The Causal Effects of Global Supply Chain Disruptions on Macroeconomic Outcomes: Evidence and Theory

ASSA Annual Meeting

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Motivation

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- What are the **causal effects** of supply chain disruptions?
- How can we measure the state of the global supply chain?
  - Shipping prices, NY Fed's GSCPI, etc.
- How do supply chain shocks differ from other shocks in theory?
  - Aggregate demand, productive capacity, etc.
- Can we quantify their contribution to inflation before, during, and after COVID-19?

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- **A new spatial clustering algorithm** that transforms satellite data on container ships into a high-frequency measure of port congestion applicable to major ports worldwide.
- **A novel and simple analytical framework** for studying supply chain disruptions, capturing the coexistence of upstream economic slack and downstream supply scarcity.
- **A causality assessment using SVARs and LPs** that integrates our congestion indices with theory-predicted sign restrictions and domain-knowledge-based zero restrictions on structural shocks.

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- **A causality assessment using SVARs and LPs** that integrates our congestion indices with theory-predicted sign restrictions and domain-knowledge-based zero restrictions on structural shocks.
- **A state-dependence analysis** examining the interaction between supply chain disruptions and the effectiveness of monetary policy in controlling inflation and output —*Not today*.

Related Literature

- **Disruption in the goods market**: Barro and Grossman (1971); Michaillat and Saez (2015, 2022); Ghassibe and Zanetti (2022); Ghassibe (2024); Fernández-Villaverde *et al.* (2025).
- **Supply chain shocks for macroeconomic outcomes**: Cerdeiro and Komaromi (2020); Benigno *et al.* (2022); Cerrato and Gitti (2022); Finck and Tillmann (2022); Acharya *et al.* (2023); Benigno and Eggertsson (2023, 2024); Blanchard and Bernanke (2023); Comin *et al.* (2023); di Giovanni *et al.* (2023); Franzoni *et al.* (2023); Harding *et al.* (2023); Ascari *et al.* (2024); Finck *et al.* (2024).
- **Transportation sector and economic activity**: Allen and Arkolakis (2014); Brancaccio *et al.* (2020, 2024); Bai and Li (2022); Li *et al.* (2022); Smirnyagin and Tsyvinski (2022); Acharya *et al.* (2023); Alessandria *et al.* (2023); Brancaccio *et al.* (2023); Dunn and Leibovici (2023).
- **SVARs for causal inference**: Uhlig (2005); Mountford and Uhlig (2009); Rubio-Ramírez *et al.* (2010); Arias *et al.* (2018, 2025).

Road Map

1. Introduction
2. Measuring the State of the Global Supply Chain
3. A Model of the Global Supply Chain
4. The Causal Effects of Global Supply Chain Disruptions
5. Conclusion

Why Containerized Trade?

- We measure the state of the global supply chain by estimating **congestion at container ports**.
  - Containerized trade $\approx$ 46% of world trade;
  - For the U.S., container shipping accounts for $>$ 50% of trade by weight and $\approx$ 30% by value;
  - Computer chips (by air) + motherboards/hard drives (by sea) $\Rightarrow$ computers.

Sign Restrictions Zero Restrictions

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  - Computer chips (by air) + motherboards/hard drives (by sea) ⇒ computers.
- Containerized shipping features two short-run frictions that work in our favor:
  - **Economic:** service contracts fix invoiced freight rates for at least a one-month horizon, keeping the "reservation" transportation cost rigid when profitability is unchanged;
  - **Operational:** fixed rotations, berth windows, and alliance schedules make arrivals rigid, with adjustments only every 3–6 months.

Sign Restrictions Zero Restrictions

Anchorage vs. Berth

- In containerized trade, seaports serve as international hubs for freight collection and distribution.
- **Port congestion**: a container ship must first moor in an **anchorage** within the port (random areas to lower anchors) before docking at a **berth** (designated spots to load/unload cargo).

Figure: Anchorage.

Figure: Berth.

Why Port Congestion?

1. Before the pandemic, port waits lasted only a few hours, but COVID-19 disruptions extended them to **2–3 days** at major ports.
2. **≈ 80%** of world trade is shipped indirectly, and the average shipment stops at **5 additional ports** before reaching its destination.
3. The industry is surprisingly concentrated, with only **5,589** container ships worldwide, of which roughly **500** belong to the larger size classes.

MSC Loreto

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   ⇒ **Even mild congestion has tremendous financial and logistical consequences.**

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Estimating Port Congestion

- We use movement data from container ships via the **Automatic Identification System (AIS)**.
  - A real-time satellite tracking system with virtually no measurement error, mandated by the International Maritime Organization (IMO), ensuring compliance across the global shipping industry;
  - Each data entry includes the vessel's IMO number, timestamp, current draft, speed, heading, and geographical coordinates;
  - The AIS updates information as frequently as every two seconds.
- Machine learning allows us to process spatial-temporal data from container ships at the top 50 container ports worldwide from January 2016 to March 2025.

AIS Transceiver

Sample AIS Data

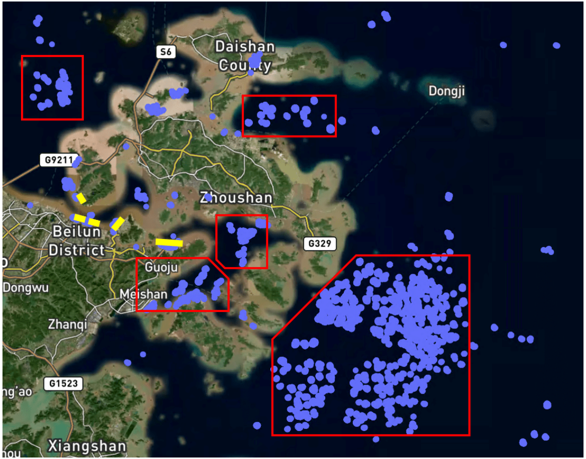

Figure: First 50,000 AIS Records in the Port of Ningbo-Zhoushan Since January 1, 2020.

A Machine Learning Spatial Clustering Algorithm

1. Data preprocessing and mooring area identification:
   - Noise elimination;
   - Frequency reduction.
2. Anchorage and berth identification:
   - Iterative approach for generalized and suitable parameter setting;
   - Inclusion of multiple attributes: geographical coordinates, headings, and timestamps.

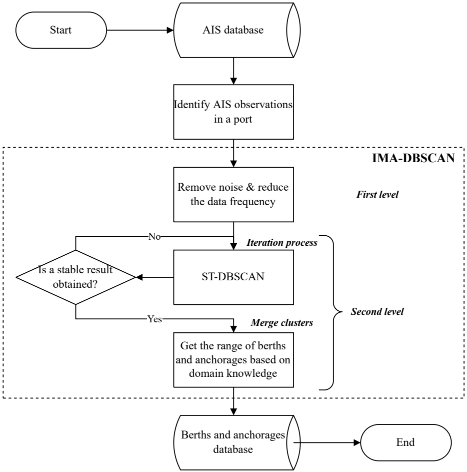

Figure: The IMA-DBSCAN Algorithm.

Granular Information in the AIS Data

Figure: Headings at an Anchorage.

Figure: Headings at a Berth.

Ningbo-Zhoushan

Figure: Anchorages.

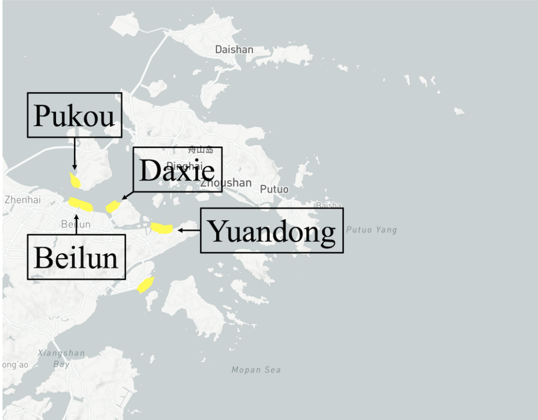

Figure: Berths.

Los Angeles, Long Beach, Rotterdam, & Singapore

From Identification to Aggregation

Identifying Anchorages & Berths → Counting Delayed Ships → Normalization → Aggregation

1. Map the geographical boundaries of anchorages and berths for the top 50 container ports ($\mathscr{P}$).

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3. Calculate the congestion rate for each port p by dividing the number of delayed ship visits by the total number of ship visits ($\text{Delayed}_{p,t} + \text{Undelayed}_{p,t}$),

$$\text{Congestion}_{p,t} \equiv \frac{\text{Delayed}_{p,t}}{\text{Delayed}_{p,t} + \text{Undelayed}_{p,t}}, \quad \forall p \in \mathscr{P}.$$

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4. Calculate the Average Congestion Rate (ACR_t), weighted by the relative number of ship visits,

$$\text{ACR}_t = \sum_{p \in \mathscr{P}} \left[\frac{\text{Delayed}_{p,t} + \text{Undelayed}_{p,t}}{\sum_{p \in \mathscr{P}} \left(\text{Delayed}_{p,t} + \text{Undelayed}_{p,t} \right)} \cdot \text{Congestion}_{p,t} \right].$$

Congestion at Individual Ports

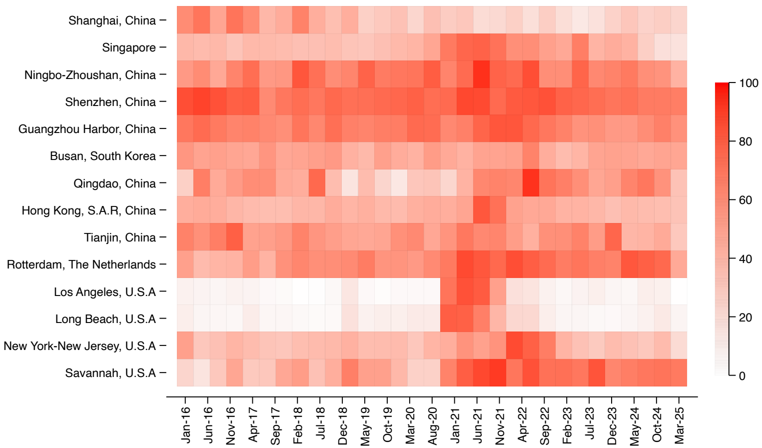

Figure: Congestion Rates at Major Global and U.S. Container Ports.

Average Congestion Rate

- Declined before 2018 and bottomed near 25% by mid-2020 after global port upgrades.
- Surged to 37% in June 2021 amid COVID-19.
- Stayed high through 2022, then normalized around 30% by mid-2023.
- Rose again in 2024 due to Red Sea and Panama Canal disruptions, before dropping below 25% in early 2025.

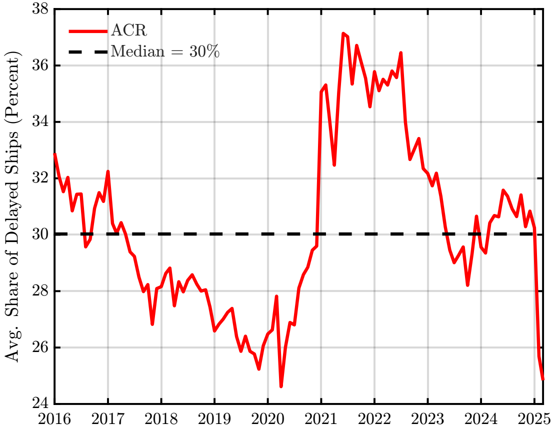

Figure: ACR for January 2016 to March 2025.

Why the ACR Index?

- Identification of supply chain shocks = SVARs or LPs with macro aggregates

Operational Rigidity | ACR & MP Shock | ACR & Oil Price | Back

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- The ACR index provides a measure that tracks the flow of tradable goods worldwide with virtually no measurement error.

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- However, ACR captures a broad range of factors affecting the global supply chain beyond disruptions in goods transportation (e.g., demand shifts, capacity constraints).

Operational Rigidity ACR & MP Shock ACR & Oil Price Back

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- Short-run operational rigidities in container shipping ⇒ ACR will not immediately respond to demand or capacity shocks within the first month.

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  + **domain-knowledge-based zero restrictions**.

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Road Map

A Model of the Global Supply Chain

- **Producers**:
  - Exogenous unit mass;
  - Produce goods with capacity determined by a fixed-factor endowment l;
  - Ship goods subject to idiosyncratic transportation costs z;
  - Supply goods to retailers at a wholesale price r, but matching frictions prevent full capacity utilization.
- **Retailers**:
  - Endogenous measure;
  - Purchase goods by visiting producers at a fixed cost ρ, but not all visits result in a match;
  - Resell goods to the representative household at price p.
- **Representative household**:
  - Consumes goods and holds money m;
  - Moves goods and owns firms.

Matching Process

- The matching function determines the number of meetings m between producers and retailers:

$$m = (x_U^{-\xi} + i_U^{-\xi})^{-\frac{1}{\xi}},$$

where x_U and i_U: numbers of unmatched producers and retailers, respectively; $\xi > 0$: elasticity of substitution between them.

- Product market tightness θ is defined as:

$$\theta \equiv \frac{i_U}{x_U}.$$

- Tightness θ determines the matching probabilities for producers and retailers:

$$f(\theta) = \frac{m}{x_U} = (1 + \theta^{-\xi})^{-\frac{1}{\xi}}, \quad q(\theta) = \frac{m}{i_U} = (1 + \theta^{\xi})^{-\frac{1}{\xi}}.$$

Transportation Cost

- Producers pay an idiosyncratic per-unit transportation cost to ship goods to retailers.
- Households receive these payments for transporting goods.
- Each period, producers draw a transportation cost z from a log-normal distribution $G(z)$:

$$G(z) \equiv \Phi\left(\frac{\ln z - \gamma}{\sigma}\right),$$

  where $\Phi(\cdot)$: standard normal CDF.
- A reservation transportation cost $\bar{z}$ exists, above which matches are unprofitable.
- Matches with $z > \bar{z}$ are severed, while those with $z \leq \bar{z}$ continue.

Producers

- The value of a matched producer, $X_M(z)$, is given by:

$$X_M(z) = (r(z) - z)\, l + \beta \mathbb{E}_{z'} \left[\max \left(X_M(z'), X_U \right) \right],$$

where $r(z)$: endogenous wholesale price; z: transportation cost; β: discount factor; z': next period's transportation-cost draw.

- The value of an unmatched producer, X_U, satisfies:

$$X_U = \beta f(\theta) \mathbb{E}_{z'} \left[\max \left(X_M(z'), X_U \right) \right] + \beta \left[1 - f(\theta) \right] X_U,$$

where $f(\theta)$: probability that a producer meets a retailer.

Retailers

- The value of a matched retailer, $I_M(z)$, is given by:

$$I_M(z) = (p - r(z))\, l + \beta \mathbb{E}_{z'} \left[\max \left(I_M(z'), I_U \right) \right],$$

where p: endogenous retail price.

- The value of an unmatched retailer, I_U, satisfies:

$$I_U = -\rho l + \beta q(\theta) \mathbb{E}_{z'} \left[\max \left(I_M(z'), I_U \right) \right] + \beta \left[1 - q(\theta) \right] I_U,$$

where ρ: per-unit fixed cost paid during each visit; $q(\theta)$: probability that a retailer meets a producer.

- Free entry drives the value of an unmatched retailer to zero in equilibrium:

$$I_U = 0.$$

Nash Bargaining

- Nash bargaining divides the total surplus from a match between the producer and the retailer.
- The total surplus is:

$$S(z) = X_M(z) - X_U + I_M(z) - I_U.$$

- The producer receives a constant share η of the surplus, while the retailer receives the remaining share $1-\eta$, implying:

$$\eta\,[I_M(z) - I_U] = (1-\eta)\,[X_M(z) - X_U]\,.$$

- The wholesale price that splits the surplus according to Nash bargaining is:

$$r(z) = \eta\,(p + \rho\theta) + (1-\eta)z.$$

Match Separation and Creation

- Because $X_M(z) + I_M(z)$ is strictly decreasing in $z \in (0, +\infty)$, there exists a cutoff transportation cost $\bar{z}$ such that matches with $z > \bar{z}$ are severed and those with $z \leq \bar{z}$ continue. At $\bar{z}$, total surplus satisfies:

$$S(\bar{z}) = 0.$$

- The match separation condition links price p, reservation cost $\bar{z}$, and market tightness θ:

$$\mathbb{F}(p, \bar{z}, \theta) = (p - \bar{z})l + (1 - \eta f(\theta))\beta \mathbb{E}_{z'}\left[S(z')\right] = 0,$$

where $\mathbb{E}_{z'}\left[S(z')\right] = \int_0^{\bar{z}} S(z')\, dG(z')$.

- Using the free-entry condition $I_U = 0$, the match creation condition is:

$$\mathbb{H}(\bar{z}, \theta) = \frac{\rho l}{q(\theta)} - (1 - \eta)\beta \mathbb{E}_{z'}\left[S(z')\right] = 0.$$

Aggregate Supply

- Aggregate supply equals the quantity of goods traded by producers and retailers that survive separation, given productive capacity l.
- The law of motion for matched producers:

$$x'_M = G(\bar{z})x_M + f(\theta)G(\bar{z})x_U.$$

- Using $x_M + x_U = 1$, this becomes:

$$x'_M = f(\theta)G(\bar{z}) + [G(\bar{z}) - f(\theta)G(\bar{z})]\, x_M.$$

- Aggregate supply is the output of matched producers for a given capacity:

$$c_s(\bar{z}, \theta) = x_M(\bar{z}, \theta)\, l.$$

Representative Household

- The representative household derives utility from consuming goods and holding real money balances:

$$u\left(c, \frac{m}{p}\right) = \frac{\chi}{1+\chi} c^{\frac{\varepsilon-1}{\varepsilon}} + \frac{1}{1+\chi} \left(\frac{m}{p}\right)^{\frac{\varepsilon-1}{\varepsilon}},$$

  where $\chi > 0$: taste for consumption over money; $\varepsilon > 1$: elasticity of substitution between c and m/p.

- Budget constraint:

$$pc + m \leq \underbrace{\mu}_{\text{Money Endowment}} \underbrace{+ pc_s(\bar{z}, \theta) - \rho l\, i_U - \int_0^{\bar{z}} z' c_s(\bar{z}, \theta)\, dG(z')}_{\text{Profits of Producers \& Retailers}} + \underbrace{\int_0^{\bar{z}} z' c_s(\bar{z}, \theta)\, dG(z')}_{\text{Transportation Income}}.$$

- Optimality condition:

$$\frac{\chi}{1+\chi} c^{-\frac{1}{\varepsilon}} = \frac{1}{1+\chi} \left(\frac{m}{p}\right)^{-\frac{1}{\varepsilon}}.$$

Aggregate Demand

- Aggregate demand is the level of consumption that maximizes utility at a given price when the money market clears.
- Substituting $m = \mu$ in the household's optimality condition gives:

$$c_d(p) = \chi^{\varepsilon} \frac{\mu}{p},$$

which is strictly decreasing and convex in p for $p > 0$.

General Equilibrium

- General equilibrium requires that both the upstream (producer–retailer) and downstream (retailer–household) markets clear simultaneously.

Definition 1

General equilibrium is characterized by a price p, a reservation transportation cost $\bar{z}$, and a product market tightness θ such that the match separation and creation conditions hold simultaneously:

$$\mathbb{F}(p, \bar{z}, \theta) = \mathbb{H}(\bar{z}, \theta) = 0,$$

and the retailer–household market clears:

$$c_s(\bar{z}, \theta) = c_d(p),$$

where aggregate supply $c_s(\bar{z}, \theta)$ evolves according to the law of motion for matched producers.

Steady State: Core Relationships

- We focus on the steady state where the number of matched producers is constant, $x'_M = x_M$.
- The steady-state share of matched producers:

$$x_M^{ss}(\bar{z},\theta) = \frac{f(\theta)G(\bar{z})}{1 - G(\bar{z}) + f(\theta)G(\bar{z})}.$$

- Steady-state aggregate supply:

$$c_s^{ss}(\bar{z},\theta) = x_M^{ss}(\bar{z},\theta)\, l = \frac{f(\theta)G(\bar{z})}{1 - G(\bar{z}) + f(\theta)G(\bar{z})}\, l.$$

- Comparative statics of the steady state identify the effects of structural shocks in our empirical analysis.

Steady State: Definition and Existence

Definition 2

The steady state of the economy consists of a price p, a reservation transportation cost $\bar{z}$, and a product market tightness θ that jointly satisfy the match separation condition, the match creation condition, and the retailer–household market-clearing condition:

$$\mathbb{F}(p, \bar{z}, \theta) = (p - \bar{z})l + (1 - \eta f(\theta))\beta \mathbb{E}_{z'}\left[S(z')\right] = 0,$$

$$\mathbb{H}(\bar{z}, \theta) = \frac{\rho l}{q(\theta)} - (1 - \eta)\beta \mathbb{E}_{z'}\left[S(z')\right] = 0,$$

$$c_s^{ss}(\bar{z}, \theta) = \frac{f(\theta)G(\bar{z})}{1 - G(\bar{z}) + f(\theta)G(\bar{z})} l = \chi^{\varepsilon}\frac{\mu}{p} = c_d(p).$$

Graphical Representation of the Steady State

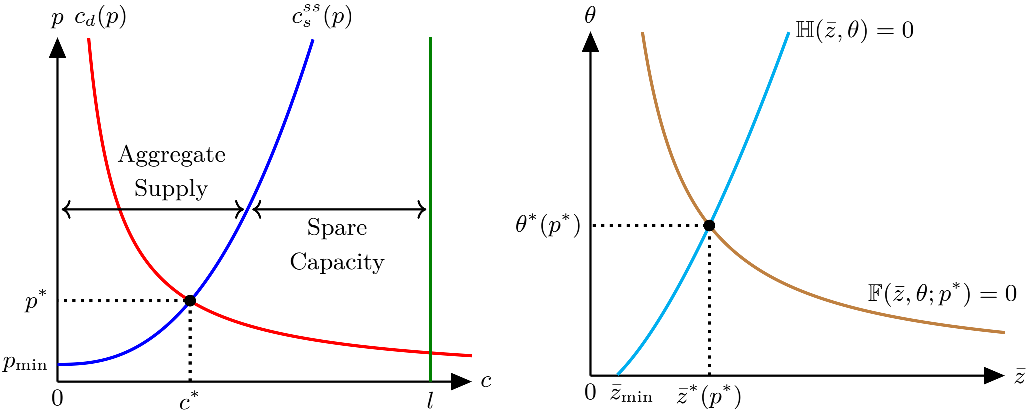

Figure: Aggregate Supply–Demand and Match Separation–Creation.

Analytical Properties of Aggregate Supply

Comparative Statics

- We study how macro aggregates respond to (unanticipated) adverse shocks when the economy is initially at the steady state:
  - **Aggregate demand:** lower money supply (μ) or weaker consumption preference (χ);
  - **Productive capacity:** smaller fixed-factor endowment (l);
  - **Supply chain:** higher transportation costs (γ in $G(\cdot)$).
- Numerical exercises show that the transition dynamics are consistent with the identification restrictions:
  - Convergence to the new steady state occurs within a one-month horizon;
  - The adjustment is monotonic.

Aggregate Demand Shock

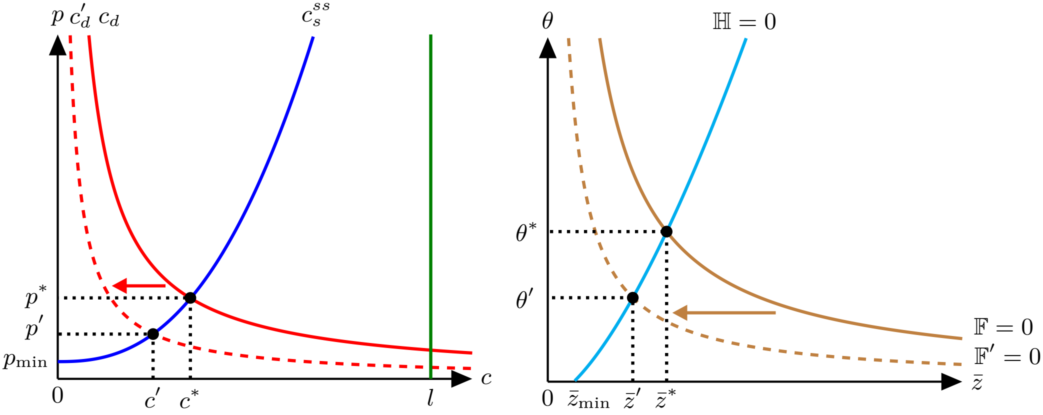

Figure: Money Supply ↓ or Taste for Consumption ↓.

Productive Capacity Shock

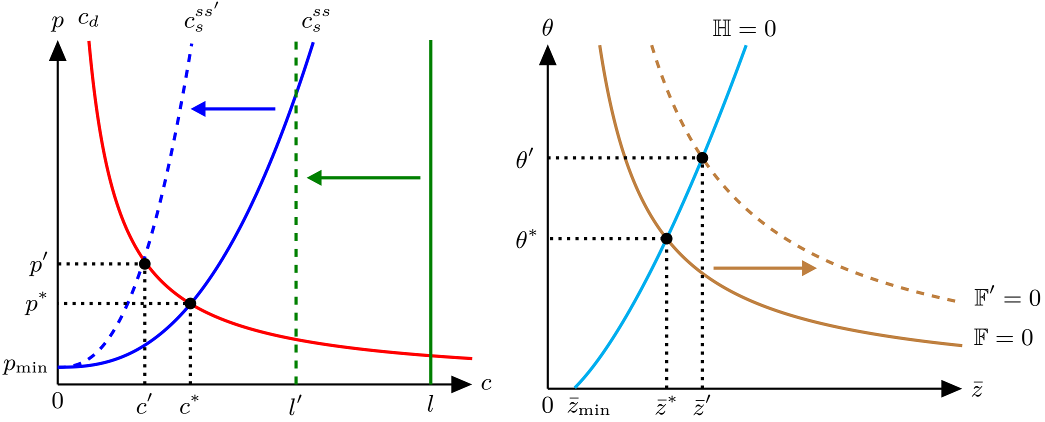

Figure: Productive Capacity ↓.

Supply Chain Shock

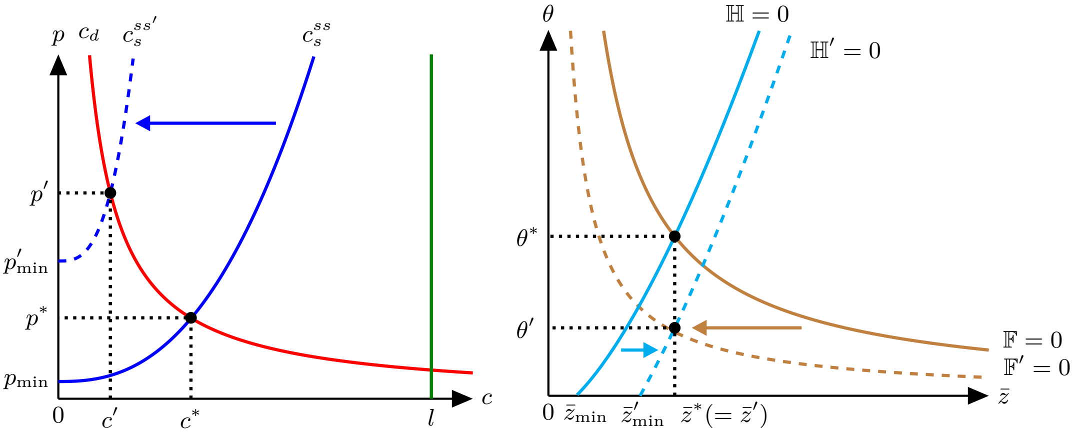

Figure: Transportation Costs ↑.

Bound on Upstream Slackening

Theory-Predicted Sign Restrictions

Adverse Shock To:	Effects On:					
	Consumption (or Output)	Price	Reservation Transportation Cost	Product Market Tightness	Wholesale Price	Spare Capacity
	c	p	$\bar{z}$	θ	r	$l - c$
Aggregate Demand ($\mu \downarrow$ or $\chi \downarrow$)	$-$	$-$	$-$	$-$	$-$	$+$
Productive Capacity ($l \downarrow$)	$-$	$+$	$+$	$+$	$+$	$-$
Assuming sticky $\bar{z}$ in short-run,						
Supply Chain ($\gamma \uparrow$)	$-$	$+$	0	$-$	$\pm$	$+$

Economic Rigidity | Back

Road Map

A SVAR Model with Sign and Zero Restrictions

- We examine the causal effects of global supply chain disruptions using an SVAR framework following Rubio-Ramírez *et al.* (2010) and Arias *et al.* (2018):

$$\boldsymbol{y}_t'\boldsymbol{A}_0 = \boldsymbol{x}_t'\boldsymbol{A}_+ + \boldsymbol{\varepsilon}_t', \quad 1 \leq t \leq T.$$

- The model includes six endogenous variables:
  1. U.S. real PCE;
  2. U.S. PCE chain-type price index;
  3. **Spare capacity**;
  4. **Product market tightness**;
  5. U.S. import price;
  6. ACR.
- All series are seasonally adjusted. The sample spans January 2016 to March 2025.

Setting Up the SVAR

Spare Capacity and Product Market Tightness

- We compute the average spare capacity rate of the top five exporters to the U.S., weighted by U.S. goods imports from each country in 2016:

$$\text{SpareCapacityRate}_t = \sum_{i \in \mathscr{C}} \left[\frac{\text{Import}_{i,2016}}{\sum_{i \in \mathscr{C}} \text{Import}_{i,2016}} \cdot \left(1 - \text{CapacityUtilization}_{i,t}\right) \right],$$

  where $\mathscr{C} \equiv \{\text{Mexico, Canada, China, Germany, Japan}\}$.

- We measure product market tightness as the ratio of total U.S. manufacturers' new orders to the import-weighted average spare capacity of the same trading partners:

$$\text{Tightness}_t = \frac{\text{ManufactureNewOrder}_t}{\text{SpareCapacityDollar}_t},$$

$$\text{SpareCapacityDollar}_t = \sum_{i \in \mathscr{C}} \left[\frac{\text{Import}_{i,2016}}{\sum_{i \in \mathscr{C}} \text{Import}_{i,2016}} \cdot \left(\frac{\text{IP}_{i,t}}{\text{CapacityUtilization}_{i,t}} - \text{IP}_{i,t} \right) \right].$$

Identification Restrictions

- **An adverse aggregate demand shock** leads to a negative response of real PCE, the PCE price index, product market tightness, and the import price index, as well as a positive response of spare capacity at $k = 1$. *The ACR index does not respond at* $k = 1$.
- **An adverse productive capacity shock** leads to a negative response of real PCE and spare capacity, and a positive response of the PCE price index, product market tightness, and the import price index at $k = 1$. *The ACR index does not respond at* $k = 1$.
- **An adverse supply chain shock** leads to a negative response of real PCE and product market tightness, and a positive response of the PCE price index, spare capacity, and the ACR index at $k = 1$.

Theory-Predicted Sign Restrictions | Domain-Knowledge-Based Zero Restrictions

Estimation Details

- We use two lags in the baseline specification; results are robust to longer lag lengths.
- Real PCE, the PCE price index, product market tightness, and the import price index enter the SVAR in log points, while spare capacity and the ACR index enter in percentages.
- Estimation is Bayesian, with a Normal–Generalized-Normal (NGN) prior distribution over $\{\boldsymbol{A}_0, \boldsymbol{A}_+\}$.
- We verify robustness along several dimensions, including the use of monthly inflation instead of price levels, checks for invertibility, variable substitutions, and estimation using the prior robust approach.

Response to an Aggregate Demand Shock

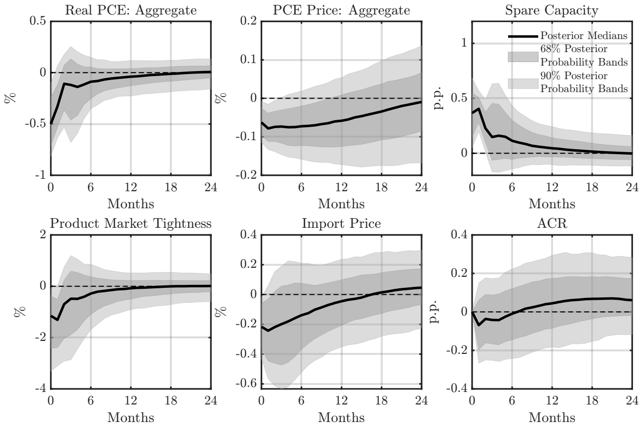

Figure: IRFs of U.S. Variables to a One-S.D. Adverse Demand Shock.

Response to a Productive Capacity Shock

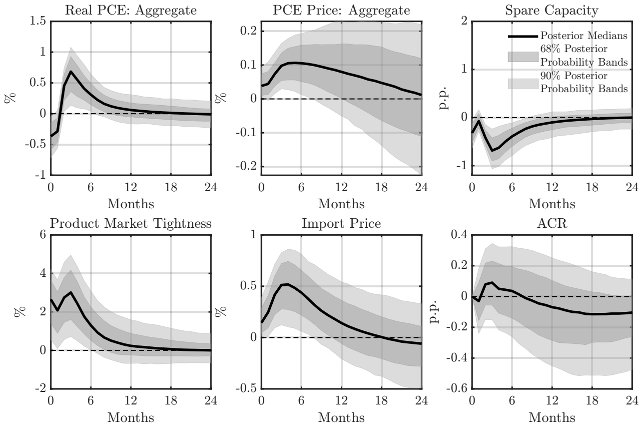

Figure: IRFs of U.S. Variables to a One-S.D. Adverse Capacity Shock.

Response to a Supply Chain Shock

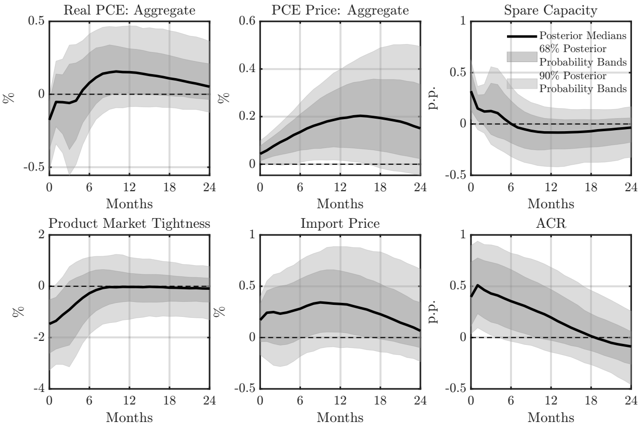

Figure: IRFs of U.S. Variables to a One-S.D. Adverse Supply Chain Shock.

Which Shock Matters?

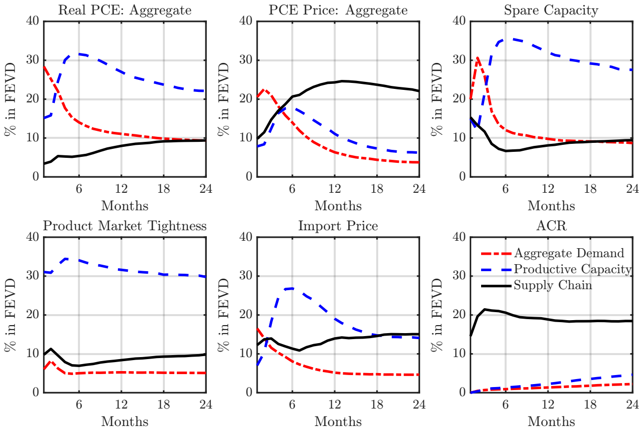

Figure: Forecast Error Variance Decompositions from the SVAR.

What Drove U.S. Inflation?

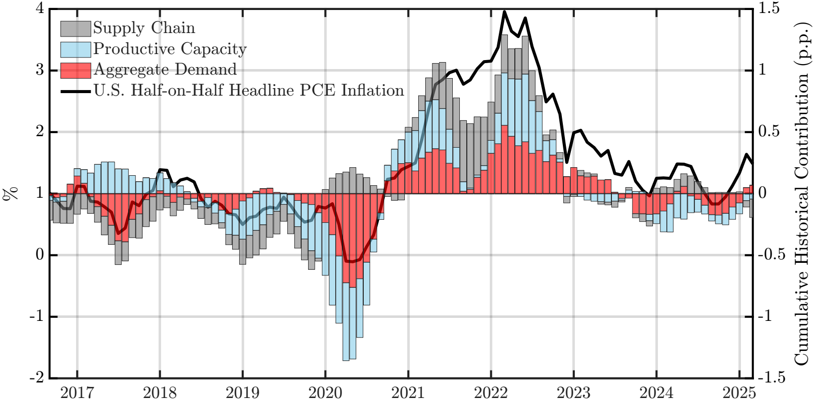

Figure: Historical Decomposition of U.S. Half-on-Half Headline PCE Inflation.

U.S. Goods vs. Services Inflation
EA Goods Inflation

Comparing Price IRFs Across Proxies

- ACR-based SVAR ⇒ larger and sharper inflation responses.
- Zero restrictions ($k = 1$) on ACR/ACT/Trans-Pacific ACR ⇒ even sharper identification.
- HARPEX, GSCPI, SDI ⇒ weaker and imprecise responses.

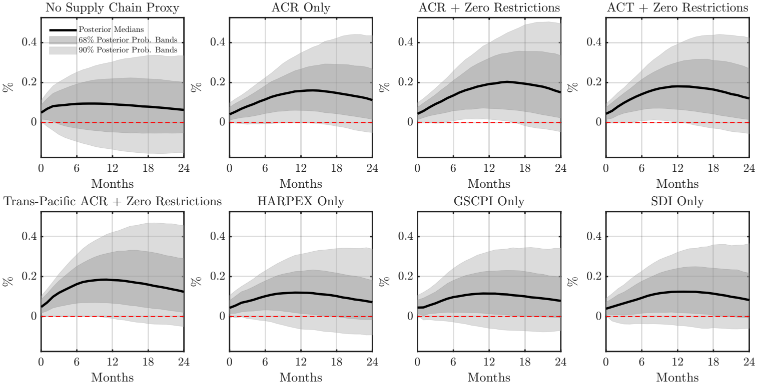

Figure: PCE Price Responses to a Supply Chain Shock.

PCE Goods Price

Comparing Price FEVDs Across Proxies

- Congestion indices ⇒ larger price variance share from supply chain disturbances.
- Other proxies ⇒ variance dominated by demand shocks.

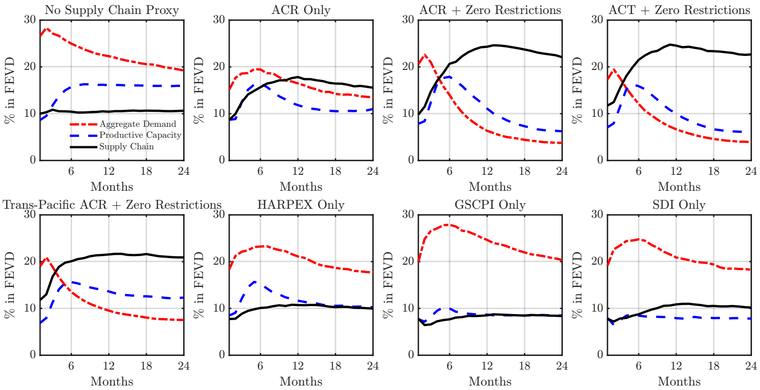

Figure: Posterior-Median FEVD Shares of PCE Price Variance.

PCE Goods Price

Road Map

Conclusion

- We estimate the causal effects of global supply chain disruptions —stagflationary, **generating upstream spare capacity while slackening the downstream market**.
- This is achieved by constructing a new index, developing a novel theory, and integrating them with state-of-the-art methods for assessing causality in time series.
- Far from being just a postmortem of what happened during the COVID-19 pandemic, our analysis distills important lessons for both the present and the future.

Public Goods and Extensions

- We are happy to share the following datasets upon request:
  - Average Congestion Rate (ACR);
  - Average Congestion Time (ACT);
  - Individual port congestion indices.
- We are currently working on two extensions:
  - "Shipping to America";
  - "Dynamic Prioritization Failures in Maritime Logistics: Evidence from the Panama Canal".

Bypassing the Suez Canal

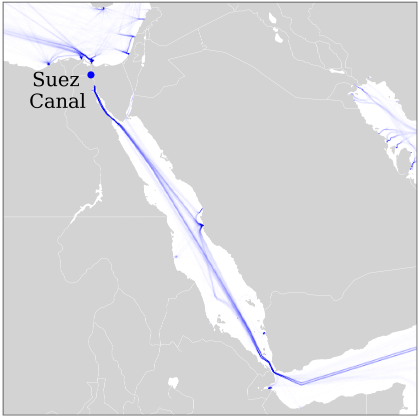

Figure: 26/10/2023 – 26/12/2023.

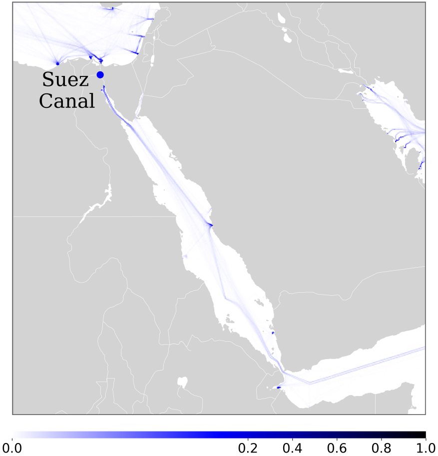

Figure: 27/12/2023 – 27/02/2024.

Taking the Cape Route Instead

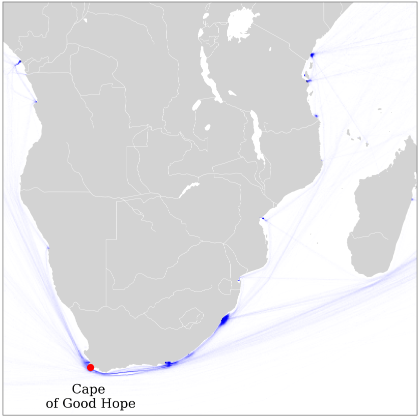

Figure: 26/10/2023 – 26/12/2023.

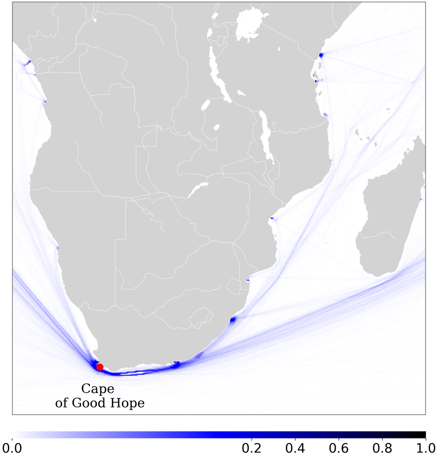

Figure: 27/12/2023 – 27/02/2024.

Additional Slides

The World's Largest Container Ship

Figure: MSC Loreto.

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AIS Transceiver

Raymarine AIS 4000 Class A AIS Transceiver

RAYMARINE AIS 4000 Class A AIS - Designed for commercial vessels, luxury yachts, and SOLAS high-seas shipping, the AIS4000 Automatic Identification System (AIS) transceiver delivers robust Class A AIS network capability and is engineered to withstand the harsh weather, shock, and vibration of any vessel class. Power supply: 12 to 24 VDC. Frequency: 156.025 MHz to 162.025 MHz. E70601 **Free US Shipping.**

Reference: E70601 **In Stock:** 1

Reg Price: $2,799.99
CPlus Price: $2,701.99

What is Citimarine Plus Membership?
Click here for details

Figure: Example of an AIS Transceiver.

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Los Angeles and Long Beach

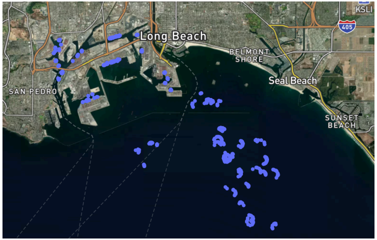

Figure: Sample AIS Data.

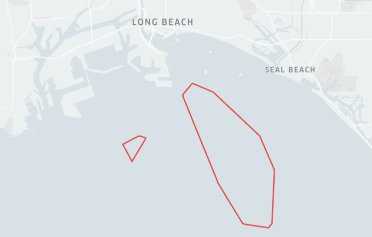

Figure: Anchorages.

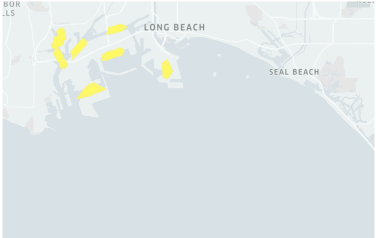

Figure: Berths.

Rotterdam

Figure: Sample AIS Data.

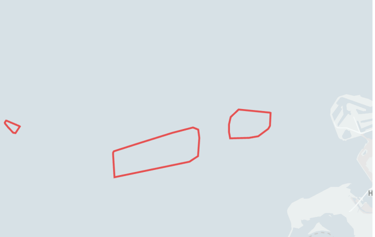

Figure: Anchorages.

Figure: Berths.

Singapore

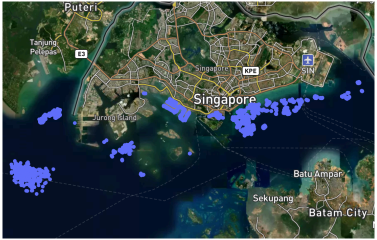

Figure: Sample AIS Data.

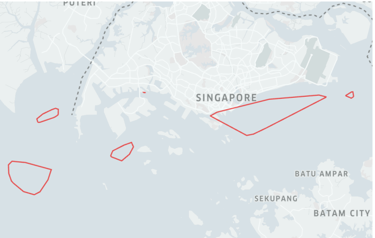

Figure: Anchorages.

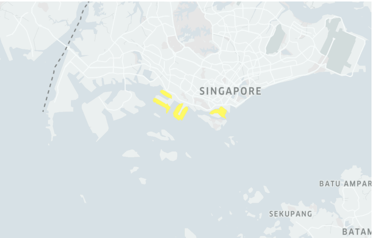

Figure: Berths.

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Testing Short-Run Rigidity in Container Shipping: Setup

- We formally test whether the ACR index responds immediately to monetary policy shocks.
- Estimation uses LPs:

$$\text{ACR}_{t+k} = \alpha_k + \beta_k \, \text{MP}_t + u_{k,t+k}, \quad 0 \le k \le K,$$

  where MP_t: monthly orthogonalized Bauer–Swanson monetary policy surprise (FRB San Francisco).
- To smooth noisy estimates, we apply Smooth Local Projections (Barnichon and Brownlees, 2019) using B-spline basis functions.
- Standard errors are Newey–West adjusted to allow for serial correlation.

Testing Short-Run Rigidity in Container Shipping: Results

- On-impact response of ACR is near zero $\Rightarrow$ short-run rigidity.
- Medium-run decline $\Rightarrow$ monetary tightening gradually reduces port congestion.
- Confirms that policy effects on global shipping are **delayed, not immediate**.

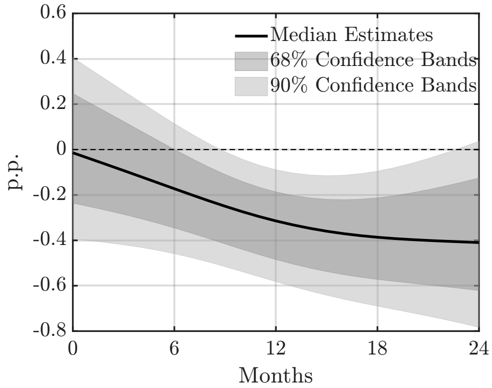

Figure: IRF of ACR to a Monetary Policy Shock.

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Oil Price, Vessel Speed, and Port Congestion

- Fuel costs make up 50–60% of liner shipping expenses, and fuel use rises roughly with the cube of vessel speed.
  - A 1% rise in Brent price $\Rightarrow$ vessel speed $\downarrow$ by 0.022% ($p = 0.004$).
- Yet, port congestion shows no significant link to oil prices ($p = 0.313$, $R^2 = 0.021$).
- Interpretation: oil prices drive cost-based speed adjustments, not congestion, which is shaped by **scheduling rigidities** and the "hurry up and wait" nature of port operations.

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Steady-State Aggregate Supply Schedule

Proposition 1

For any $\bar{z} \geq \bar{z}_{\min}$ *satisfying* $\int_0^{\bar{z}_{\min}} G(z')\,dz' = \rho/\left[(1-\eta)\beta\right]$, *define*

$$p(\bar{z}) = \bar{z} - (1 - \eta f(\bar{z}))\,\beta \int_0^{\bar{z}} G(z')\,dz', \quad f(\bar{z}) = \left(1 - q(\bar{z})^{\xi}\right)^{1/\xi}, \quad q(\bar{z}) = \rho/\left[(1-\eta)\beta \int_0^{\bar{z}} G(z')\,dz'\right].$$

Then the steady-state aggregate supply schedule $p \mapsto c_s^{ss}(p)$*, represented by* $(p(\bar{z}), c_s^{ss}(\bar{z}))$*, satisfies:*

1. $p(\bar{z})$ *is continuously differentiable and strictly increasing, implying a unique, smooth* $c_s^{ss}(p)$*;*
2. $\lim_{p \to p_{\min}} c_s^{ss}(p) = 0$ *and* $\lim_{p \to \infty} c_s^{ss}(p) = l$*, where* $p_{\min} = \bar{z}_{\min} - \rho/(1-\eta)$*;*
3. $c_s^{ss}(p)$ *is strictly increasing and convergent as* $p \to \infty$*;*
4. *Near* $p_{\min}$*: convex if* $\xi \in (0,1)$*, linear if* $\xi \geq 1$*, concave for large* p*.*

Back

Bound on Upstream Slackening

- To ensure that the price increase does not overturn the immediate slackening in the upstream market caused by a supply chain disturbance, we impose a bound on the response of product market tightness θ to the cost parameter γ:

$$\theta_\gamma \in \left[-\frac{\mathbb{F}_\gamma}{\mathbb{F}_\theta}, 0\right),$$

  where $\mathbb{F}_\gamma$ and $\mathbb{F}_\theta$: partial derivatives of $\mathbb{F}(p, \bar{z}, \theta; \gamma) = 0$ with respect to γ and θ.

- This restriction limits the extent of upstream slack so that the price-feedback effect on match separation does not dominate the direct effect of the shock.

- It guarantees the coexistence of a decline in upstream market tightness and a rise in the downstream retail price.

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Setting Up the SVAR

- The SVAR model can be written compactly as:

$$\boldsymbol{y}_t' \boldsymbol{A}_0 = \boldsymbol{x}_t' \boldsymbol{A}_+ + \boldsymbol{\varepsilon}_t', \quad \forall t \in [1, T],$$

  where $\boldsymbol{y}_t$: an $n \times 1$ vector of endogenous variables; $\boldsymbol{x}_t' = \left[\boldsymbol{y}_{t-1}' \ \cdots \ \boldsymbol{y}_{t-L}' \ 1 \ t\right]$; $\boldsymbol{\varepsilon}_t$: an $n \times 1$ vector of structural shocks; $\boldsymbol{A}_0$: an $n \times n$ invertible matrix of parameters; $\boldsymbol{A}_+$: an $(nL+2) \times n$ matrix of parameters; L: lag length; T: sample size.

- Conditional on past information and initial conditions $\{\boldsymbol{y}_0, \ldots, \boldsymbol{y}_{1-L}\}$, $\boldsymbol{\varepsilon}_t \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{I}_n)$.

- The matrices $\{\boldsymbol{A}_0, \boldsymbol{A}_+\}$ constitute the structural parameters of the model.

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Extended U.S. SVAR: Sectoral Substitution and Energy

- We estimate an augmented eleven-variable SVAR including:
  - Real PCE and PCE prices for goods and services;
  - Spare capacity, product market tightness, import price index, and ACR;
  - WTI spot price, effective federal funds rate, and average hourly earnings.
- The model identifies three shocks:
  - Sectoral substitution shock;
  - Adverse oil price shock;
  - Adverse supply chain shock.
- We keep the sample, lag length, deterministic terms, and priors the same as in the baseline specification.

Identification Restrictions

- **A sectoral substitution shock** leads to a positive response of real PCE of goods, the PCE goods price index, product market tightness, and the import price index, and a negative response of real PCE of services, the PCE services price index, and spare capacity at $k = 1$. The WTI spot price and ACR do not respond at $k = 1$.
- **An adverse oil price shock** leads to a negative response of real PCE of goods and spare capacity, and a positive response of the PCE goods price index, product market tightness, the import price index, and the WTI spot price at $k = 1$. The ACR index does not respond at $k = 1$.
- **An adverse supply chain shock** leads to a negative response of real PCE of goods and product market tightness, and a positive response of the PCE goods price index, spare capacity, and the ACR index at $k = 1$. The WTI spot price does not respond at $k = 1$.

What Drove U.S. Goods Inflation?

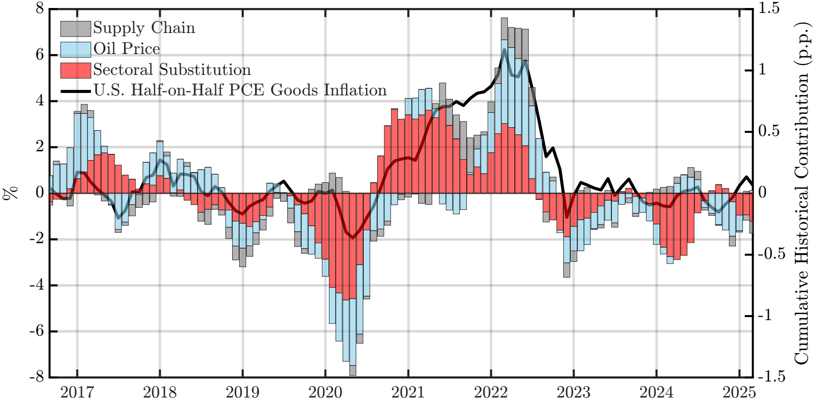

Figure: Historical Decomposition of U.S. Half-on-Half PCE Goods Inflation.

What Drove U.S. Services Inflation?

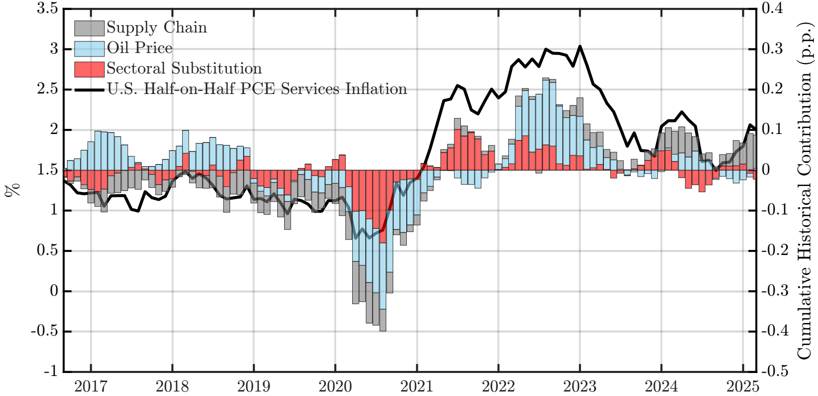

Figure: Historical Decomposition of U.S. Half-on-Half PCE Services Inflation.

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Euro Area SVAR: Goods Demand and Energy

- Monthly sample: January 2016–June 2024.
- Variables:
  - Industrial production and HICP goods price index;
  - Import-weighted spare capacity of China and U.S. (top 2 EA trading partners), product market tightness, import price index, and ACR;
  - Brent crude oil price and ECB deposit facility rate.
- The model identifies three shocks:
  - Positive goods demand shock;
  - Adverse oil price shock;
  - Adverse supply chain shock.
- Identification uses the same lag length, deterministic terms, and priors as the U.S. model.

Identification Restrictions

- **A positive goods demand shock** leads to a positive response of industrial production, the HICP goods price index, product market tightness, and the import price index, and to a negative response of spare capacity at $k = 1$. The Brent crude oil price and ACR do not respond at $k = 1$.
- **An adverse oil price shock** leads to a negative response of industrial production and spare capacity, and to a positive response of the HICP goods price index, product market tightness, the import price index, and the Brent crude oil price at $k = 1$. The ACR index does not respond at $k = 1$.
- **An adverse supply chain shock** leads to a negative response of industrial production and product market tightness, and to a positive response of the HICP goods price index, spare capacity, and the ACR index at $k = 1$. The Brent crude oil price does not respond at $k = 1$.

What Drove EA Goods Inflation?

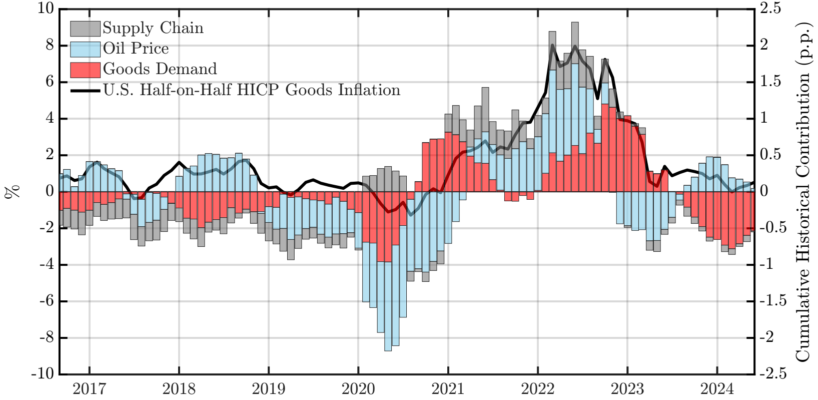

Figure: Historical Decomposition of EA Half-on-Half HICP Goods Inflation.

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Comparing Goods Price IRFs Across Proxies

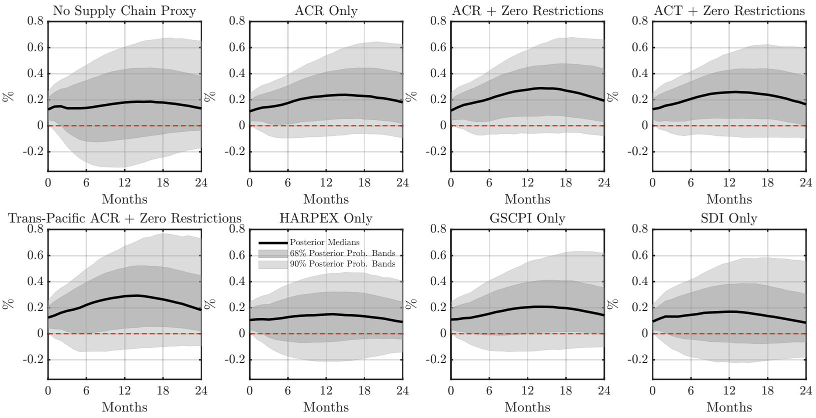

Figure: PCE Goods Price Responses to a Supply Chain Shock.

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Comparing Goods Price FEVDs Across Proxies

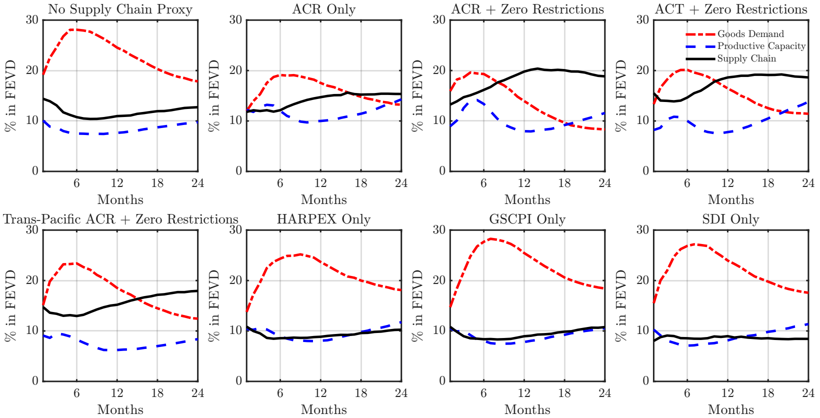

Figure: Posterior-Median FEVD Shares of PCE Goods Price Variance.

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