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

Xiwen Bai[1] Jesús Fernández-Villaverde[2] Yiliang Li [3] Francesco Zanetti[4]

December 4, 2023

[1]Tsinghua University

[2]University of Pennsylvania

[3]University of International Business and Economics

[4]University of Oxford

Introduction

- Lots of media attention, policy discussions, and research about the health of the global supply chain motivated by COVID-19.
- What are the *causal effects* and *policy implications* of global supply chain disruptions?
- In particular: how does a supply chain disruption shock differ from other shocks?
  - Demand shock.
  - Productive capacity shock.
- And what are the policy implications?
  - Monetary tightening vs. a hold-steady approach.

Our contributions

- A new spatial clustering algorithm to transform the satellite data of containerships into a high-frequency measure of port congestion applicable to major ports worldwide.
- A novel (and simple) model to study supply chain disruptions.
- A causality assessment using structural VARs to integrate our measure of global supply chain disruptions and the theory-predicted identification restrictions on structural shocks: inflation in 2020 vs. 2021 vs. 2022.
- A state-dependent analysis to study 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).
- **Supply-chain shocks for inflation and output**: Acharya *et al.* (2023); Benigno and Eggertsson (2023); Blanchard and Bernanke (2023); Cerdeiro and Komaromi (2020); Cerrato and Gitti (2002); Comin *et al.* (2023); di Giovanni *et al.* (2023); Franzoni *et al.* (2023); Harding *et al.* (2023).
- **Transportation sector and economic activity**: Allen and Arkolakis (2014); Brancaccio *et al.* (2020); Dunn and Leibovici (2023); Smirnyagin and Tsyvinski (2022); Brancaccio *et al.* (2023); Acharya *et al.* (2023); Alessandria *et al.* (2023); Bai and Li (2022); Li *et al.* (2022).
- **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).

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).
- You want to think about containerships as regular flights or bus lines: regular schedules, picking up/delivering containers from/to feeders.
  - Routes and speed are rarely changed (e.g., speed has next-to-no relation with oil prices).
  - “Hurry up and wait.”
- 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.
- MSC Loreto: carries around 24,346 TEUs, with 240k tons of cargo.
    - As a comparison, OSN 5, the most famous convoy of WWII, carried 219k tons of cargo in 49 merchant vessels.
- Important: personnel restrictions did not cause port delays, as these essential workers were exempted from COVID-19 restrictions.


MSC LORETO
M S C
msc
FleetMon
Tracking the Seven Seas

The AIS system

- 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: situation of ships at top 50 container ports worldwide.

AISLINK CA2

AISLink CA2

$1,999.99

The AISLink CA2 Automatic Identification System (AIS) Transponder is a fully compliant Class A transceiver designed to complement the existing range of automatic identification systems ais maritime safety equipment from ACR Electronics. This compact, single-unit solution is capable of exchanging dynamic and static ship data with marine traffic-utilizing other AIS equipment. Real-time marine traffic information is continuously interpreted using a powerful internal processing engine and displayed on a 7" full-color, rapid-response LCD. The coastline map view and radar view have various orientation display options allowing for user preference whilst a standard target list display gives immediate detailed listings of nearby vessels which can be sorted to the owner's desire.

Warning: Prop 65

1

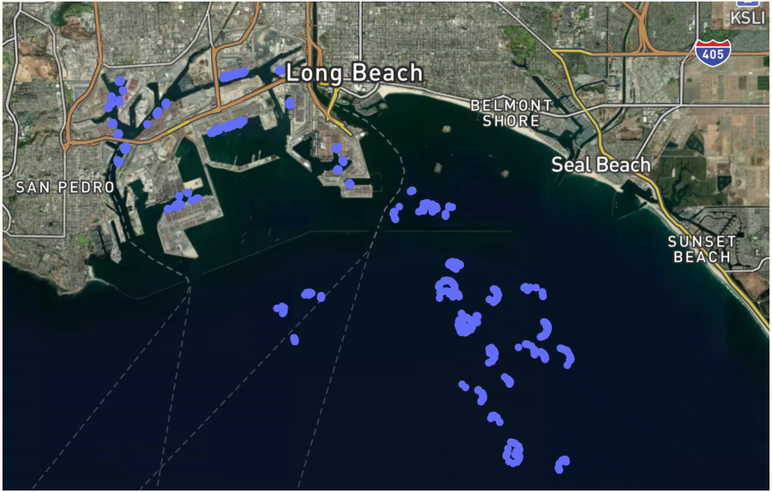
ADD TO CART

FIND A DEALER

SKU: 2666

Category: MARINE

Sample AIS data



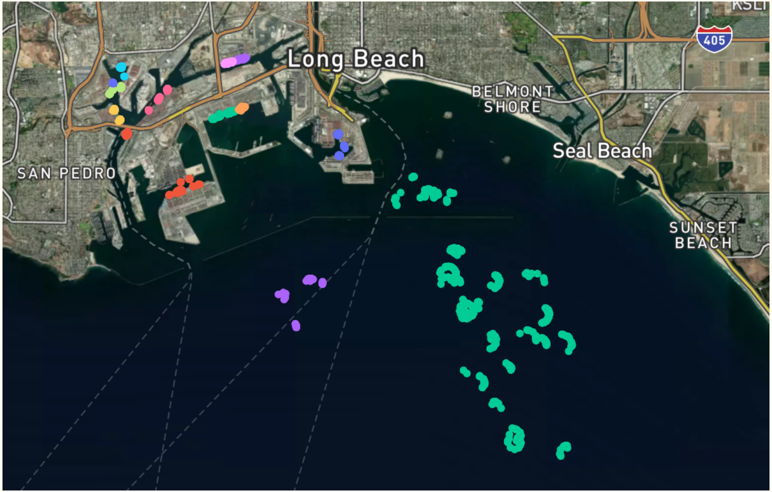
The first 50,000 AIS observations of containerships entering the Ports of Los Angeles and Long Beach since January 1, 2020.

A machine learning, spatial clustering algorithm

Headings at a berth.

Headings at an anchorage.

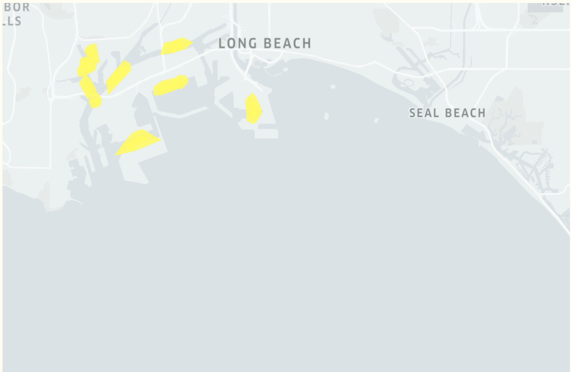
Results, I



Identification of anchorages (cyan and purple) and berths (other colors) in Los Angeles and Long Beach ports.

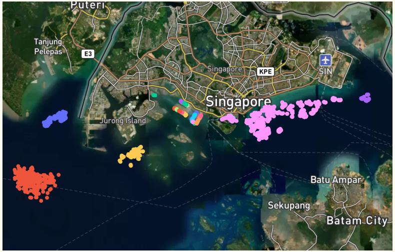
Results, II

Anchorages.

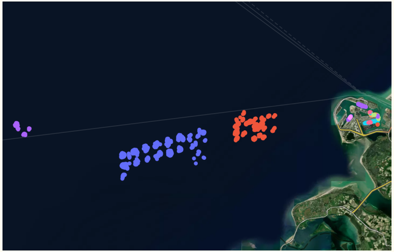


Berths.

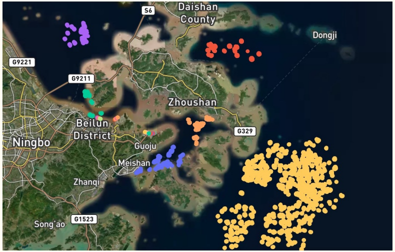
Other ports



Singapore.



Rotterdam.



Ningbo-Zhoushan.

Quantifying port congestion: Average Congestion Rate

Identifying berths & anchorages | Counting delayed ships | Normalization | Aggregation

1. Map the geographical boundaries of berths and anchorages for the top 50 container ports ($\mathcal{P}$) using AIS data and clustering algorithm.

Quantifying port congestion: Average Congestion Rate

Identifying berths & anchorages | **Counting delayed ships** | Normalization | Aggregation

2. Count the number of ships at each port p at time t that first moor in an anchorage before docking at a berth at monthly frequency ($Delayed_{pt}$).

Quantifying port congestion: Average Congestion Rate

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

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

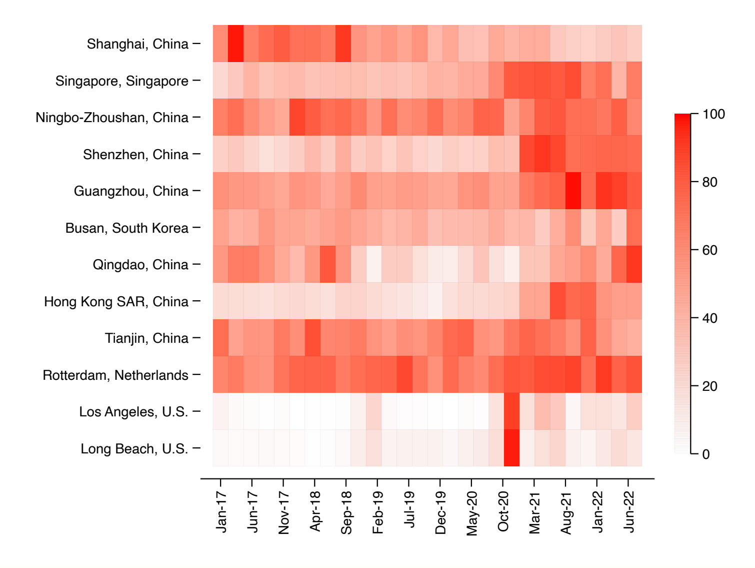
Quantifying port congestion: Average Congestion Rate

Identifying berths & anchorages | Counting delayed ships | Normalization | **Aggregation**

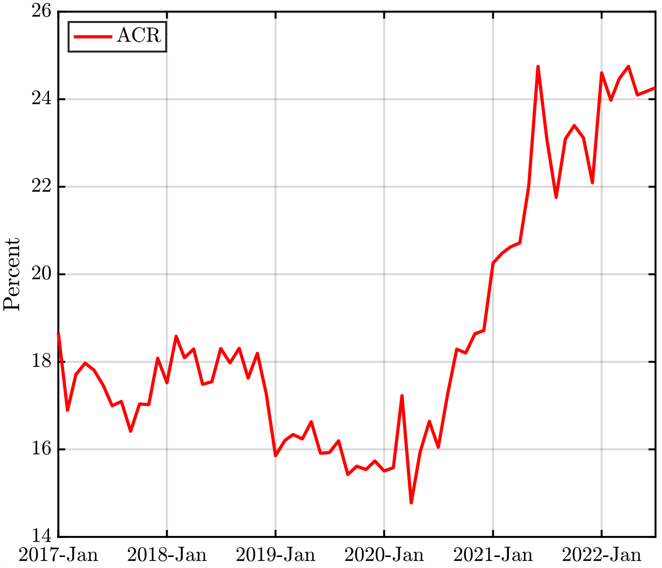
4. Calculate the average congestion rate (ACR_t), weighted by the total number of ship visits,

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

ACR for the top 10 container ports



Average congestion rate (ACR)

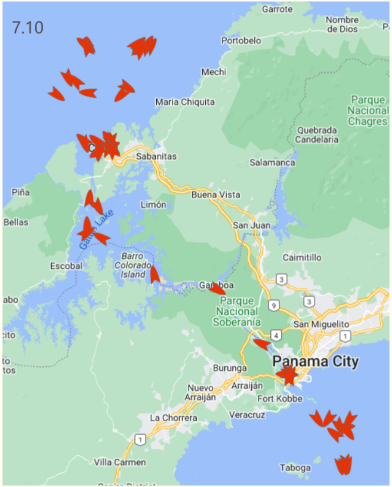


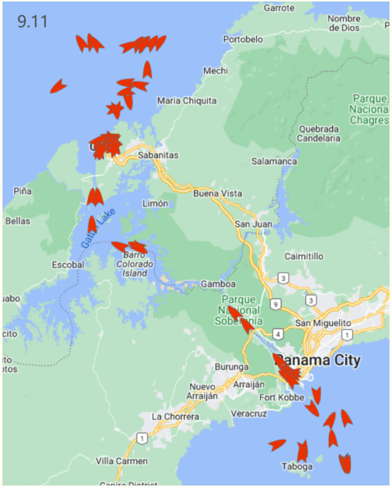
Accuracy and independence from demand

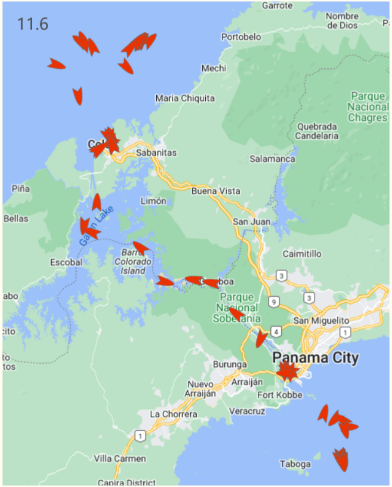
- Satellite data is accurate in tracking containerships, with virtually no measurement error.
- Our ACR index is exogenous to changes in demand:
    1. Unchanged itineraries and fixed routes independent from variations in demand.
    2. The global nature of our index "averages out" any changes in port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

Extensions

- Canals and other choke points.
- Different weights:
  - Average Congestion Time (ACT).
  - Regional indices.
  - Indices for bulk, specialized, and liner.
- Comparison with Harper Peterson Time Charter Rates Index (HARPEX), New York Fed's Global Supply Chain Pressure Index (GSCPI), and the Supply Disruptions Index (SDI).
- (Later): consider the ACR as a noisy measure and estimate a SVAR with measurement error.
- Webpage: https://zhongjunma.github.io/port-congestion/congestion.html

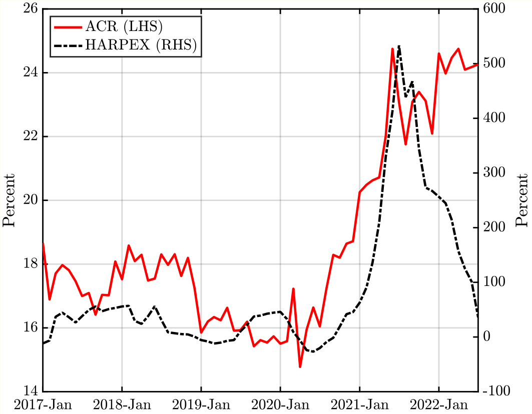

7.10
Garrote
Nombre de Dios
Portobelo
Mechi
Maria Chiquita
Parque Nacional Chagres
Quebrada Candelaria
Sabanitas
Salamanca
Piña
Buena Vista
Limón
Bellas
San Juan
Escobal
Barro Colorado Island
Caimitillo
Parque Nacional Soberanía
San Miguelito
Panama City
Burunga
Arraiján
Nuevo Arraiján
Fort Kobbe
La Chorrera
Veracruz
Villa Carmen
Taboga


9.11
Garrote
Nombre de Dios
Portobelo
Mechi
Maria Chiquita
Quebrada Candelaria
Sabanitas
Salamanca
Piña
Buena Vista
Limón
Bellas
San Juan
Escobal
Barro Colorado Island
Caimitillo
Gamboa
San Miguelito
Burunga
Arraiján
Nuevo Arraiján
Fort Kobbe
La Chorrera
Veracruz
Villa Carmen
Taboga


11.6
Garrote
Nombre de Dios
Portobelo
Mechi
Maria Chiquita
Parque Nacional Chagres
Quebrada Candelaria
Sabanitas
Salamanca
Piña
Buena Vista
Limón
Bellas
San Juan
Escobal
Caimitillo
San Miguelito
Panama City
Burunga
Arraiján
Nuevo Arraiján
Fort Kobbe
La Chorrera
Veracruz
Villa Carmen
Taboga
Capira District

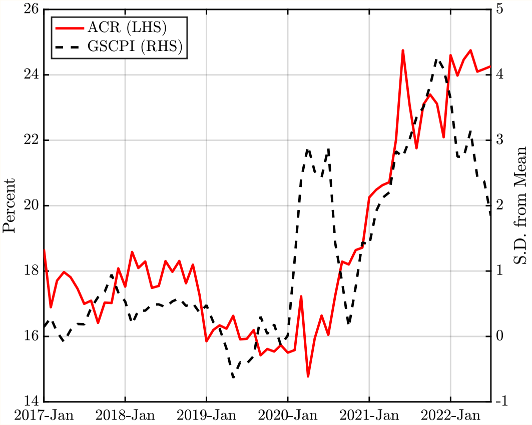
Comparison: ACR to HARPEX

- Harper Peterson Time Charter Rates Index (HARPEX):
  - A widely-used cross-border transportation cost.
  - Fluctuated at historical average before 2020.
  - Rose significantly in the second half of 2020.
  - Plummeted since mid-2021.



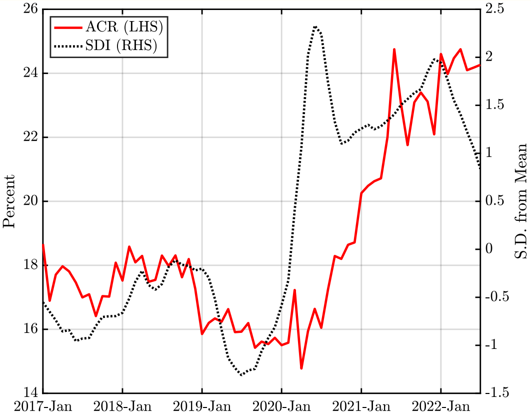
Comparison: ACR to GSCPI

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



Comparison: ACR to SDI

- Supply Disruptions Index (SDI):
  - See Smirnyagin and Tsyvinski (2022).
  - Behaved similarly to GSCPI.



Why a model?

- We want a model that accounts for high spare production capacity jointly with supply scarcity in the retail market.
- Furthermore, we want a model that will provide us with identification restrictions for standard causality assessment methods in economics (SVARs, LPs, ...).
- Model must have the three shocks that researchers and policymakers have discussed as driving inflation after COVID-19:
    1. Demand shock.
    2. Productive capacity shock.
    3. Global supply chain shock.
- Why not a fully structural estimation?

Which model?

- Three ways to go:
    1. A network model: interesting, but hard to handle with random shocks (although I am working on such a model right now).
    2. A New Keynesian model with transportation costs.
    3. 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 I believe that, for this application, a search and matching model is more transparent.

A model of congestion and sparse capacity

- Producers:
  - Produce goods with a capacity determined by labor inputs and subject to stochastic transportation costs.
  - Supply goods to retailers, yet matching frictions prevent full capacity utilization.
- Retailers:
  - Purchase goods by visiting producers (at a cost), yet not all visits would result in a match due to matching frictions.
  - Sell goods to the representative household.
- Representative household. Consumes, supplies labor inputs inelastically, and holds money.

Matching between producers and retailers

- Matching function:

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

  where x_U and i_U: the number of unmatched producers and retailers.

- Product market tightness θ:

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

- Transaction probabilities for producers and retailers:

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

- Tightness enhancing for producers: $f'(\theta) > 0$, but detrimental for retailers $q'(\theta) < 0$.

Transportation cost

- Producers pay an idiosyncratic transportation cost.
- In each period, producers draw the 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.

Matched and unmatched producers

- The total capacity in the economy $x_M + x_U = 1$.
- Law of motion for the number of matched producers at the beginning of the next period:

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

- Number of unmatched producers at the beginning of the next period:

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

- The steady-state number of matched producers:

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

Value functions

- The value for a matched producer is:

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

where $r(z)$ is the wholesale price.

- The value of an unmatched producer is:

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

- The value of a matched retailer is:

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

where p is retail price of goods.

- The value of an unmatched retailer is:

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

where ρ is the period search cost. By free entry, $I_U = 0$.

Nash bargaining

- The wholesale price $r(z)$ determined by Nash bargaining.
- Total surplus from matching:

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

  - Since $X_M(z) + I_M(z)$ is strictly decreasing in z, there exists a $\bar{z}$ such that $S(\bar{z}) = 0$.

- Nash bargaining: share η to the producer ($1 - \eta$ to the retailer):

$$\eta\big(I_M(z) - I_U\big) = (1 - \eta)\big(X_M(z) - X_U\big)$$

- The wholesale price is:

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

Match creation and separation conditions

- The free entry condition $I_U = 0$ determines the creation of new matches:

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

  where $\mathbb{E}_{z'} S(z') = \int_0^{\bar{z}} S(z') dG(z')$.

- The match separation condition is a function of p, $\bar{z}$, and θ:

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

- Transportation costs diminish expected surplus, thus decreasing new matches and tightness.

Equilibrium tightness

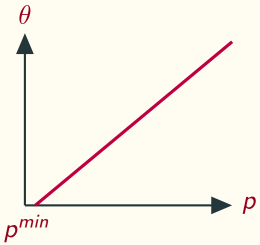
- The equilibrium θ simultaneously satisfies the conditions for match creation and separation:

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

- Rearranging terms:

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

- For a given $\bar{z}$, θ increases with p and falls with supply chain shock (i.e., shift to the right of distribution of transportation costs).



Aggregate supply

- Aggregate supply = number of matched producers × capacity

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

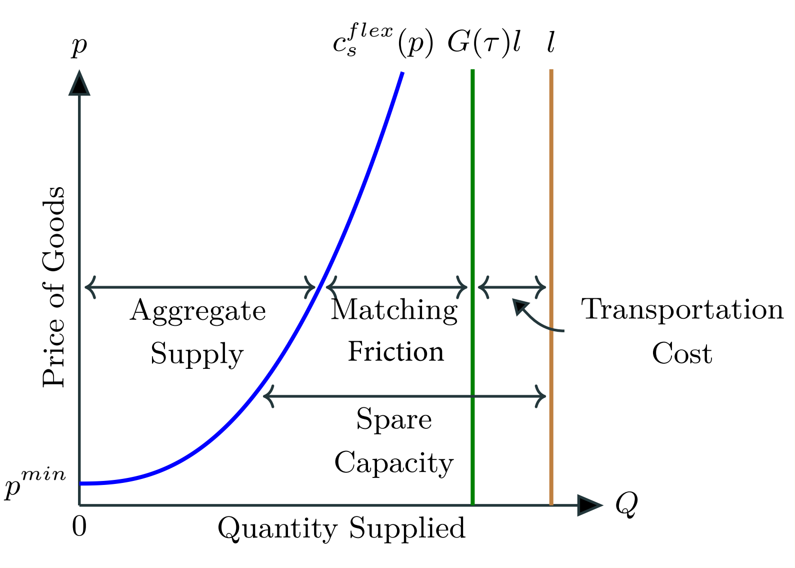
where:

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

- Equilibrium indeterminacy of search models. Two match conditions and three unknowns: $\{\bar{z},\theta,p\}$.
- We assume flexible prices and fixed reservation transportation cost ($\bar{z}=\tau$). Thus, we refer to aggregate supply with:

$$c_s^{flex}(p)$$

Supply side


p
$c_s^{flex}(p)$
$G(\tau)l$
l
Price of Goods
Aggregate Supply
Matching Friction
Transportation Cost
Spare Capacity
p^{min}
0
Quantity Supplied
Q

Households

- The household supplies labor inelastically and derives utility from consumption c and real money holdings m/p:

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

- The budget constraint:

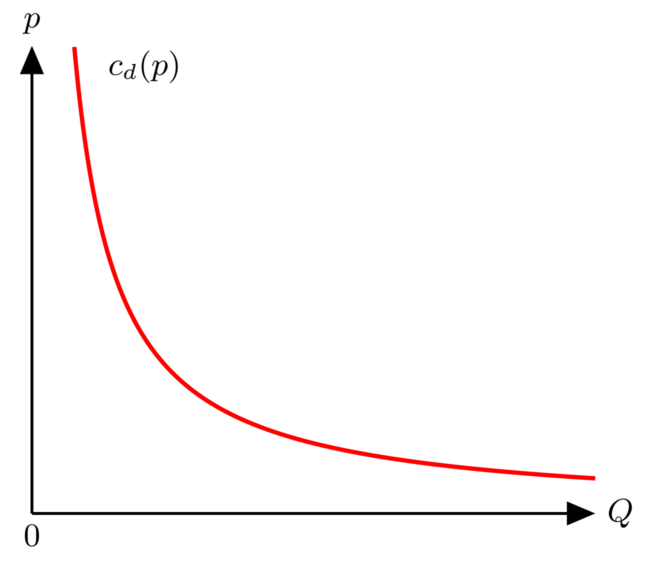
$$pc + m \leq \mu + \underbrace{pc_s^{flex}(p) - \int_0^{\tau} z' c_s^{flex}(p) dG(z')}_{\text{Profits of Producers \& Retailers}} + \underbrace{\int_0^{\tau} z' c_s^{flex}(p) dG(z')}_{\text{Profits of Shipping Firms}}$$

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

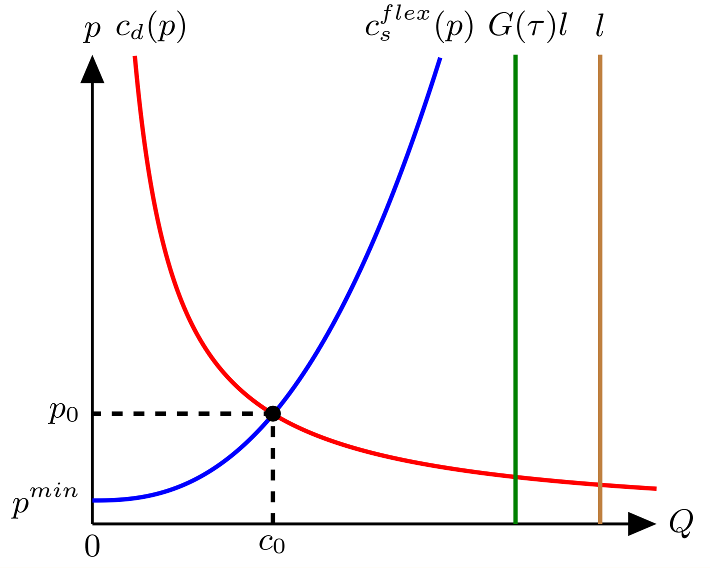
where μ is the endowment of nominal money.

- Aggregate demand: $c_d(p) = \chi^{\varepsilon} \frac{\mu}{p}$.

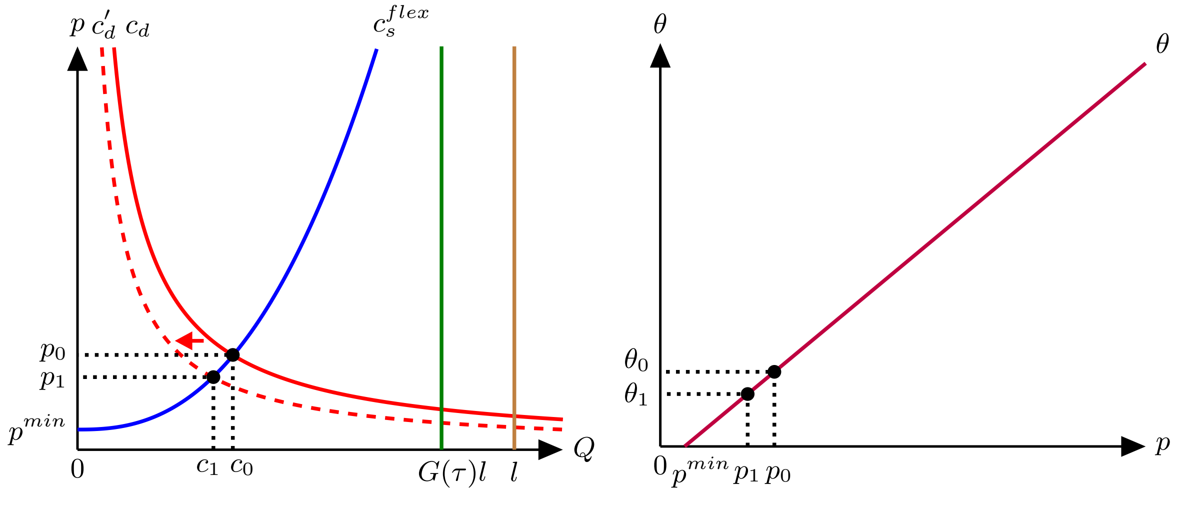
Demand side



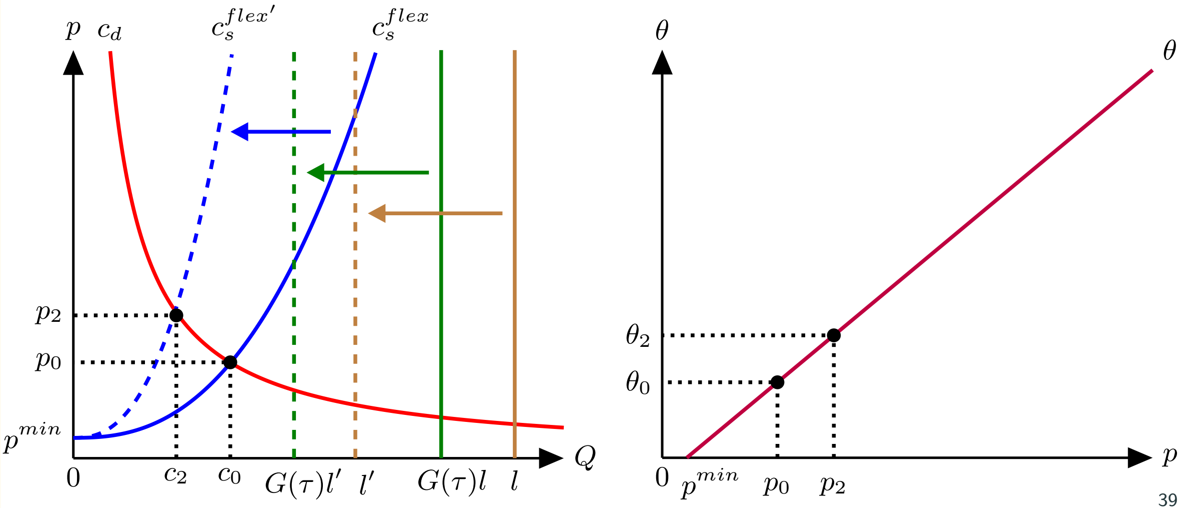
Equilibrium



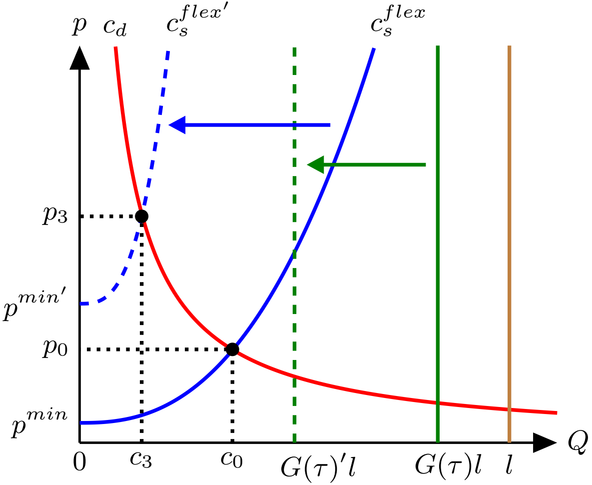
An adverse shock to aggregate demand

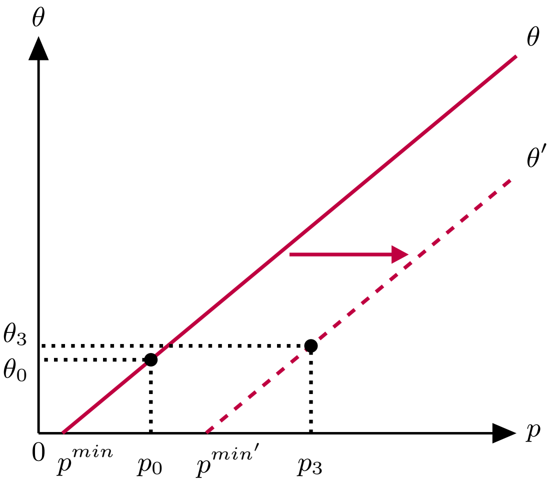


An adverse shock to productive capacity



An adverse shock to supply chain





Identification restrictions on structural shocks

Table 1: Comparative Statics

Adverse Shock to:	**Effects On:** Consumption (Output) c	Retail Price p	Tightness θ	Wholesale Price r	Matching Frictions $G(\tau)l - c$	Spare Capacity $l - c$
Aggregate Demand	$-$	$-$	$-$	$-$	$+$	$+$
Productive Capacity	$-$	$+$	$+$	$+$	$-$	$-$
Supply Chain	$-$	$+$	N/A	N/A	N/A	$+$

Shocks and identification restrictions

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

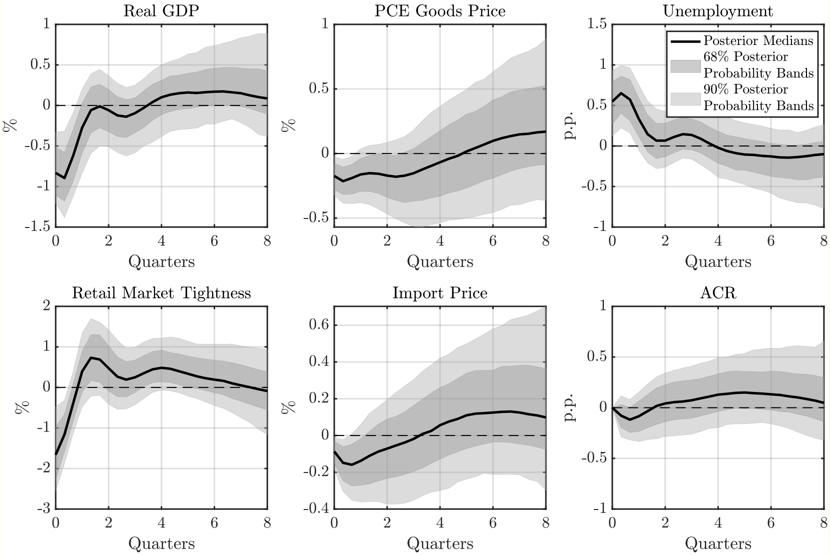
A SVAR model with sign and zero restrictions

- Approach based on Uhlig (2005), Rubio-Ramírez *et al.* (2010), and Arias *et al.* (2018):

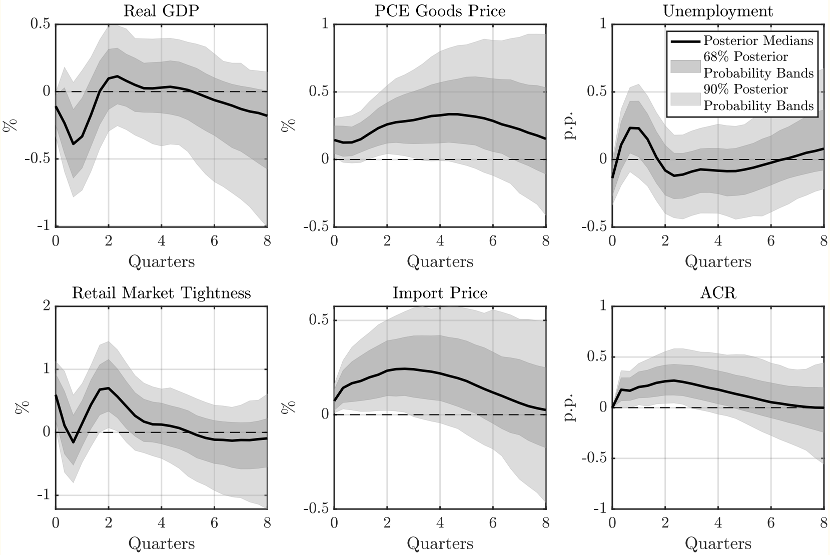
$$\boldsymbol{y}_t' \boldsymbol{A}_0 = \boldsymbol{x}_t' \boldsymbol{A}_+ + \boldsymbol{\epsilon}_t', \quad \forall t \in [1, T]$$

- Six endogenous variables: real GDP, PCE goods price, unemployment, retail market tightness, import price, and ACR index.
- All the series are seasonally adjusted. The sample runs from 2017M1 through 2022M7.
- We set two lags in the baseline specification, but the results are robust to considering other lags.
- Bayesian estimation with a normal-generalized-normal (NGN) prior distribution over $\{\boldsymbol{A}_0, \boldsymbol{A}_+\}$.
- Check robustness with the prior robust approach in Giacomini and Kitagawa (2021).

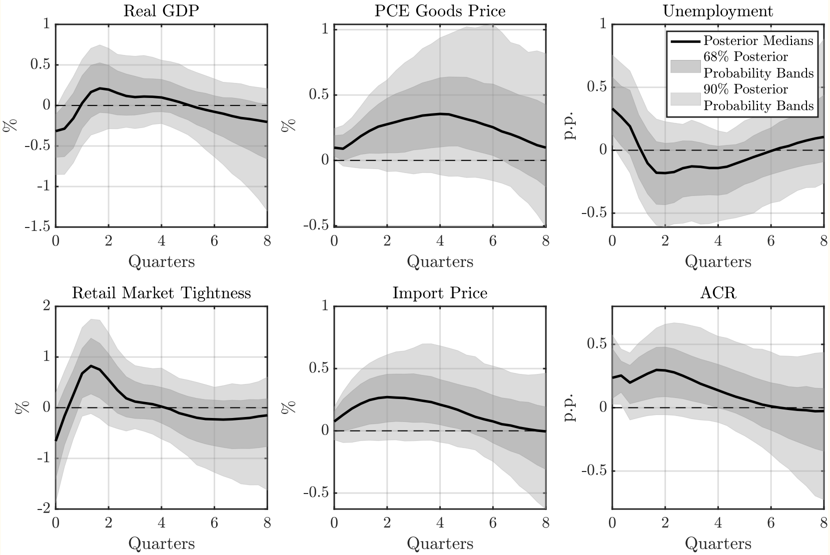
IRFs to an adverse shock to aggregate demand



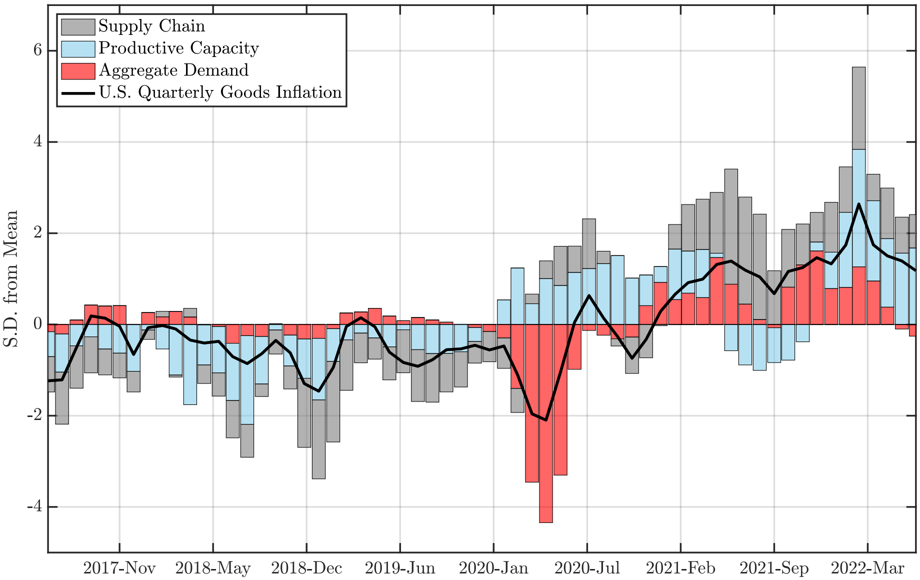
IRFs to an adverse shock to productive capacity



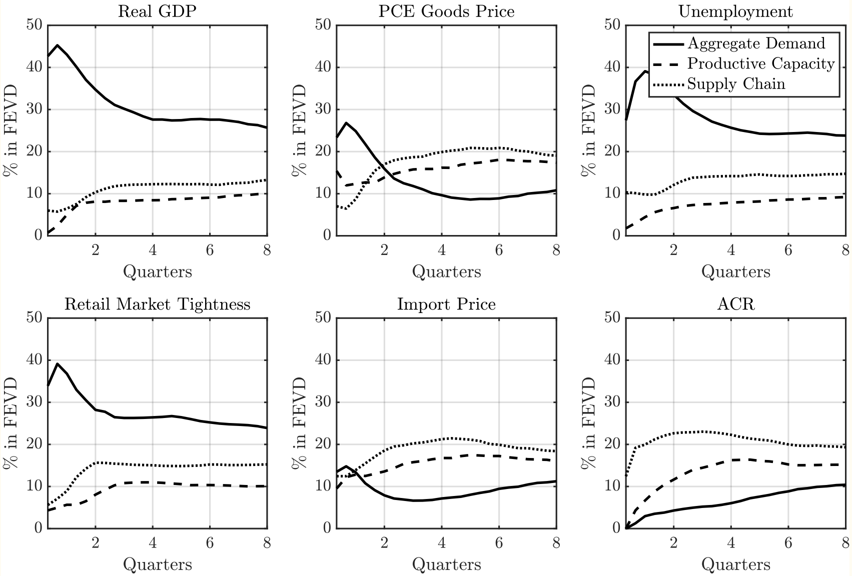
IRFs to an adverse shock to supply chain



Historical contribution of each shock to U.S. inflation



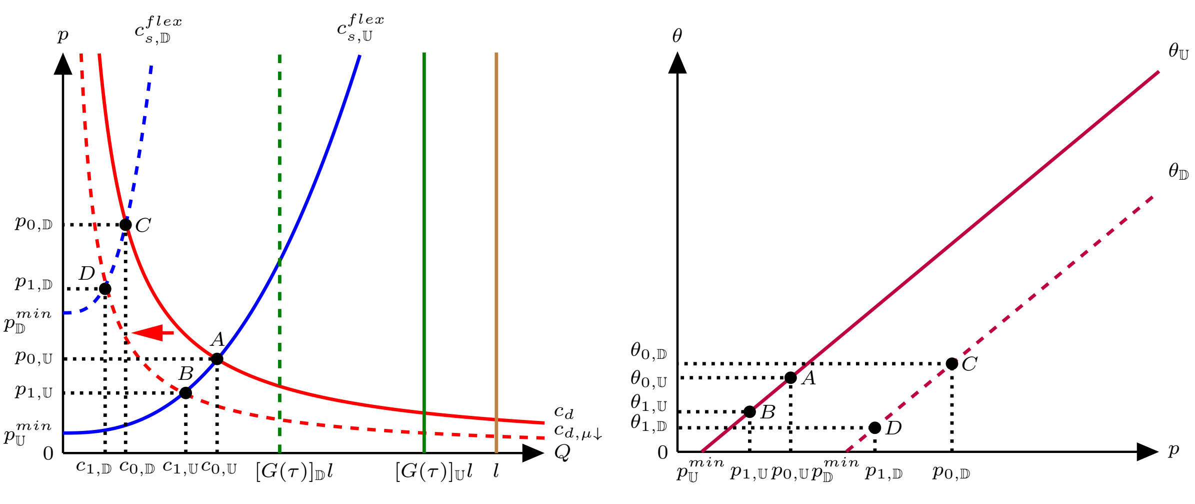
Forecast error variance decomposition



Supply chain disruptions and the effectiveness of monetary policy

- When the product market tightness is sufficiently reactive to the supply chain disruption, a contractionary monetary policy shock induces:
  - A smaller decrease in consumption (or output).
  - Larger decreases in price and product market tightness.
  - Smaller increases in matching cost and idle capacity (or unemployment).
- Intuition:
  - When the increase in product market tightness is sufficiently large during 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.
- Linked with the evidence that the New Keynesian Phillips curve has become steeper.

The state-dependence of monetary policy shocks



Shock and identification restrictions

- **Restriction on monetary shock: A contractionary monetary policy shock** leads to a negative response of real GDP, GDP deflator, and import price, as well as to a positive response of unemployment and FFR at horizon $k = 1$. ACR does not respond at horizon $k = 1$.
- This restriction is imposed using a penalty function (Uhlig, 2005).

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.
- Six endogenous variables: FFR, real GDP, GDP deflator, unemployment, import price, and ACR.
- Switches between the regimes are governed by the indicator variable $I_t \in \{0, 1\}$:

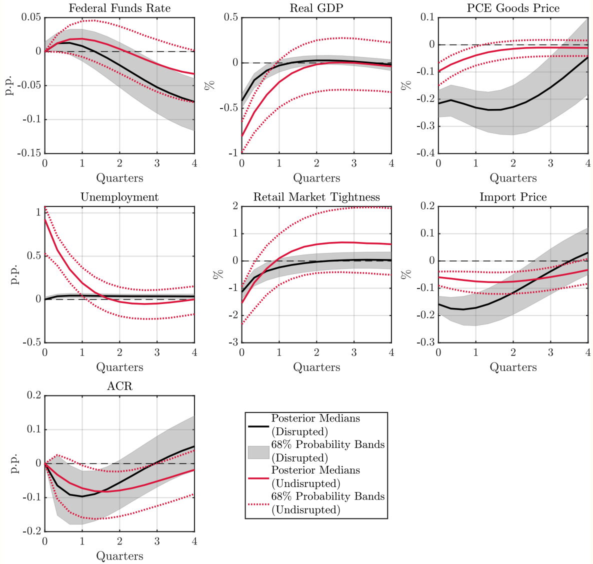
$$I_t = \begin{cases} 1, & \text{if } ACR_{t-1} > \overline{ACR} \\ 0, & \text{if } ACR_{t-1} \leq \overline{ACR} \end{cases}$$

- 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.

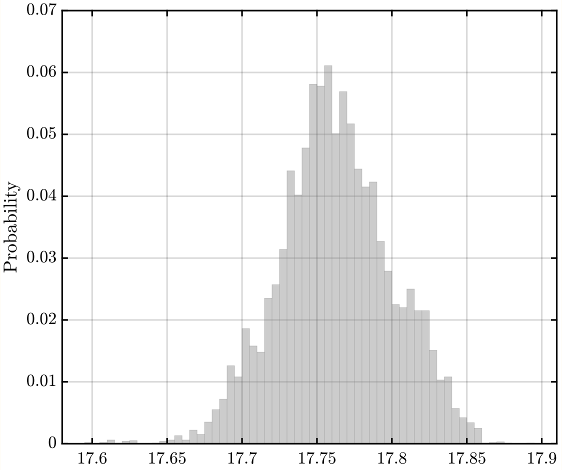
Estimation

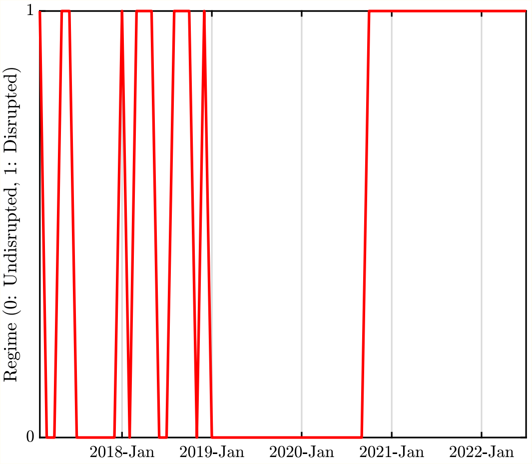
- We include one lag in the TVAR model, and our results are robust to different lag structures (i.e., two or three lags) and looser priors.
- We retain the same sample period from January 2017 to July 2022, and all the series are seasonally adjusted except for the FFR.
- Real GDP, GDP deflator, and import price enter the TVAR in log percent, whereas the FFR, unemployment, and ACR enter in percent.
- We compute the identified set of IRFs using a Bayesian approach.
- We also estimate LPs (potentially easier to estimate non-linear responses in finite samples).

IRFs to a contractionary monetary policy shock

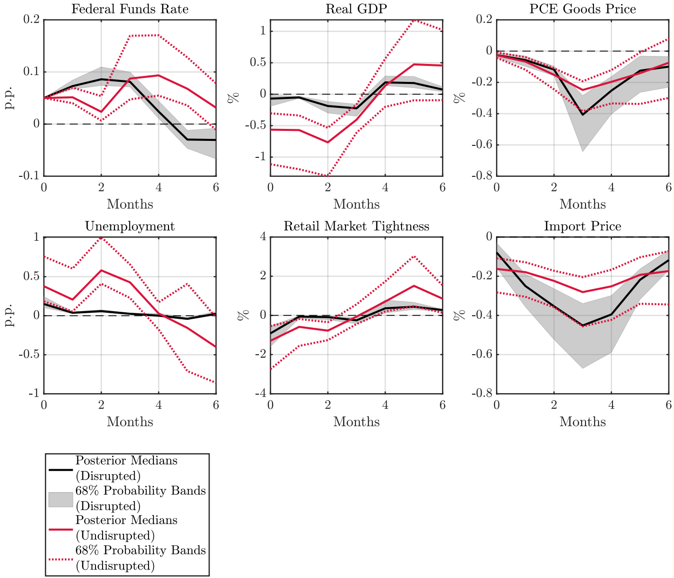


Posterior of $\overline{ACR}$ and regime switches





IRFs to a contractionary monetary policy shock (LPs)



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 state-of-the-art methods for assessing causality in time series.
- Two main results:
    1. Supply chain disruptions generate stagflation accompanied by an increase in spare capacity.
    2. Monetary tightening can tame inflation at reduced costs of real activity during times of supply chain disruption.