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

Inaugural Conference of the ChaMP Research Network

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Introduction

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  - and more recently, the Red Sea crisis and rising geopolitical fragmentation.
- What are the **causal effects** and **policy implications** of global supply chain disruptions?
- How can we measure the size of a supply chain disruption shock?
  - Shipping costs;
  - New York Fed's GSCPI.
- How does a supply chain disruption shock differ from other shocks?
  - Demand shock;
  - Productive capacity shock.
- What are the policy implications?
  - Monetary tightening vs. a hold-steady approach;
  - Lower inflation vs. contraction in output/employment.

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- **A causality assessment using structural VARs** to integrate our measure of global supply chain disruptions and the theory-predicted identification restrictions on structural shocks.
- **A state-dependence analysis** that studies the interplay between supply chain disruptions and the changes in the effectiveness of monetary policy to control inflation and output.

Related Literature

- **Disruption in the goods market**: Barro and Grossman (1971); Michaillat and Saez (2015, 2022); Ghassibe and Zanetti (2022); Ghassibe (2024).
- **Supply chain shocks for inflation and output**: Cerdeiro and Komaromi (2020); Cerrato and Gitti (2022); Acharya *et al.* (2023); Benigno and Eggertsson (2023, 2024); Blanchard and Bernanke (2023); Comin *et al.* (2023, 2024); di Giovanni *et al.* (2023); Franzoni *et al.* (2023); Harding *et al.* (2023); Ascari *et al.* (2024).
- **Transportation sector and economic activity**: Allen and Arkolakis (2014); Brancaccio *et al.* (2020); 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).
- **SVAR models for causal inference**: Uhlig (2005); Rubio-Ramírez *et al.* (2010); Arias *et al.* (2018); Brinca *et al.* (2021); Finck and Tillmann (2022); Gordon and Clark (2023); Finck *et al.* (2024).

Road Map

Why Containerized Trade?

- We measure disruptions to the global supply chain by studying **congestion at container ports**.
  - Containerized trade accounts for $\approx 46\%$ of world trade.
  - Most of the rest is accounted for by bulk cargo (e.g., oil) and specialized vessels (e.g., roll-on/roll-off).

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- You want to think about containerships as regular flights or bus lines: regular schedules, picking up/delivering containers from/to feeders.
  - Unlike dry bulk ships or oil tankers (Brancaccio *et al.*, 2020), the routes and speed of container ships are rarely changed except in exceptional circumstances. The Red Sea Crisis

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- In the realm of containerized trade, seaports serve as international hubs for freight collection and distribution.

Why Port Congestion?

- **Port congestion**: a containership must first moor in an **anchorage** within the port (random areas to lower anchors) before docking at a **berth** (designated spots to load/unload the cargo).
- Prior to the pandemic, waiting times at ports were just a few hours. However, general disruptions related to the COVID-19 pandemic led to extended delays, with waiting times reaching 2-3 days at several major ports.
- Even mild congestion has tremendous financial and logistic consequences.

Berth vs. Anchorage

Figure 1: Berth.

Figure 2: Anchorage.

Estimating Port Congestion

- We use movement data of containerships from the **Automatic Identification System (AIS)**.
    - A real-time satellite tracking system mandated by the IMO.
    - Each data entry includes the 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 handle the data – spatial-temporal data of container ships at top 50 container ports worldwide.

Automatic Identification System (AIS)

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 3: Example of an AIS Transceiver.

Sample AIS Data

Figure 4: First 50,000 AIS Observations of Ships Entering the Port of Rotterdam Since 1 January 2020.

A Machine Learning Spatial Clustering Algorithm

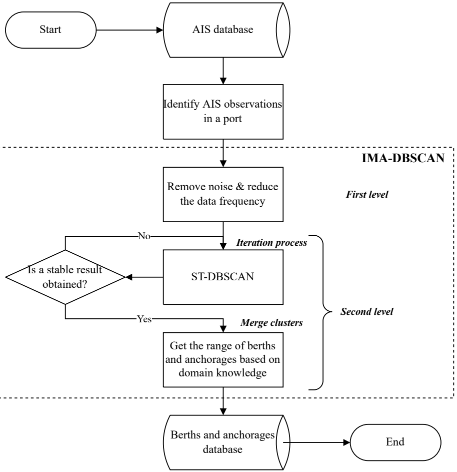

Figure 5: The IMA-DBSCAN Algorithm. Details

Granular Information in the AIS Data

Figure 6: Headings at a Berth.

Figure 7: Headings at an Anchorage.

Timestamps

Identification Results

Figure 8: Berths (Other Colors) and Anchorages (Purple, Blue, and Red) in the Port of Rotterdam.

Los Angeles, Long Beach, Singapore, & Ningbo-Zhoushan

Identification Results (cont.)

Figure 9: Berths.

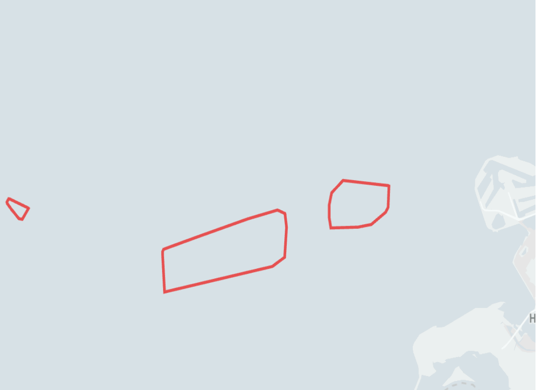

Figure 10: Anchorages.

From Identification to Aggregation

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

1. Map the geographical boundaries of berths and anchorages for the top 50 container ports ($\mathscr{P}$) using AIS data and IMA-DBSCAN.

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3. Calculate the congestion rate for each port p by dividing the number of delayed ships by the total number of ship visits ($Delayed_{pt} + Undelayed_{pt}$),

$$Congestion_{pt} \equiv \frac{Delayed_{pt}}{Delayed_{pt} + Undelayed_{pt}}, \ \forall p \in \mathscr{P}.$$

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

$$ACR_t = \sum_{p \in \mathscr{P}} \left[\frac{Delayed_{pt} + Undelayed_{pt}}{\sum_{p \in \mathscr{P}} (Delayed_{pt} + Undelayed_{pt})} \cdot Congestion_{pt} \right].$$

Congestion at Major Container Ports Worldwide

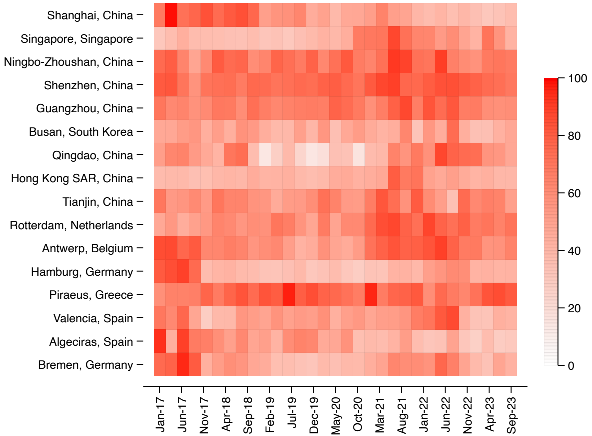

Figure 11: Congestion Rates for the Top 10 Container Ports Worldwide and the Other Major Ports in Europe.

Average Congestion Rate (ACR)

- On a declining trend before the onset of the pandemic in early 2020.
- Rose to reach its peak at 37% in June 2021.
- Remained elevated until the second half of 2022.
- Reverted to a sample median at 29.1% in 2023.

Figure 12: ACR for 2017:M1 – 2023:M9.

Exogeneity and Accuracy

- Our ACR index is largely independent of changes in demand:
  1. Unchanged itineraries and fixed routes of containerships ensure port congestion is exogenous to variations in demand;
  2. The global nature of our index "averages out" any changes in port congestion resulting from infrequent adjustments in shipping capacity across routes;
  3. The normalization also "nets out" the movements in the index from changes in demand.
  4. Close to zero correlation between congestion rate and ship visits.
- It also separates disruptions to production and those to transportation.
- Satellite data is accurate in tracking containerships, with virtually no measurement error.

Comparing ACR to HARPEX

- Harper Peterson Time Charter Rates Index (HARPEX):
  - A widely-used cross-border transportation cost;
  - Fluctuated at a historical average before 2020;
  - Rose significantly in the second half of 2020;
  - Remained elevated until mid-2022.

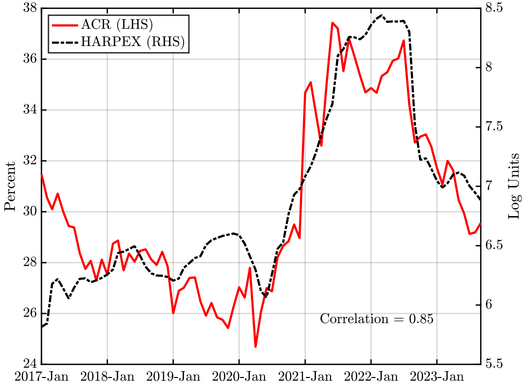

Figure 13: ACR vs. HARPEX.

Comparing ACR to GSCPI

- New York Fed's Global Supply Chain Pressure Index (GSCPI):
  - See di Giovanni *et al.* (2022);
  - Jump in early 2020 → initial Chinese lockdown;
  - Fall in late 2020 → partial reopening of China and Europe.

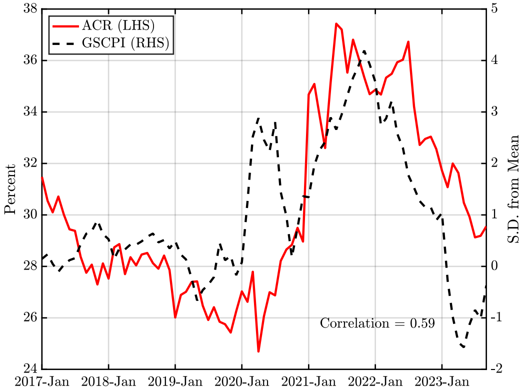

Figure 14: ACR vs. GSCPI.

Extensions

- Attacks on commercial ships in the Red Sea (Al Jazeera, 2023) – *Done*.
- Draught at the Panama Canal (LaRocco, 2023) – *Done*.
- Illegal oil trade and Russia's "dark fleet" (Cook and Sheppard, 2023) – *Ongoing*.
- Different weights:
  - Average Congestion Time (ACT) – *Done*.
  - Regional disaggregated indices – *Done*.
  - Indices for bulk, specialized, and liner ships – *Ongoing*.
- The ACR index as a noisy measure and estimation of SVARs with measurement errors – *Ongoing*.
- `https://globalportcongestion.github.io/blog/intro.html`.

Vessel Rerouting and the Red Sea Crisis

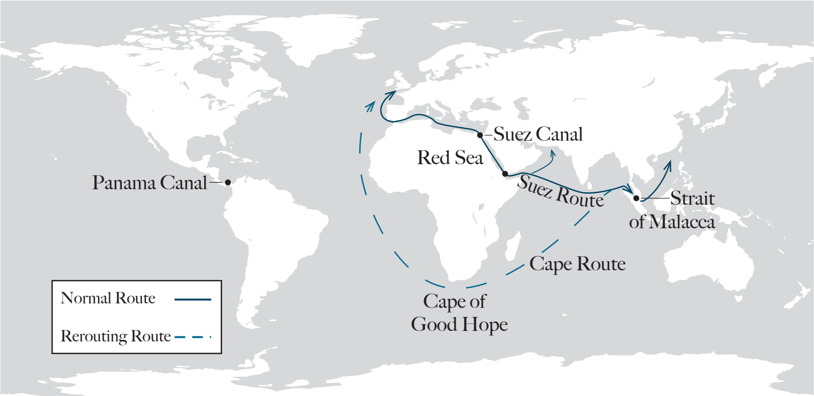

Figure 15: Vessel Rerouting Path.

Vessel Rerouting and the Red Sea Crisis (cont.)

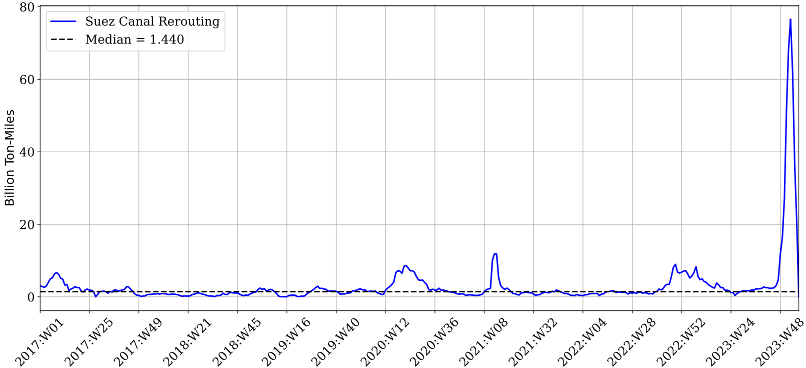

Figure 16: Suez Canal Rerouting Ton-Miles, 2017:W1 – 2024:W5.

Back

Draught at the Panama Canal

- The climate crisis is increasingly impacting global supply chains and trade routes.
- Cargo ships have been forced to wait days and weeks to cross the Panama Canal because of severe drought and the subsequent El Niño effect.

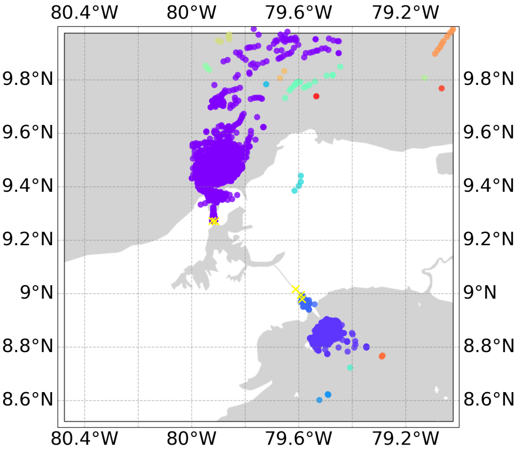

Figure 17: Congested Areas at the Panama Canal.

... and the Resulting Canal Congestion

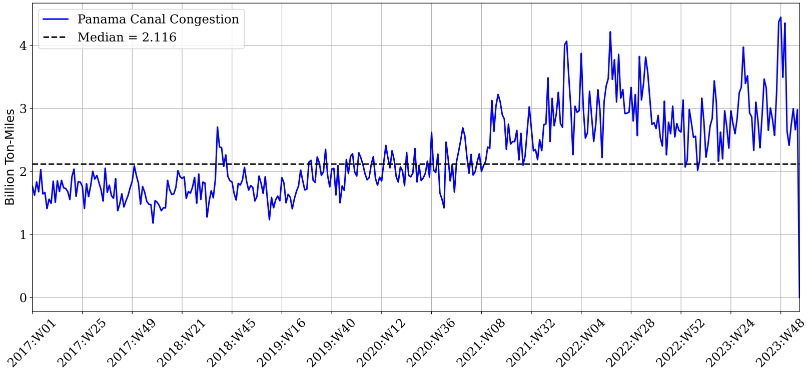

Figure 18: Reduction in Maritime Supply Due to Panama Canal Congestion, 2017:W1 – 2024:W5.

Road Map

Why a Model?

- We want a model that accounts for both spare productive capacity and scarcity in retail supply.
- We also want a model that provides identification restrictions for standard causality assessment in time series (SVARs, LPs).
- The model must have the three shocks that researchers and policymakers have been discussing as driving inflation post-COVID:
  - Demand shock;
  - Productive capacity shock; and
  - Supply chain disruption shock.
- A full structural estimation is also possible, but ...

Which Model?

- Three classes of models:
  - A production network model;
  - A New Keynesian model with transportation costs; or
  - A search and matching model with transportation costs.
- The last two classes of models can be mapped into each other in terms of identification, but we believe that, for this application, a search and matching model is more transparent.
- **Key features:** (i) matching frictions between producers and retailers in the product market; and (ii) endogenous separation of producer-retailer matches on transportation cost.

Aggregate Supply | Aggregate Demand | Flexible Price Steady State

Supply Side of the Economy with Flexible Prices

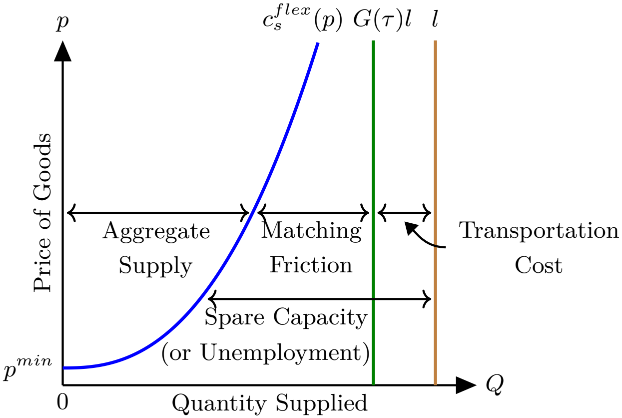

Figure 19: Aggregate Supply and Spare Capacity.

Comparative Statics

- We use comparative statics to study the responses of the macro aggregates to (unanticipated) adverse shocks to aggregate demand, productive capacity, and the supply chain, when the economy is at the steady state.
- Numerical exercises also show that the full transition dynamics are consistent with the identification restrictions.

An Adverse Shock to Aggregate Demand

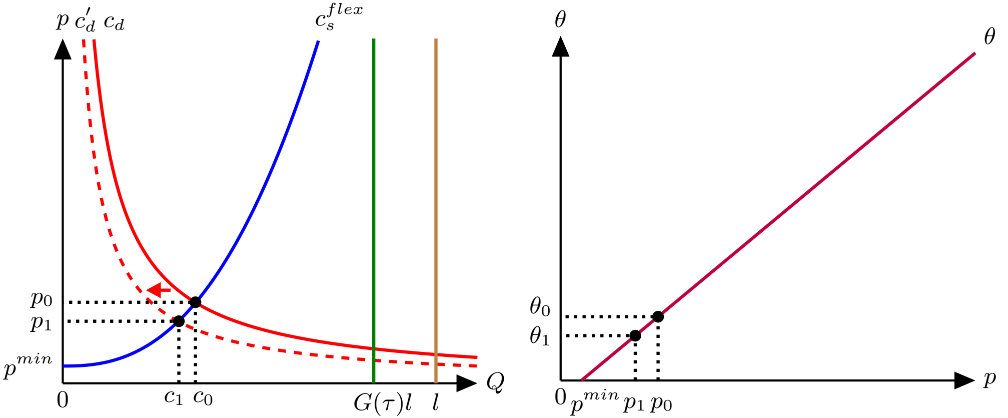

Figure 20: Money Supply ↓ or Taste for Consumption ↓.

An Adverse Shock to Productive Capacity

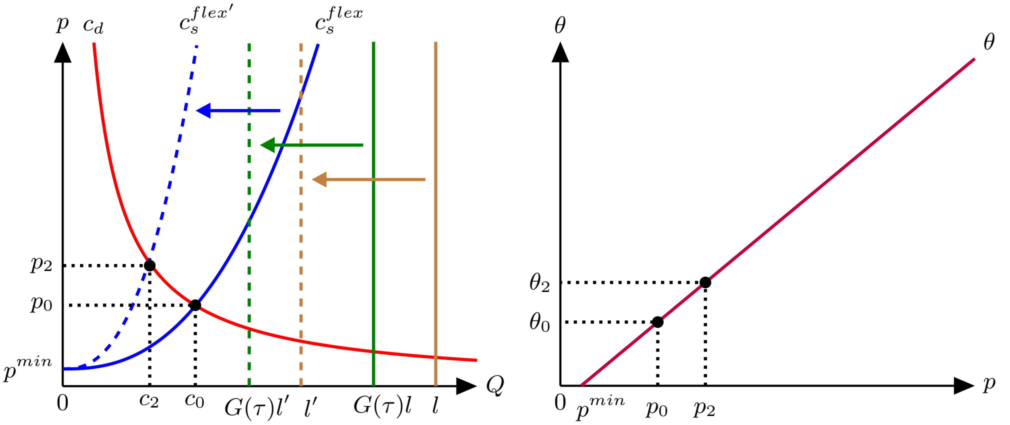

Figure 21: Productive Capacity (Labor Supply) ↓.

An Adverse Shock to the Supply Chain

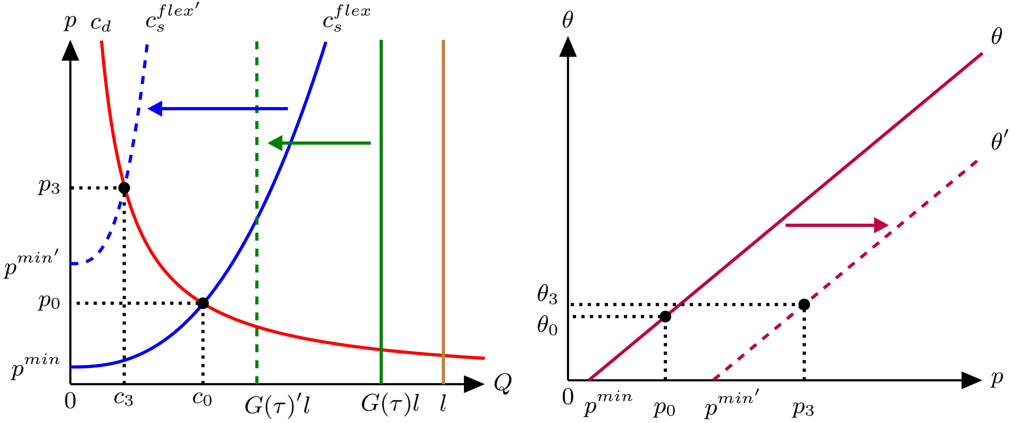

Figure 22: Scale Parameter of the Log-normal Distribution of Transportation Costs ↑.

Identification Restrictions

Table 1: Comparative Statics.

Adverse Shock To:	Effects On:					
	Consumption (or Output)	Price	Product Market Tightness	Wholesale Price	Matching Cost	Spare Capacity (or Unemployment)
	c	p	θ	r	$\frac{AG(\tau)}{1-(1-A)G(\tau)}l - c$	$l - c$
Aggregate Demand ($\mu \downarrow$ or $\chi \downarrow$)	−	−	−	−	+	+
Productive Capacity ($l \downarrow$)	−	+	+	+	−	−
Supply Chain ($\gamma \uparrow$)	−	+	Undetermined	Undetermined	Undetermined	+
Supply Chain ($A \downarrow$)	−	+	+	+	Undetermined	+

Back

Road Map

A SVAR Model With Sign and Zero Restrictions

- We address the causal effects of global supply chain disruptions using the SVARs as in Uhlig (2005), Rubio-Ramírez *et al.* (2010), and Arias *et al.* (2018):

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

- We include six endogenous variables:
  1. Real GDP;
  2. PCE goods price;
  3. Unemployment;
  4. Retail market tightness
  5. Import price;
  6. ACR.
- All the series are seasonally adjusted. The sample runs from 2017:M1 through 2023:M9.

Setting Up the SVAR

Shocks and Identification Restrictions

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

Comparative Statics

Estimation Details

- We set two lags in the baseline specification, but the results are robust to considering longer lags.
- Real GDP, PCE goods price, retail market tightness, and import price enter the SVAR in log percent, while unemployment and the ACR index enter in percent.
- Bayesian estimation with a Normal-Generalized-Normal (NGN) prior distribution over $\left\{\boldsymbol{A}_0, \boldsymbol{A}_+\right\}$.
- We also check the robustness of our results across many other dimensions, e.g., dropping the zero restrictions, variable substitutions, an estimation using the prior robust approach, etc.

Impulse Response Functions (IRFs)

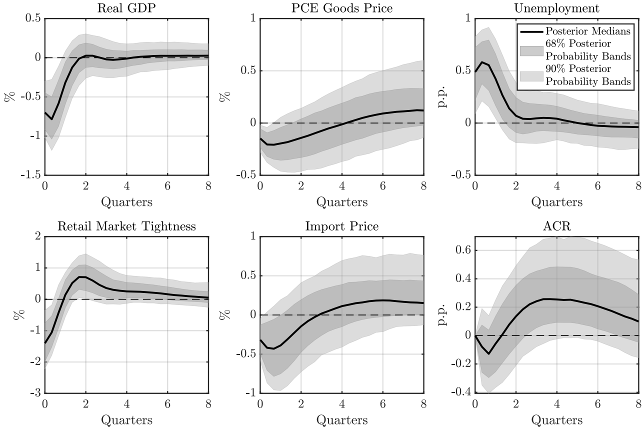

Figure 23: IRFs to an Adverse Shock to Aggregate Demand.

IRFs (cont.)

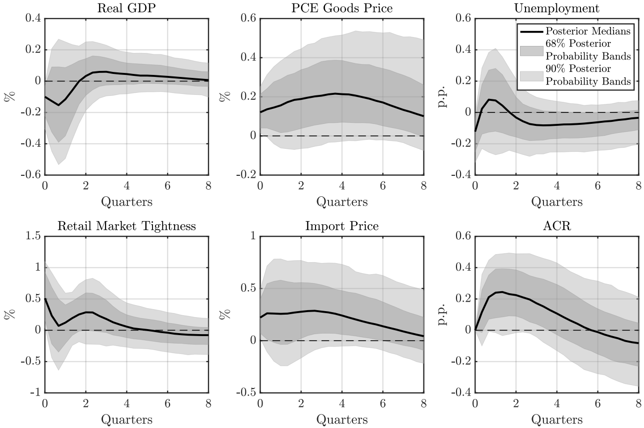

Figure 24: IRFs to an Adverse Shock to Productive Capacity.

IRFs (cont.)

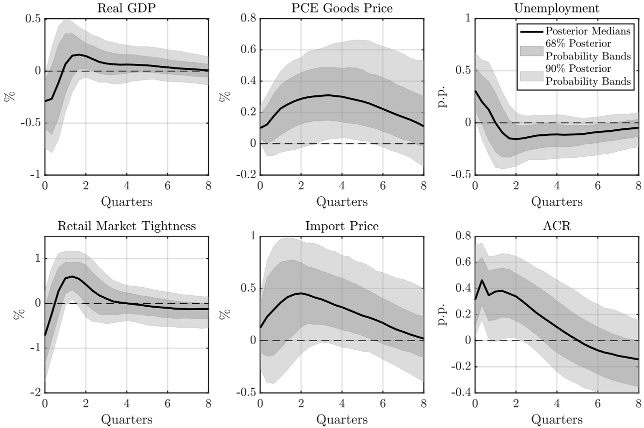

Figure 25: IRFs to an Adverse Shock to the Supply Chain.

Forecast Error Variance Decomposition (FEVD)

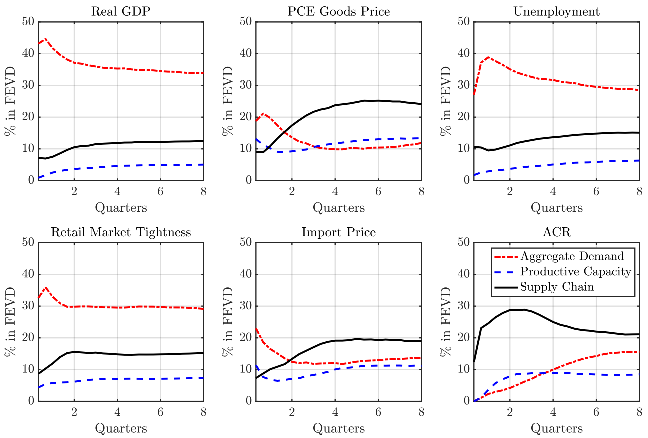

Figure 26: FEVD From the SVAR.

Historical Decomposition (HD) of the U.S. Goods Inflation

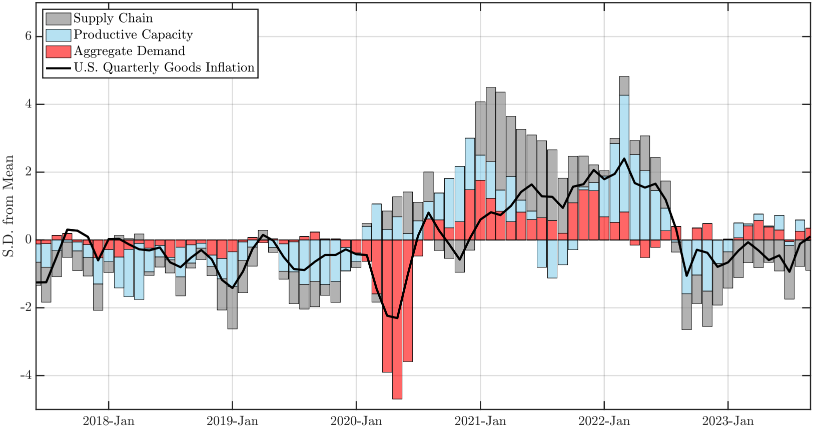

Figure 27: Cumulative Historical Contribution of Each Shock to U.S. Quarter-On-Quarter Goods Inflation.

HD of the U.S. Goods Inflation (cont.)

Table 2: Cumulative Historical Contribution of Each Shock to U.S. Year-On-Year Goods Inflation.[1]

Date	U.S. Goods Inflation (Y-O-Y, Percent)	Cumulative Historical Contribution: Aggregate Demand (%)	Productive Capacity (%)	Supply Chain (%)
2018:M6	1.4	-16.6	-47.1	-23.1
2019:M6	-0.6	35.2	95.9	68.7
2020:M6	-1.8	85.2	15.7	-0.4
2021:M6	5.7	17.8	14.8	18.6
2022:M6	10.8	6.8	9.7	8.8
2023:M6	1.1	31.2	-17.7	-62.4

[1] U.S. goods inflation rate, calculated as the year-on-year growth of the PCE goods price index, along with the cumulative historical contribution of shocks to aggregate demand, productive capacity, and the supply chain to goods inflation, measured as a percentage of the corresponding year-on-year goods inflation rate for each sampling year from 2018 to 2023. For interpretation, if the goods inflation rate is positive (negative), a positive cumulative historical contribution implies that the shock is contributing to the rise (fall) in inflation, and *vice versa*.

Road Map

Effectiveness of Monetary Policy: Theoretical Prediction

- Do supply chain disruptions alter the **stabilization trade-off** between inflation and output?

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- Theoretically,
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  - Supply chain disruptions $\rightarrow$ scale parameter of the distribution of transportation cost $\uparrow$:
    - Mean transportation cost $\uparrow$;
    - Probability that a random draw of transportation cost lies above the reservation level $\uparrow$.

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    - Mean transportation cost $\uparrow$;
    - Probability that a random draw of transportation cost lies above the reservation level $\uparrow$.
- In the paper, we also show that the results are essentially the same in the case where the matching efficiency (A) falls.

Effectiveness of Monetary Policy: Theoretical Prediction (cont.)

- When the increase in product market tightness is sufficiently large during the supply chain disruption, it **intensifies** the fall in inflation while **dampening** the fall in consumption (or, equivalently, output) that is associated with a contractionary monetary policy shock.

Partial & Cross Derivatives Back

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- Intuition:
  - When the increase in product market tightness is sufficiently large due to the supply chain disruption, the aggregate supply curve becomes steeper;
  - The probability of producers participating in trade responds less to price variations when the product market is already tight, as the number of matches is constrained by the shorter side, i.e., the number of unmatched producers.

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- Linked with the evidence that the Phillips curve has become steeper post-COVID (Cerrato and Gitti, 2022; Benigno and Eggertsson, 2023, 2024).

Partial & Cross Derivatives Back

Graphical Representation

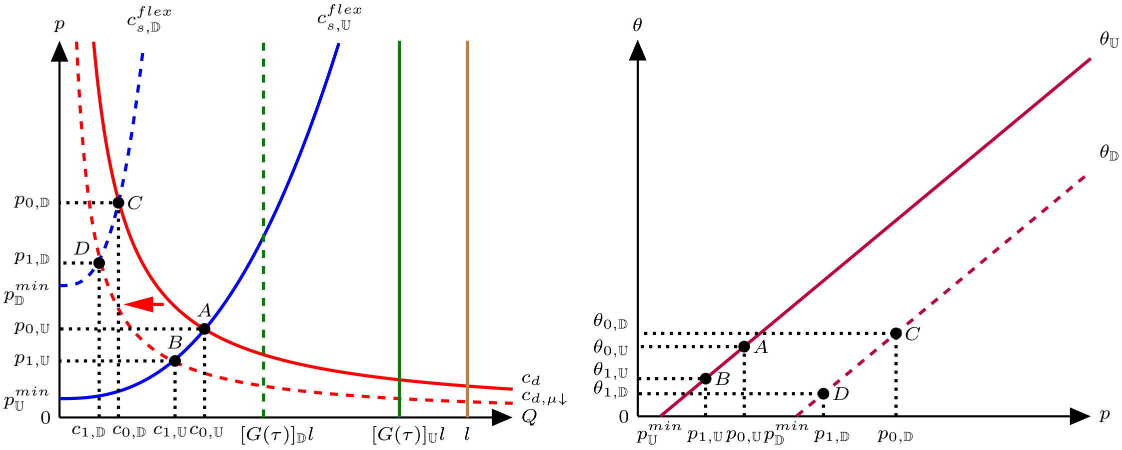

Figure 28: State-Dependent Effects of a Contractionary Monetary Policy Shock: Theoretical Prediction.

Effectiveness of Monetary Policy: Empirical Validation

- We validate our theoretical prediction using a TVAR model, which allows the VAR parameters to vary between the supply chain disrupted ($\mathbb{D}$) and undisrupted ($\mathbb{U}$) states.
- We include seven endogenous variables:
  1. Federal Funds Rate;
  2. Real GDP;
  3. PCE goods price;
  4. Unemployment;
  5. Retail market tightness;
  6. Import price;
  7. ACR.

Setting Up the TVAR

Shock and Identification Restrictions

- ***A contractionary monetary policy shock*** leads to a negative response of real GDP, PCE goods price, retail market tightness, and import price, as well as to a positive response of unemployment and the Federal Funds Rate at $k = 1$. The ACR does not respond at $k = 1$.
- Such a restriction is imposed using the Penalty Function Approach (Uhlig, 2005; Mountford and Uhlig, 2009).

Theoretical Prediction Back

Estimation Details

- We include one lag in the TVAR, and our results are robust to different lag structures.
- We retain the same sample period from 2017M1 to 2023M9, and all the series have been seasonally adjusted except for the Federal Funds Rate.
- Real GDP, PCE goods price, retail market tightness, and import price enter the TVAR in log percent, whereas the Federal Funds Rate, unemployment, and the ACR index enter in percent.
- We compute the identified set of IRFs using a Bayesian approach as in Pizzinelli *et al.* (2020) and Bratsiotis and Theodoridis (2022).
- Once again, our results are robust to a wide array of modifications, e.g., using the Wu-Xia shadow Federal Funds Rate, dropping the zero restriction, looser priors, etc.

IRFs to a Contractionary Monetary Policy Shock

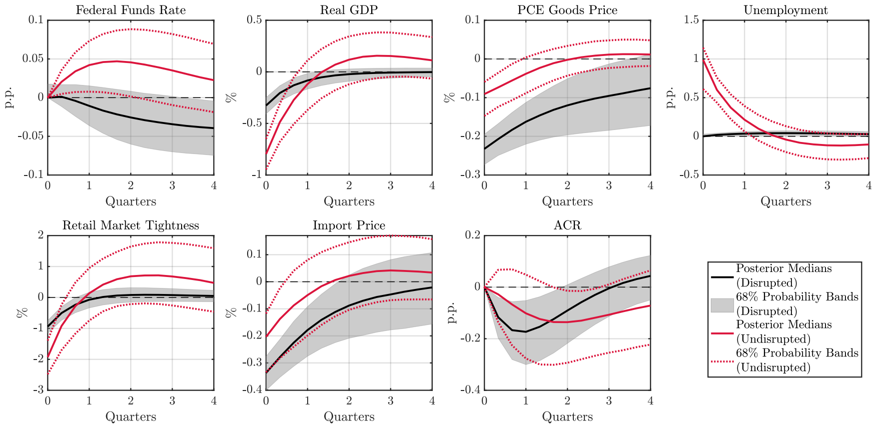

Figure 29: State-Dependent Effects of a Contractionary Monetary Policy Shock: Empirical Validation. LPs

Road Map

Conclusion

- We study the causal effects and policy implications of global supply chain disruptions.
- We construct a new index, develop a novel theory, and integrate them with the state-of-the-art methods for assessing causality in time series.
- We establish two main results:
  1. Supply chain disruptions generate stagflation accompanied by an increase in spare capacity;
  2. Monetary tightening could tame inflation at reduced costs of real activities during times of supply chain disruption.
- Far from being just a postmortem of what happened during COVID-19, our analysis distills important lessons for now and the future.

Additional Slides

Estimating Port Congestion Using AIS Data and IMA-DBSCAN

- To quantify port congestion, we follow the maritime literature by estimating the likelihood that a vessel will first moor in an anchorage area within the port before docking at a berth (Talley and Ng, 2016; Bai *et al.*, 2023).
- IMA-DBSCAN identifies these different areas by focusing on the density of ships' mooring points recorded in the AIS data, which include all historical visits of containerships to each port, with each visit containing numerous AIS data points.
- Specifically, the algorithm operates in two layers of clustering:
  - The first layer identifies high-density areas, which are considered potential berths and anchorages;
  - The second layer refines these areas by considering additional domain knowledge (e.g., headings of ships during mooring, timestamps of port calls).

Back

Granular Information in the AIS Data (cont.)

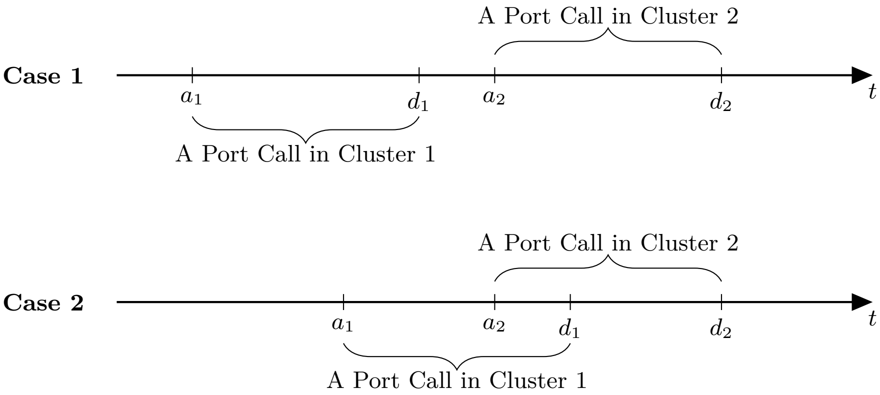

Figure A.1: Merging Clusters.

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More Identification Results

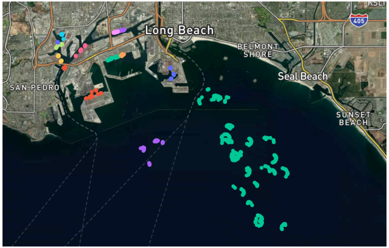

Figure A.2: L.A. and L.B., U.S.

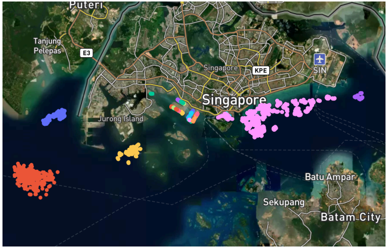

Figure A.3: Singapore.

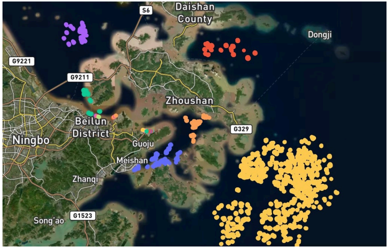

Figure A.4: Ningbo-Zhoushan, China.

Back

Firms

- **Producers**:
  - An exogenous unit mass;
  - Produce goods with a productive capacity determined by labor inputs $l > 0$ that are inelastically supplied by households;
  - Supply goods to retailers, yet matching frictions prevent their full capacity from being sold.
- **Retailers**:
  - An endogenous measure;
  - Purchase goods by visiting producers, yet not all visits would result in a match due to matching frictions;
  - Resell goods to households for a price.
- Households own the producers and retailers, accruing all the profits in the economy.

Matching Process

- The matching function establishes 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: the number of unmatched producers and retailers; $\xi > 0$: elasticity of substitution between x_U and i_U.

- Product market tightness θ is defined by:

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

- The tightness determines the probabilities that producers and retailers meet each other:

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

Transportation Cost

- Producers pay a per-unit idiosyncratic transportation cost to ship their goods to retailers.
- Households receive the shipping cost as a payment for moving the goods.
- In each period, producers obtain a draw of transportation cost z from a log-normal distribution $G(z)$:

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

  where $\Phi(\cdot)$: standard normal CDF.
- There exists a reservation transportation cost $\bar{z}$, above which matches are not profitable.
- All matches with a draw of transportation cost $z > \bar{z}$ are severed, whereas those with $z \leq \bar{z}$ continue.

Value Functions

- The value for a matched producer $X_M(z)$:

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

where $r(z)$: (endogenous) wholesale price; z: transportation cost; β: discount factor; z': draw of transportation cost at the beginning of the next period.

- The value for an unmatched producer X_U is:

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

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

Value Functions (cont.)

- For a matched retailer, its value can be expressed as:

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

where p: retail price.

- For an unmatched retailer, its value can be expressed as:

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

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

- We assume free entry that drives the value for an unmatched retailer to zero in equilibrium:

$$I_U = 0.$$

Nash Bargaining

- Nash bargaining splits the total surplus from the matching between the producer and the retailer.
- The total surplus from matching is equal to:

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

- The producer earns a constant share η of the total surplus, and the retailer earns the remaining share $1-\eta$, which in equilibrium yields:

$$\eta\left(I_M(z) - I_U\right) = (1-\eta)\left(X_M(z) - X_U\right).$$

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

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

Match Separation

- Since $X_M(z) + I_M(z)$ is strictly decreasing in z on $(0, +\infty)$, there exists a cut-off transportation cost $\bar{z}$ above (below) which both sides choose to sever (continue) their match, and at $\bar{z}$, the total surplus is:

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

- Hence, we define the match separation condition as a function of price p, reservation transportation cost $\bar{z}$, and product market tightness θ, defined for all $p \in (0, +\infty)$, $\bar{z} \in (0, +\infty)$, and $\theta \in [0, +\infty)$, satisfying:

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

where the expected surplus is defined by $\mathbb{E}_{z'} S(z') = \int_0^{\bar{z}} S(z') dG(z')$.

Match Creation

- Using the free entry condition $I_U = 0$, we define the match creation condition as a function of reservation transportation cost $\bar{z}$ and product market tightness θ, defined for all $\bar{z} \in (0, +\infty)$ and $\theta \in [0, +\infty)$, satisfying:

$$\mathbb{H}(\bar{z}, \theta) = \frac{\rho l}{q(\theta)} - (1 - \eta)\beta \mathbb{E}_{z'} S(z') = 0. \tag{2}$$

Aggregate Supply

- The aggregate supply in the economy results from the equilibrium in the product market, defined as:

Definition 1

The equilibrium in the product market consists of a price p, a reservation transportation cost $\bar{z}$, and a product market tightness θ such that the conditions for match separation (1) *and match creation* (2) *simultaneously hold:*

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

Aggregate Supply (cont.)

Proposition 1

In equilibrium, the price p, reservation transportation cost $\bar{z}$, and product market tightness θ satisfy:

$$\theta(p, \bar{z}) = \frac{1-\eta}{\eta\rho}\left(p - \bar{z} + \beta \int_0^{\bar{z}} G(z')dz'\right), \tag{3}$$

where $G(.)$: log-normal CDF. Hence, θ has the following properties:

1. $\theta(p^{min}, \bar{z}) = 0$ *and* $\lim_{p \to +\infty} \theta(p, \bar{z}) = +\infty$, *where* p^{min} *satisfies* $p^{min} - \bar{z} + \beta \int_0^{\bar{z}} G(z')dz' = 0$;
2. $\theta(p, \bar{z})$ *is strictly increasing on* $[p^{min}, +\infty)$;
3. $\theta(p, \bar{z})$ *is linear on* $[p^{min}, +\infty)$;
4. $\lim_{\bar{z} \to 0+} \theta(p, \bar{z}) = (1-\eta)p/(\eta\rho)$ *and* $\theta(p, \bar{z}^{max}) = 0$, *where* $\bar{z}^{max}$ *satisfies* $p - \bar{z}^{max} + \beta \int_0^{\bar{z}^{max}} G(z')dz' = 0$;
5. $\theta(p, \bar{z})$ *is strictly decreasing on* $(0, \bar{z}^{max}]$; *and*
6. $\theta(p, \bar{z})$ *is convex on* $(0, \bar{z}^{max}]$.

Aggregate Supply (cont.)

- The aggregate supply comprises the quantity of goods traded by the producers and retailers that survive separation for a given productive capacity, equal to the total labor supply l.
- Consider the law of motion for the number of matched producers,

$$x'_M = G(\bar{z})x_M + f(\theta)G(\bar{z})x_U, \tag{4}$$

and that for the number of unmatched producers,

$$x'_U = [1 - f(\theta) + f(\theta)\left(1 - G(\bar{z})\right)]\, x_U + \left(1 - G(\bar{z})\right) x_M. \tag{5}$$

- Setting $x'_M = x_M$ in (4) and using that $x_M + x_U = 1$, the steady state number of matched producers is:

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

where θ, as in (3), will be solved as a constant once we impose the market clearing condition.

Aggregate Supply (cont.)

- The (steady state) aggregate supply is the quantity of goods supplied by matched producers given l:

$$c_s(\bar{z},\theta) = x_M^{ss}(\bar{z},\theta)l = \frac{f(\theta)G(\bar{z})}{1-G(\bar{z})+f(\theta)G(\bar{z})}l. \tag{6}$$

- Substituting in the expressions for $f(\theta)$ and θ, we express aggregate supply as:

Definition 2

The aggregate supply c_s, expressed as a function of p and $\bar{z}$, equals:

$$c_s(p,\bar{z}) = \frac{\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\bar{z})}{1-G(\bar{z})+\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\bar{z})}l, \tag{7}$$

for all $(p,\bar{z})$ satisfying:

$$p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz' \geq 0. \tag{8}$$

Flexible Price Aggregate Supply

- Since c_s is determined by two endogenous variables, infinite combinations of p and $\bar{z}$'s would yield the same c_s, as long as they satisfy the constraint (8).
- For tractability, we select the equilibrium (and its steady state) where p is flexible while $\bar{z}$ is fixed:

Definition 2′

For an arbitrary reservation transportation cost $\tau \in (0, +\infty)$, the flexible price aggregate supply c_s^{flex} is the function of p defined by:

$$c_s^{flex}(p) = \frac{\left\{1 + \left[\frac{1-\eta}{\eta\rho}\left(p - \tau + \beta\int_0^\tau G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}} G(\tau)}{1 - G(\tau) + \left\{1 + \left[\frac{1-\eta}{\eta\rho}\left(p - \tau + \beta\int_0^\tau G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}} G(\tau)} l, \tag{9}$$

for all $p \in [p^{min}, +\infty)$, where p^{min} satisfies $p^{min} - \tau + \beta \int_0^\tau G(z')dz' = 0$.

Flexible Price Aggregate Supply (cont.)

Proposition 2

The flexible price aggregate supply c_s^{flex} has the following properties:

1. $c_s^{flex}(p^{min}) = 0$ *and* $\lim_{p \to +\infty} c_s^{flex}(p) = G(\tau)l$;
2. $c_s^{flex}(p)$ *is strictly increasing in* p *on* $[p^{min}, +\infty)$; *and*
3. $c_s^{flex}(p)$ *is concave on* $[p^{min}, +\infty)$.

- The flexible price aggregate supply in (9) essentially represents the quantity of goods traded that satisfies (7) when $\bar{z} = \tau$.
- Therefore, the interaction between the price and tightness in the product market determines the aggregate supply.

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Households

- The representative household derives utility from consumption c and holding real money balances m/p:

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

  where $\chi > 0$: taste for consumption relative to holding money; $\epsilon > 1$: elasticity of substitution between c and m/p.

- The budget constraint faced by the representative household is given by:

$$pc + m \leq \mu + \underbrace{pc_s^{flex}(p) - \int_0^{\tau} z' c_s^{flex}(p) dG(z')}_{\text{Profits of Producers \& Retailers}} + \underbrace{\int_0^{\tau} z' c_s^{flex}(p) dG(z')}_{\text{Transportation Costs}} \tag{10}$$

$$= \mu + p\left[\frac{f(\theta(p))\, G(\tau)}{1 - G(\tau) + f(\theta(p))\, G(\tau)} l\right],$$

  where μ: endowment of nominal money.

Aggregate Demand

- Solving the utility-maximization problem yields:

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

- The aggregate demand in the economy is equal to the level of consumption that maximizes utility at a given price when the money market clears (this condition holds in and outside the steady state):

Definition 3

The aggregate demand c_d for a given price $p \in (0, +\infty)$ equals:

$$c_d(p) = \chi^{\varepsilon} \frac{\mu}{p}. \tag{11}$$

Proposition 3

$c_d(p)$ is strictly decreasing and convex on $(0, +\infty)$.

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Flexible Price Steady State

Definition 4

Fixing the reservation transportation cost $\bar{z}$ *to an arbitrary value* $\tau > 0$, *the flexible price steady state consists of a price* p *that equates aggregate supply and aggregate demand,* $c_s^{flex}(p) = c_d(p)$, *yielding:*

$$\frac{f\left(\theta(p)\right)G(\tau)}{1 - G(\tau) + f\left(\theta(p)\right)G(\tau)} l = \chi^{\varepsilon}\frac{\mu}{p}, \tag{12}$$

where the product market tightness θ *is given by:*

$$\theta(p) = \frac{1-\eta}{\eta\rho}\left(p - \tau + \beta\int_0^{\tau} G(z')dz'\right). \tag{13}$$

In addition, the household's budget constraint (10) *also holds with equality.*

Proposition 4

$\forall\tau > 0$, *there exists a unique flexible price steady state that features positive price and consumption.*

Flexible Price Steady State (cont.)

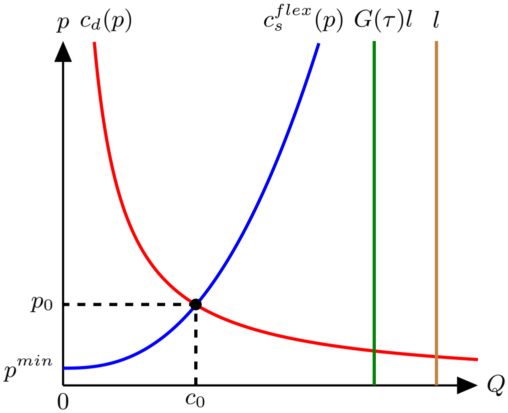

Figure A.5: Flexible Price Aggregate Supply, Aggregate Demand, and Flexible Price Steady State. Back

Setting up the SVAR

- The SVAR model can be written compactly as:

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

  where $\boldsymbol{y}_t$: an $n \times 1$ vector of endogenous variables; $\boldsymbol{x}_t' = \begin{bmatrix} \boldsymbol{y}_{t-1}' & \cdots & \boldsymbol{y}_{t-L}' & 1 & t \end{bmatrix}$; $\boldsymbol{\epsilon}_t$: 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.
- The vector $\boldsymbol{\epsilon}_t$, conditional on past information and the initial conditions $\left\{\boldsymbol{y}_0, \cdots, \boldsymbol{y}_{1-L}\right\}$, is Gaussian with mean zero and covariance matrix $\mathbf{1}_{n\times n}$.
- The matrices $\left\{\boldsymbol{A}_0, \boldsymbol{A}_+\right\}$ are the structural parameters.

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Partial & Cross Derivatives

Proposition 5

For any given threshold $\tau > 0$ *and parameter values* $\mu \in \mathbb{R}^+$ *and* $\gamma \in \mathbb{R}$ *such that the following constraint holds:*

$$\frac{\partial \theta(\mu,\gamma)}{\partial \gamma} > \frac{\theta(1+\theta^{\xi})}{(1-G(\tau))\,G(\tau)} \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(\log\tau-\gamma)^2}{2\sigma^2}\right],$$

where $G(\tau) \equiv \Phi[(\log\tau-\gamma)/\sigma]$, $\Phi(.)$ *is the standard normal CDF, the responses of the endogenous variables to a change in monetary policy are described by the partial derivatives:*

$$\frac{\partial c(\mu,\gamma)}{\partial \mu} > 0,\ \frac{\partial p(\mu,\gamma)}{\partial \mu} > 0,\ \frac{\partial \theta(\mu,\gamma)}{\partial \mu} > 0,\ \frac{\partial r(\mu,\gamma)}{\partial \mu} > 0,\ \frac{\partial}{\partial \mu}\left[G(\tau)l - c(\mu,\gamma)\right] < 0,\ \frac{\partial}{\partial \mu}\left[l - c(\mu,\gamma)\right] < 0.$$

The cross derivatives that describe the optimal interplay between a change in monetary policy and the supply chain disruption satisfy:

$$\frac{\partial^2 c(\mu,\gamma)}{\partial\mu\partial\gamma} < 0,\ \frac{\partial^2 p(\mu,\gamma)}{\partial\mu\partial\gamma} > 0,\ \frac{\partial^2 \theta(\mu,\gamma)}{\partial\mu\partial\gamma} > 0,\ \frac{\partial^2 r(\mu,\gamma)}{\partial\mu\partial\gamma} > 0,\ \frac{\partial^2}{\partial\mu\partial\gamma}\left[G(\tau)l - c(\mu,\gamma)\right] > 0,\ \frac{\partial^2}{\partial\mu\partial\gamma}\left[l - c(\mu,\gamma)\right] > 0,$$

where $c, p, \theta, r, G(\tau)l - c$, *and* $l - c$ *represent consumption (or equivalently, output), price, product market tightness, wholesale price, matching cost, and spare capacity (or equivalently, unemployment), respectively.*

Back

Setting Up the TVAR

- The reduced-form model is given by:

$$\boldsymbol{y}_t = I_t \left[\sum_{l=1}^{L} \boldsymbol{B}'_{\mathbb{D},l} \boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{D}} \boldsymbol{\omega}_t + \boldsymbol{\Sigma}_{\mathbb{D}}^{1/2} \boldsymbol{\epsilon}_t \right] + (1 - I_t) \left[\sum_{l=1}^{L} \boldsymbol{B}'_{\mathbb{U},l} \boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{U}} \boldsymbol{\omega}_t + \boldsymbol{\Sigma}_{\mathbb{U}}^{1/2} \boldsymbol{\epsilon}_t \right],$$

where $\boldsymbol{y}_t$: $n \times 1$ vector of endogenous variables; $\boldsymbol{\omega}_t = [1, t]'$: 2×1 vector of a constant and a linear trend; $\boldsymbol{\epsilon}_t$: $n \times 1$ vector of structural shocks; $\boldsymbol{B}_{\mathbb{D},l}$, $\boldsymbol{B}_{\mathbb{U},l}$: $n \times n$ matrices of coefficients for the lagged endogenous variables $\boldsymbol{y}_{t-l}$; $\boldsymbol{C}_{\mathbb{D}}$, $\boldsymbol{C}_{\mathbb{U}}$: $2 \times n$ matrices of coefficients for the constant and linear trend; $\boldsymbol{\Sigma}_{\mathbb{D}}$, $\boldsymbol{\Sigma}_{\mathbb{U}}$: covariance matrices; L: lag length; T: sample size.

Switches Between the Regimes

- Switches between the regimes are governed by the indicator variable $I_t \in \{0, 1\}$:

$$I_t = \begin{cases} 1, & \text{if } ACR_{t-1} > \overline{ACR}; \\ 0, & \text{if } ACR_{t-1} \leq \overline{ACR}. \end{cases}$$

- Under the Normal-Inverse-Wishart conjugate prior for the TVAR parameters and conditional on the value of the threshold $\overline{ACR}$, the posterior distribution of the TVAR parameter vector is a conditional Normal-Inverse-Wishart distribution, and we use the Gibbs sampler to draw from the distribution.
- Since the posterior distribution of the threshold $\overline{ACR}$ conditional on the TVAR parameters is unknown, we use a Metropolis-Hastings algorithm to obtain its posterior distribution, similar to Chen and Lee (1995), Lopes and Salazar (2006), and Pizzinelli *et al.* (2020).

Posterior of $\overline{ACR}$ and Regime Switches

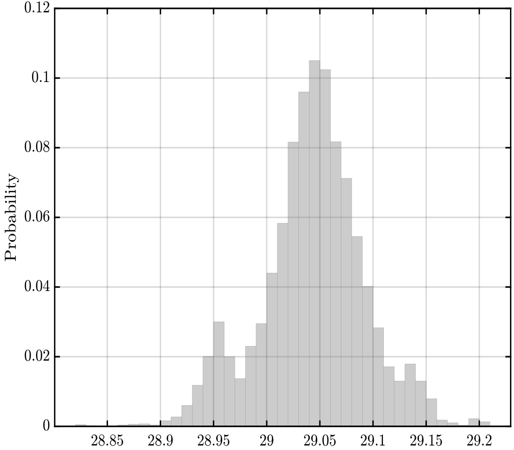

Figure A.6: Posterior Distribution of $\overline{ACR}$.

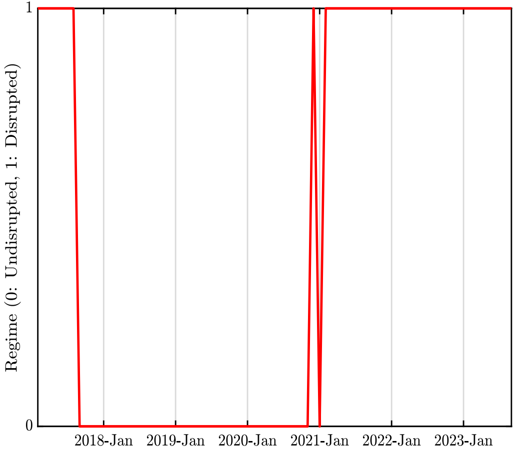

Figure A.7: Regimes Switches.

Back

Local Projections (LPs) with Interaction Terms

- We apply the LPs with interaction terms (Ramey and Zubairy, 2018; Ghassibe and Zanetti, 2022; Arias *et al.*, 2023) to study the state-dependent effects of monetary tightening.
- We include the same endogenous variables as in the TVAR except for the ACR index.
- The $n \times (K+1)$ projections are given by:

$$\begin{aligned} y_{i,t+k} = & I_t \left[\boldsymbol{\beta}'_{\mathbb{D},i,k,0} \boldsymbol{y}_t + \sum_{l=1}^{L} \boldsymbol{\beta}'_{\mathbb{D},i,k,l} \boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{D},i,k} \boldsymbol{\omega}_t \right] \\ & + (1 - I_t) \left[\boldsymbol{\beta}'_{\mathbb{U},i,k,0} \boldsymbol{y}_t + \sum_{l=1}^{L} \boldsymbol{\beta}'_{\mathbb{U},i,k,l} \boldsymbol{y}_{t-l} + \boldsymbol{C}'_{\mathbb{U},i,k} \boldsymbol{\omega}_t \right] + u_{i,k,t}, \end{aligned}$$

for $1 \leq i \leq n$ and $0 \leq k \leq K$, where $\boldsymbol{y}_t$: $n \times 1$ vector of endogenous variables. The vector of the reduced-form errors for $k = 1$, $\boldsymbol{u}_{1,t} = [u_{1,1,t} \;\; \ldots \;\; u_{n,1,t}]'$, is assumed to have mean zero and covariance matrix equal to $\mathbb{E}(\boldsymbol{u}_{1,t} \boldsymbol{u}'_{1,t}) = \boldsymbol{\Sigma}$.

Supply Chain Disrupted vs. Undisrupted

- I_t is a dummy variable that indicates whether there is a supply chain disruption.
- The disrupted regime is determined based on whether the one-month lag of the ACR index is above its sample median.

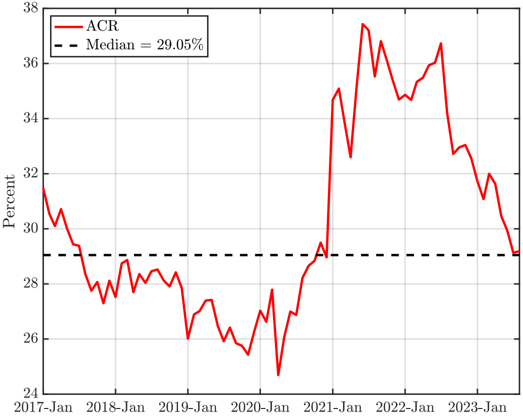

Figure A.8: ACR and Its Sample Median.

Shock and Identification Restrictions

- ***A contractionary monetary policy shock*** leads to a negative response of real GDP, PCE goods price, retail market tightness, and import price, as well as to a positive response of unemployment and the Federal Funds Rate at $k = 1, 2, 3$. In addition, the on-impact response of unemployment in p.p. is bounded to be smaller than ten times that of the Federal Funds Rate in p.p.

Identification Restrictions for TVAR

Estimation Details

- Same as in the TVAR, we include one lag in the LPs.
- We compute the identified set of IRFs for each regime by numerically solving the quadratic program outlined in the supplement to Plagborg-Møller and Wolf (2021), using Algorithm 2 from Giacomini and Kitagawa (2021).
- We impose a normalization to the identified set of IRFs so that a contractionary monetary policy shock increases the Federal Funds Rate by 0.05 p.p. on impact in both regimes.

IRFs to a Contractionary Monetary Policy Shock

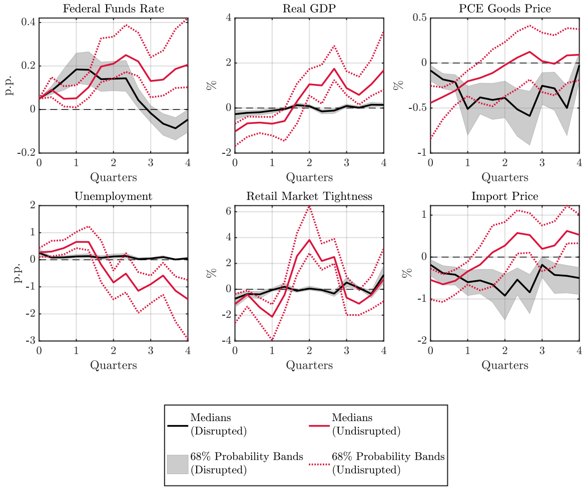

Figure A.9: State-Dependent Effects of a Contractionary Monetary Policy Shock: Using the LPs. Back