

Back

(A) Distribution of price changes
(by category)



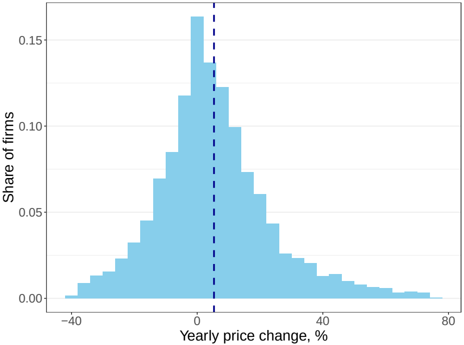
(B) Distribution of import shortfalls
(by HS2 code)



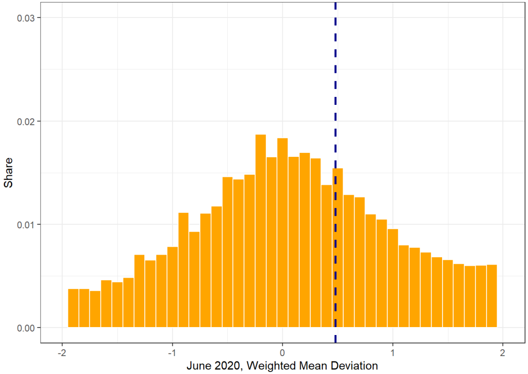
Fact 3: Heterogeneity across firms

Back

(A) Distribution of price changes (by category)

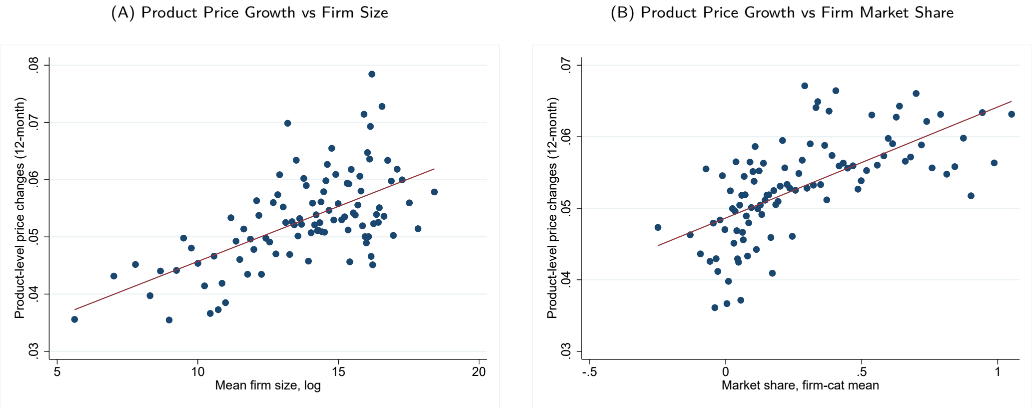


(B) Distribution of import shortfalls (by HS2 code)



Fact 4: Price changes and firm size

Back



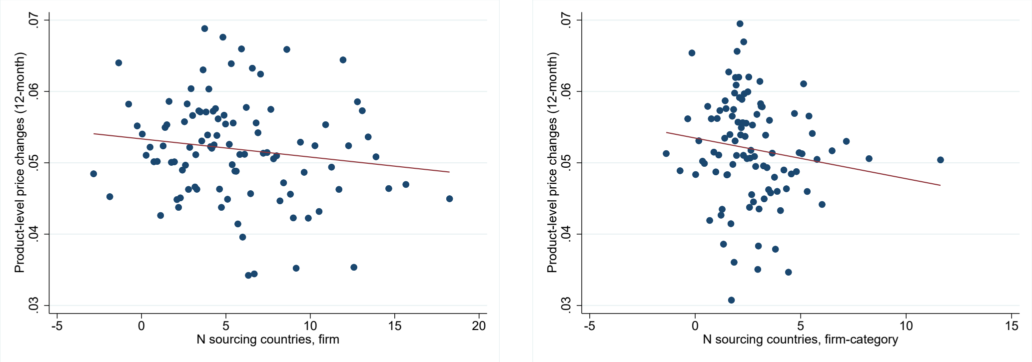
Notes: (A) Binscatters of product-level price changes against log firm size, defined as the average yearly sales of the firm in Numerator. (B) Binscatters of product-level price changes against firm market share, defined as the average firm's sales over total sales in the same product category in a year. Residualized for year and department f.e. Time series

Fact 5: Price changes and supplier diversification

Back

(A) Product Price Growth vs Supplier Countries

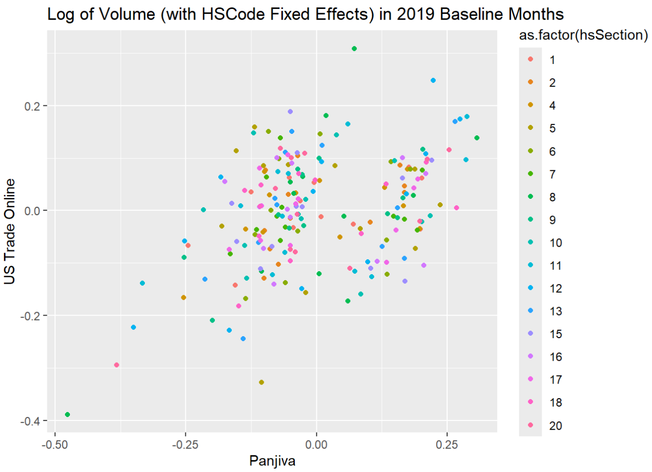
(B) Product Price Growth vs Industry-Supplier Countries



Notes: (A) Binscatters of product-level price changes against the number of countries the firm is sourcing from, controlling for firm size. (B) Binscatters of product-level price changes against the number of countries the firm is sourcing from for various HS codes, controlling for firm size. Residualized for year and department f.e.

Comparison with US Trade online

Back

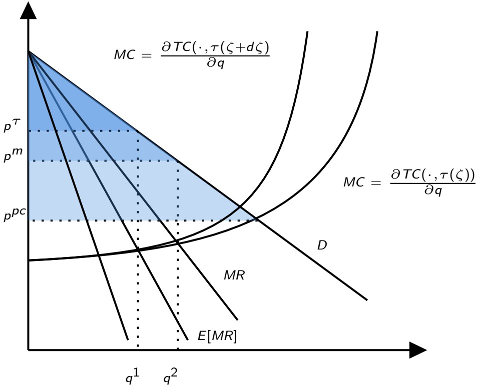


Notes: Panjiva aggregate trade volumes compared to US Trade online aggregate trade volumes, residualized with HS code fixed effects (Census, 2023, own calculation)

Monopolist Price

Back

- Increased τ might cause increased marginal cost.
- Now, price pressures also from higher marginal costs.



Data: Congestion at Intermodal Port Terminals

Back

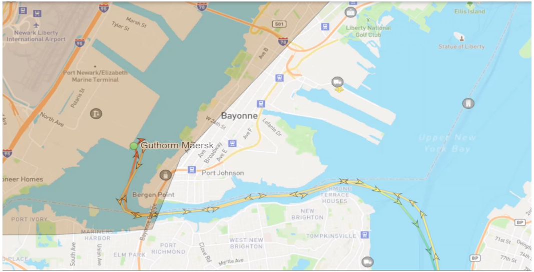
- AIS Vessel Traffic Data (June 2015–Dec 2021, Marine Cadastre):
  - 1-minute vessel locations in US waters (200 land stations), with vessel info (IMO, tonnage), position, speed, and status (moving, moored, anchored).
  - Ship dwell time: Time spent moored at zero speed.
- Port Matching: Top 30 US ports (95% container trade).

Ship Dwell Time Calculation

Back

- Ship path indicated by line, redder color = slower speed. Darker regions are port areas

CMA CGM Christophe Colomb (13.8k TEUs) at Port of LA



Guthorm Maersk (11k TEUs) at Port of Newark

Microfoundation of Stock-In Function

Back

- **Setup:** Demand arrivals are Poisson(λ), lead time is Exp(μ) (Fluid approximation of M/M/1 Queue with utilization μ)

- **Exponential 'race' logic:**
  - If replenishment (time W) occurs before the next arrival (time A), no stock-out.
  - Otherwise a sale reduces inventory ($\tau \to \tau - 1$) and the process restarts (memoryless).

- **Geom. distribution:** Number of sales before replenishment

$$N \sim \mathrm{Geom}(p), \quad p = \frac{\mu}{\lambda + \mu}.$$

- **Availability:**

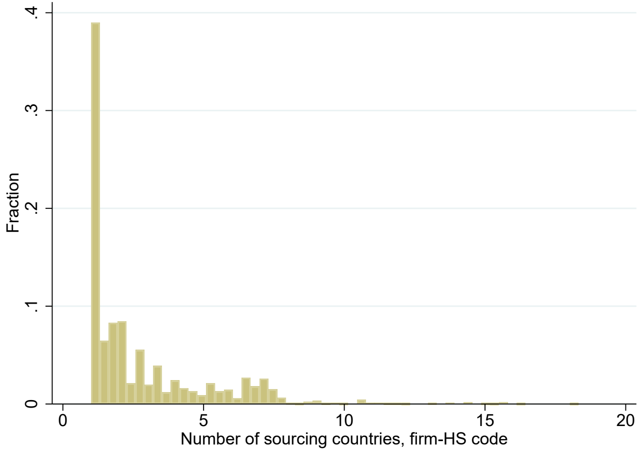
$$s(\tau, \lambda, \mu) = \Pr[N \leq \tau] = 1 - \Big(1 - p\Big)^{\tau+1} = 1 - \left(\tfrac{\lambda}{\lambda+\mu}\right)^{\tau+1}.$$

- **In terms of $\rho = \lambda/\mu$:**

$$s = 1 - \left(\tfrac{\rho}{1+\rho}\right)^{\tau+1}.$$

Number of Sourcing Countries

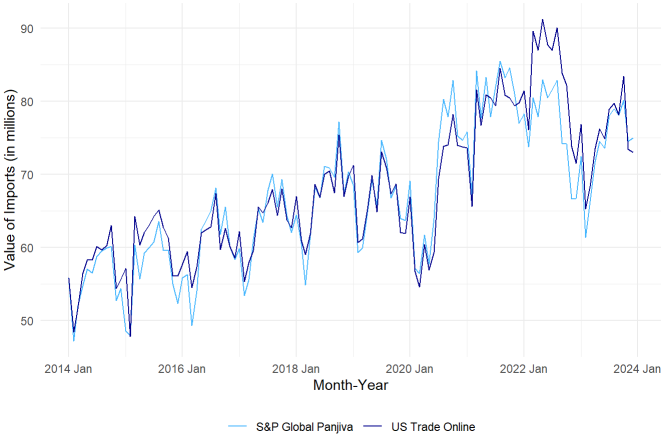
Back



Notes: Number of sourcing countries for the firm-HS2 in a year. Sample of Panjiva firms that match to Numerator.

US Imports in Panjiva vs. Census

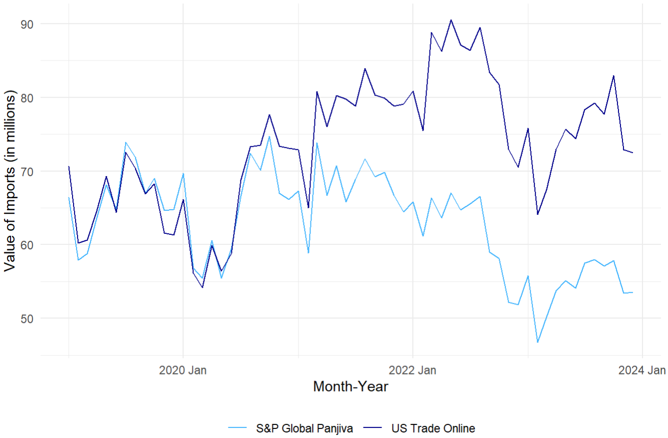
Back



Notes: Aggregate imports in BoL Panjiva against USA Trade Online - U.S. Census Bureau imports data. Panjiva import volumes are indexed to the 2019 unit value of an HS code in Census data.

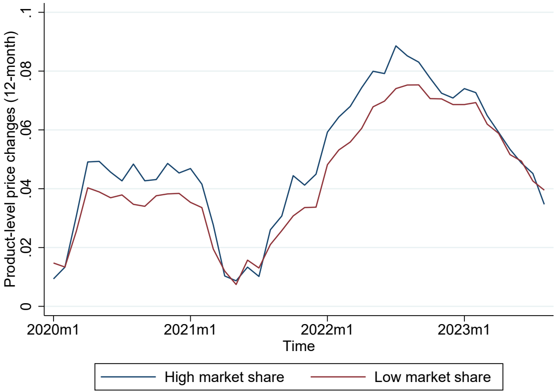
Panjiva Imports vs Census. Importing sample in 2019

Back



Fact 4 ctd.: Price changes and firm size

Back



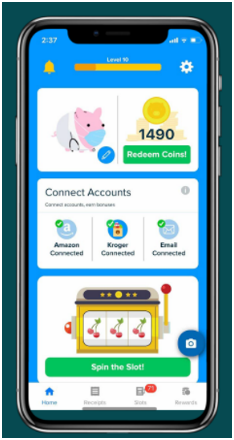
Notes: High-market share firms: in the top quartile of sales distribution in the respective product category.

Summary Statistics: Stores (Numerator) Back

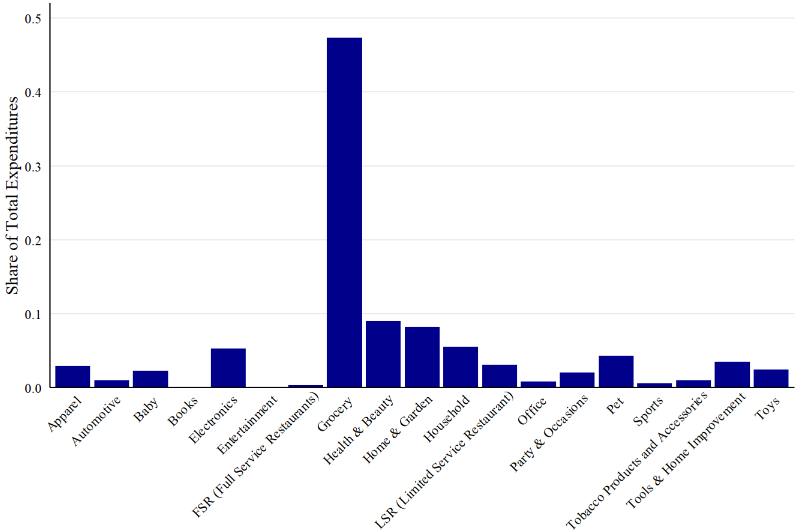
Channel	Frequency	Percent	Cum.
Food	10,142	20.85%	20.85%
FSR - Regional/Ethnic	8,428	17.32%	38.17%
Gas & Convenience	7,421	15.25%	53.43%
Liquor	2,905	5.97%	59.40%
Bodega	2,317	4.76%	64.16%
Apparel	1,692	3.48%	67.64%
Drug	1,471	3.02%	70.66%
LSR - Bakery/Cafe	1,270	2.61%	73.27%
Beauty	999	2.05%	75.33%
Pet	990	2.04%	77.36%
Home Improvement	819	1.68%	79.05%
Craft	701	1.44%	80.49%
Online	531	1.09%	81.58%
Other	515	1.06%	82.64%
LSR - Ethnic/Regional	512	1.05%	83.69%
Dispensaries	433	0.89%	84.58%
Sporting Goods Stores	424	0.87%	85.45%
Postal Services	401	0.82%	86.27%
Other Retail Store	390	0.80%	87.08%
LSR - Coffee/Bakery	385	0.79%	87.87%
Book	357	0.73%	88.60%
Other Specialty Store	331	0.68%	89.28%
Dollar	311	0.64%	89.92%
Specialty Food Retailer	300	0.62%	90.54%
Mass	237	0.49%	91.03%
Health	226	0.46%	91.49%
Electronics	219	0.45%	91.94%
Shoe	203	0.42%	92.36%

Numerator Consumer Insights and Data Company

Back

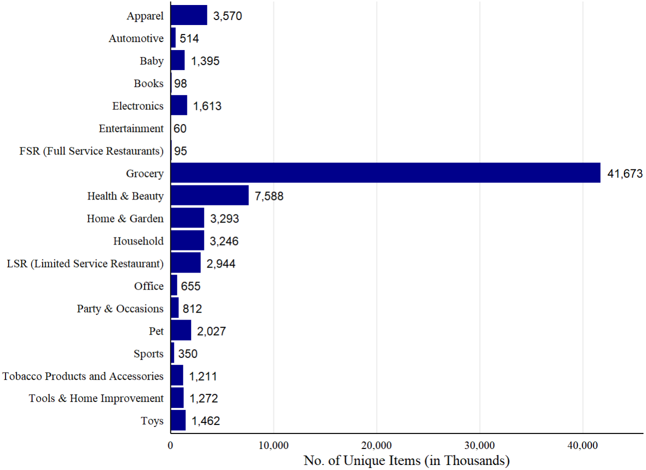


Summary Statistic: Expenditures by Sector (Numerator) Back

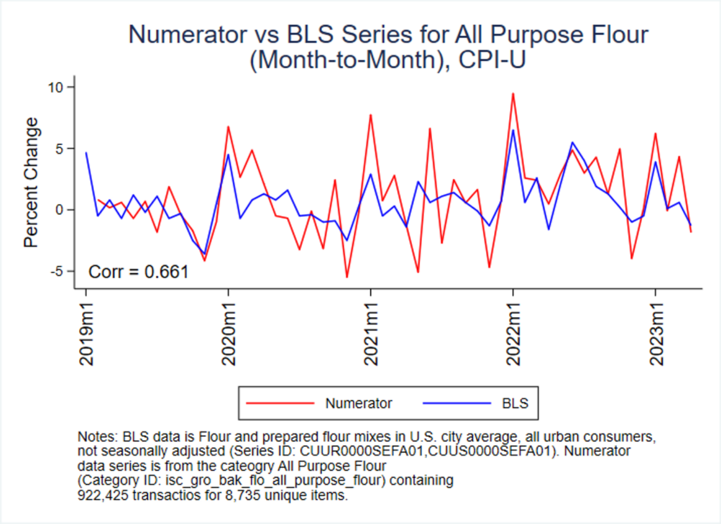


Summary Statistic: Unique Items by Sector (Numerator)

Back



Validation: Flour (Numerator) Back



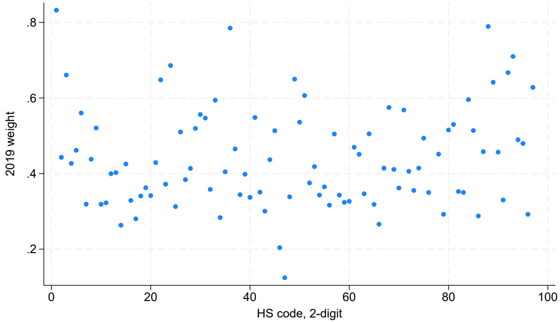
Notes: Price comparison for flour (Numerator, BLS, own calculations).

Identification. Variation in Shares

Back

Shares– $\omega_{h,f,2019}$– 2-digit HS-code import shares in 2019.

- On average, an importing Numerator firm imports 4.6 HS codes in 2019. The mean HHI of 2019 weights $= 0.73$.
- Firms rely on many different HS codes– even within the same product category: product category f.e. account for just 7% of $\omega_{h,f,2019}$ variation.



Identification. Pre-Trends

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2019 price change at a firm-category level as a function of shift-shares.

	$\Delta p2019$	$\Delta p2019$	$\Delta p2019$	$\Delta p2019$
Shortfall 2020	-0.012	-0.334	-0.007	-0.338
	(0.1675)	(0.5478)	(0.1684)	(0.5725)
$\Delta ImpC$ 2020	-0.118	-0.333	-0.152	-0.235
	(0.3155)	(1.0197)	(0.3286)	(1.0934)
Cat FE	No	Yes	No	Yes
Weights	None	Firm sales	None	Firm sales

Own passthrough estimates. Durability

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Table: Passthrough and Product Durability

	(1) Benchmark IV	(2) Durability	(3) Durability
Shortfall	-0.320***	-0.402*	-0.586**
	(0.0932)	(0.2098)	(0.2430)
Shortfall × Durability index		1.774	
		(4.0180)	
Shortfall × Durability dummy			0.558
			(0.4755)
$\Delta UnitC$	0.131**	0.134**	0.155**
	(0.0626)	(0.0633)	(0.0668)
$\Delta FreightC$	0.360***	0.309*	0.226
	(0.1247)	(0.1814)	(0.1860)
Lag Shortfall	0.036	0.036	0.081
	(0.0803)	(0.0805)	(0.0961)
Lag2 Shortfall	-0.072	-0.067	-0.009
	(0.0795)	(0.0829)	(0.1072)
Firm FE	✓	✓	✓
Cat-Quarter FE	✓	✓	✓
Observations	925638	925638	925638
Weak IV F-stat	131.833	1.182	12.545

Identification. Instrument projections

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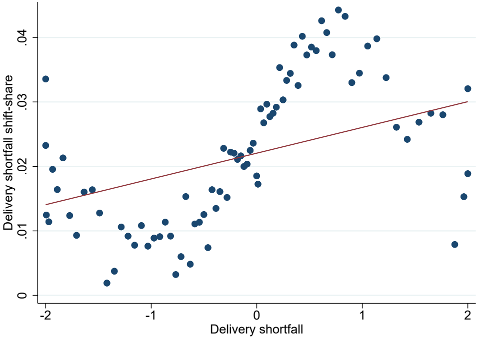
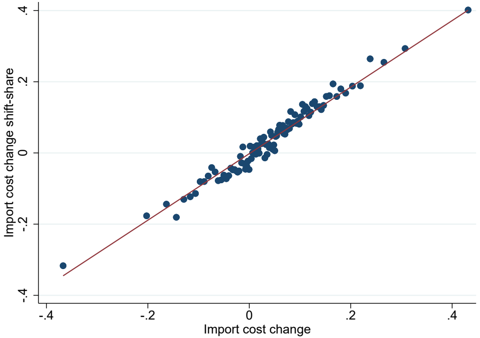
(A) Shortfall shift share on shortfall



(B) Cost change shift-share on cost change



Own pass-through: I stage

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I-stage estimates for own pass-through IV.

	(1) I stage (col3)	(2) I stage (col4)	(3) I stage (col5)
Shortfall, shift-share	0.439***	0.439***	0.439***
	(0.0171)	(0.0171)	(0.0171)
$\Delta UnitC$, shift-share	-0.050**	-0.050**	-0.050**
	(0.0255)	(0.0255)	(0.0255)
$\Delta FreightC$, shift-share	0.979***	0.979***	0.979***
	(0.0378)	(0.0378)	(0.0378)
I-stage F-stat	658.48	131.83	153.121

Strategic interactions. I stage

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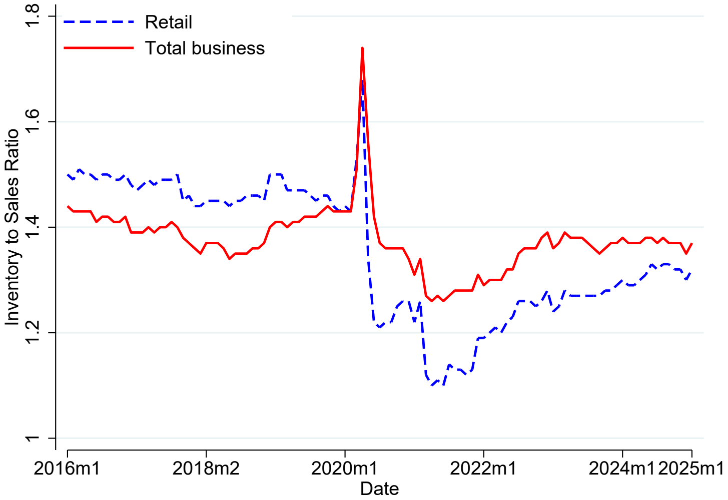
	I stage-Shortfall	I stage-Shortfall Comp
Shortfall, shift-share	0.447***	0.014
	(0.0216)	(0.0087)
Compet. shortfall, shift-share	-0.020	0.224***
	(0.0383)	(0.0297)
$\Delta UnitC$, shift-share	-0.054**	0.023**
	(0.0256)	(0.0091)
$\Delta FreightC$, shift-share	0.945***	-0.078***
	(0.0369)	(0.0123)
Compet. $\Delta UnitC$, shift-share	-0.007	-0.092
	(0.0655)	(0.0597)
Compet. $\Delta FreightC$, shift-share	-0.576***	0.448***
	(0.0851)	(0.0734)
I-stage F-stat	439.30	48.65

Inventory-to-Sales over Time



Source: FRED, Census data.