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

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  - **How** does a supply chain disruption shock differ from other shocks?
    - Demand shock;
    - Labor supply 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

- **Theory of disequilibrium**: Barro and Grossman (1971); Michaillat and Saez (2015, 2022); Ghassibe and Zanetti (2022).
- **Transportation sector and real economy**: Allen and Arkolakis (2014); Brancaccio et al. (2020); Bai and Li (2022); Finck and Tillmann (2022); Fuchs and Wong (2022); Li et al. (2022); Alessandria et al. (2023); Brancaccio et al. (2023); Dunn and Leibovici (2023).
- **Disentanglement of supply chain disturbances**: Balleer et al. (2020); Bekaert et al. (2020); Brinca et al. (2021); Shapiro (2022); Gordon and Clark (2023); Ascari et al. (2023).

# Road Map

# Measuring Global Supply Chain Disruptions

- We measure disruptions to the supply chain by studying **congestion at container ports**.
  - These ports are responsible for 60% of the total value of world seaborne trade;
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  - Random areas to lower anchors vs. designated spots to load/unload cargo.
- Such an estimation requires:
  - Movement data of containerships from the **Automatic Identification System (AIS)**;
    - A mandatory real-time satellite tracking system for containerships across major ports worldwide.
  - Identification of berths and anchorages through **IMA-DBSCAN (Bai et al., 2023)**;
    - A density-based spatial clustering algorithm that (1) automatically iterates in refining parameters and (2) considers both spatial and non-spatial attributes in clustering.

# Sample AIS Data


Figure 1: The First 50,000 AIS Observations of Containerships Entering the Ports of Los Angeles and Long Beach Since 1 January 2020.

# Sketch of the IMA-DBSCAN Algorithm

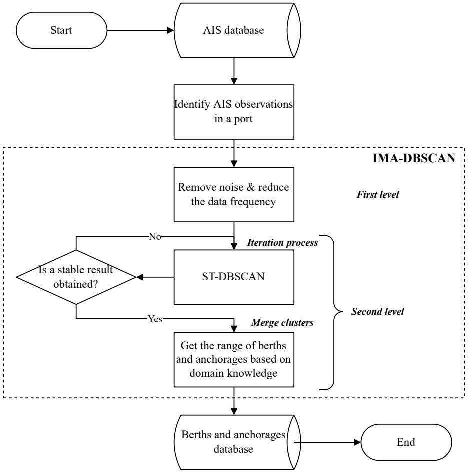


Figure 2: IMA-DBSCAN. Details

# Domain Knowledge in IMA-DBSCAN

Figure 3: Headings at a Berth.

Figure 4: Headings at an Anchorage.

# Identification Results


Figure 5: Identification of Anchorages (Cyan & Purple) and Berths (Other Colors) in the Ports of Los Angeles and Long Beach.

# Identification Results (cont.)


Figure 6: Anchorages.


Figure 7: Berths.

# Average Congestion Rate (ACR)

- **Definition**: ratio of containerships that moor at an anchorage area before docking at a berth to the total number of port calls.

Top 10 Ports, LA, & LB    ACR vs. Transportation Cost

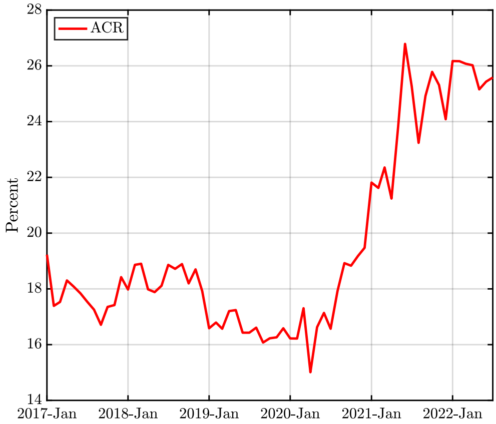


Figure 8: Weighted Average of the ACR Indices for the Top 50 Container Ports (Weights = No. of Port Calls).

# ACR as an Exogenous Measure of Global Supply Chain Disruptions

- **Existing measures** suffer from several drawbacks:
  - Endogeneity of transportation costs;
  - Measurement errors of the PMI;
  - No differentiation between labor supply shocks and supply chain disruptions.

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  - Endogeneity of transportation costs;
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  - No differentiation between labor supply shocks and supply chain disruptions.
- **Our ACR index** overcomes these drawbacks:
  - Unchanged itineraries and fixed routes of containerships ensure port congestion is minimally influenced by changes in demand (Wang et al., 2019; Brancaccio et al., 2020, 2023);
  - The global nature of the ACR "averages out" any changes in port congestion resulting from infrequent adjustments in shipping capacity across routes;
  - Satellite data offer unparalleled accuracy in tracking real-time movements of tradable goods, freeing the ACR from any measurement error.

## ACR vs. GSCPI

- **New York Fed's GSCPI index**:
  - See di Giovanni et al. (2022);
  - Jump in early 2020 → initial Chinese lockdown;
  - Fall in late 2020 → partial reopening of China and Europe.
- **Our ACR index**:
  - Fluctuated at historical average in early 2020;
  - Rose significantly in the second half of 2020;
  - Remained elevated in the first half of 2022.

ACR vs. SDI Back

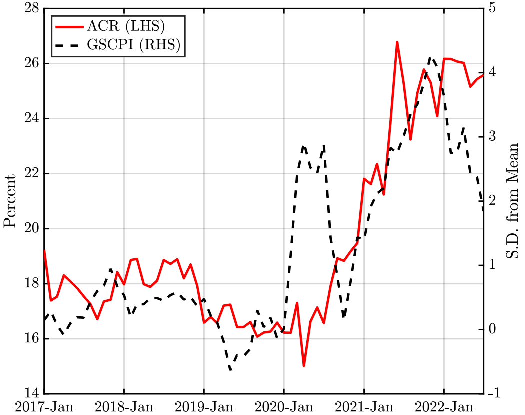


Figure 9: ACR vs. GSCPI.

# Road Map

1. Introduction
2. Measuring Global Supply Chain Disruptions
3. A Model of Congestion and Spare Capacity
4. The Causal Effects of Global Supply Chain Disruptions
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6. Conclusion

# Model Overview

- **Key features:** (1) search frictions on the international product market similar to Michaillat and Saez (2015, 2022) and Ghassibe and Zanetti (2022), and (2) endogenous separation of exporter-importer matches on transportation cost.

Aggregate Supply Aggregate Demand Flexible-Price Equilibrium

# Supply Side of the Economy

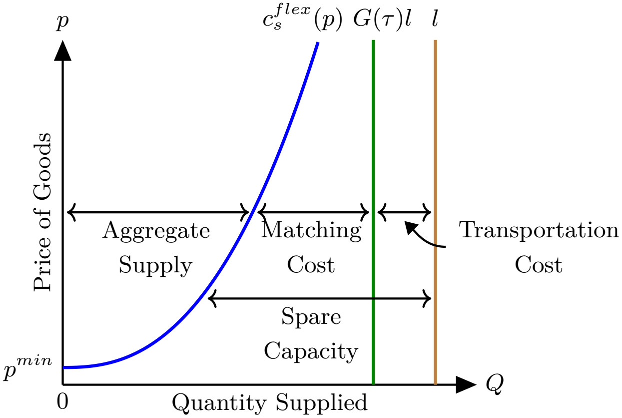


Figure 10: Aggregate Supply and Spare Capacity

# Equilibrium Dynamics: An Adverse Shock to Aggregate Demand

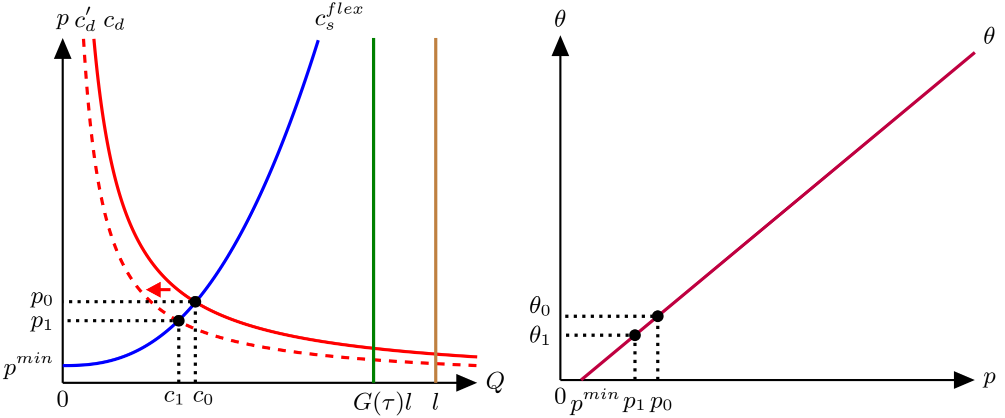


Figure 11: Money Supply ↓ or Taste for Consumption ↓.

# Equilibrium Dynamics: An Adverse Shock to Labor Supply

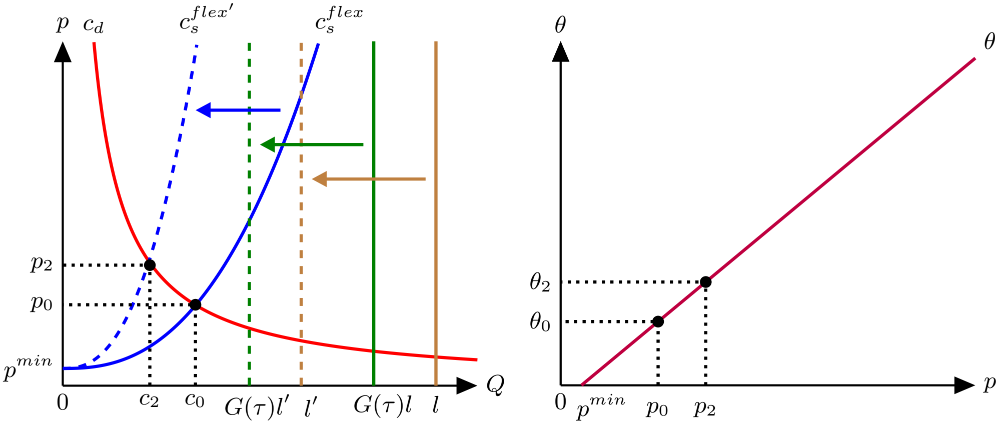


Figure 12: Labor Supply (Productive Capacity) ↓.

# Equilibrium Dynamics: An Adverse Shock to Supply Chain

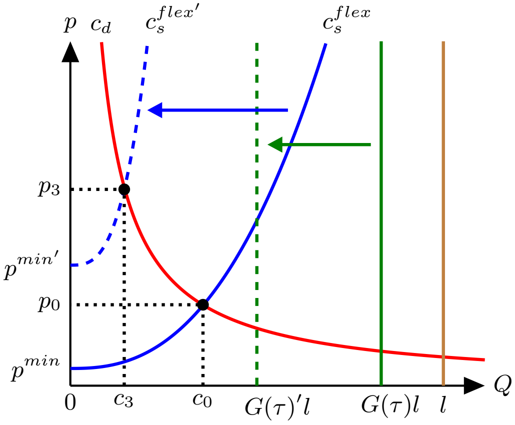


Figure 13: Scale Parameter of the Log-normal Distribution of Transportation Costs ↑.

# Identification Restrictions on Structural Shocks

Table 1: Comparative Statics.

| **Adverse Shock to:** | **Effects On:** Consumption (or Output) $c$ | Price $p$ | Product Market Tightness $\theta$ | Import Price $w$ | Matching Cost $G(\tau)l - c$ | Spare Capacity (or Unemployment) $l - c$ |
|---|---|---|---|---|---|---|
| Aggregate Demand | $-$ | $-$ | $-$ | $-$ | $+$ | $+$ |
| Labor Supply | $-$ | $+$ | $+$ | $+$ | $-$ | $-$ |
| Supply Chain | $-$ | $+$ | N/A | N/A | N/A | $+$ |

*Notes.* The table summarizes the results of comparative statics. A positive (negative) sign indicates an increase (decrease) in the endogenous variable, while N/A represents indeterminacy.

Back

# Road Map

# A SVAR Model With Sign and Zero Restrictions

- We address the causal effects of global supply chain disruptions using SVARs.
- We include five endogenous variables:
  1. Real GDP;
  2. GDP deflator;
  3. Unemployment;
  4. Import price;
  5. ACR.
- All the series are seasonally adjusted. The sample runs from 2017M1 through 2022M7.

Setting Up the SVAR

# Shocks and Identification Restrictions

- ***An adverse shock to aggregate demand*** leads to a negative response of real GDP, GDP deflator, and import price, as well as to a positive response of unemployment at horizon $k = 1$. ACR does not respond at horizon $k = 1$.
- ***An adverse shock to labor supply*** leads to a negative response of real GDP and unemployment, as well as to a positive response of GDP deflator and import price at horizon $k = 1$. ACR does not respond at horizon $k = 1$.
- ***An adverse shock to supply chain*** leads to a negative response of real GDP, as well as to a positive response of GDP deflator, unemployment, and ACR at horizon $k = 1$.

Comparative Statics

# Estimation Details

- We set two lags in the baseline specification, but the results are robust to considering one or three lags.
- The real GDP, GDP deflator, and import price are in log percent, while the unemployment and ACR are in percent.
- We estimate the SVAR model using a Bayesian approach as in Arias et al. (2018, 2019, 2023) with restrictions on the first period of response (i.e., $k = 1$), thus imposing a minimal structure as in Mumtaz and Zanetti (2012, 2015).
- We impose a normal-generalized-normal (NGN) prior distribution over $\left\{\boldsymbol{A}_0, \boldsymbol{A}_+\right\}$.

# Impulse Response Functions (IRFs)

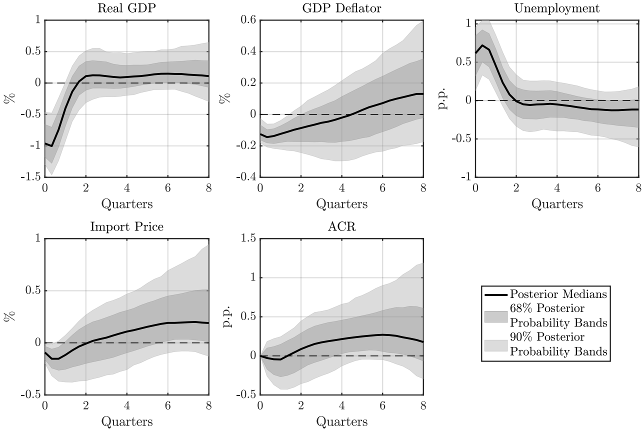


Figure 14: IRFs to an Adverse Shock to Aggregate Demand.

# IRFs (cont.)

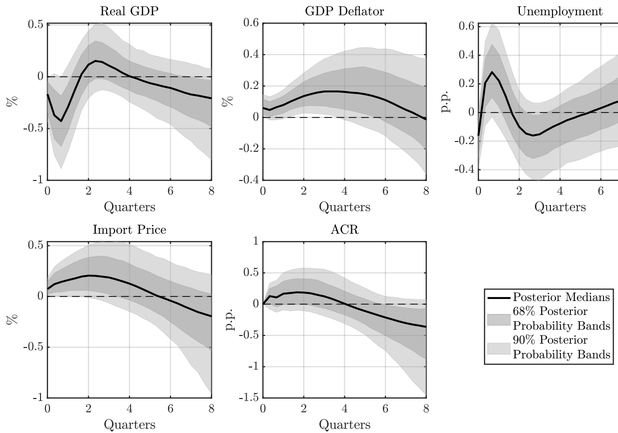


Figure 15: IRFs to an Adverse Shock to Labor Supply.

# IRFs (cont.)

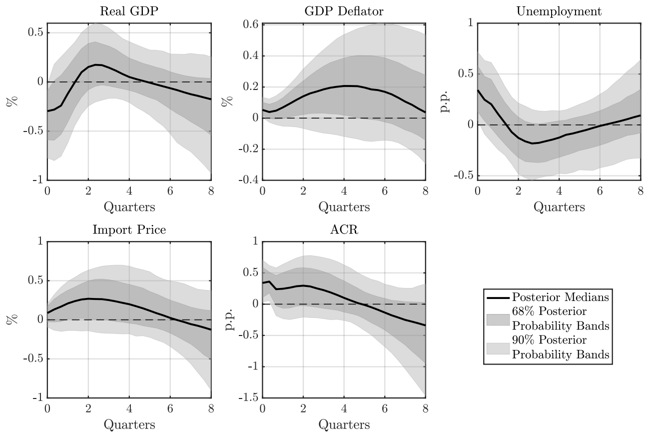


Figure 16: IRFs to an Adverse Shock to Supply Chain.

# Comparison Between the ACR and GSCPI

- We assess the implications of the differences between the ACR and GSCPI for the readings that the SVAR model makes regarding **the causal effect of supply chain disruptions on inflation** by studying:
  1. IRFs to an adverse shock to supply chain;
  2. Forecast Error Variance Decomposition (FEVD);
  3. Historical Decomposition (HD) of the U.S. inflation.

ACR vs. GSCPI

# IRFs to an Adverse Shock to Supply Chain

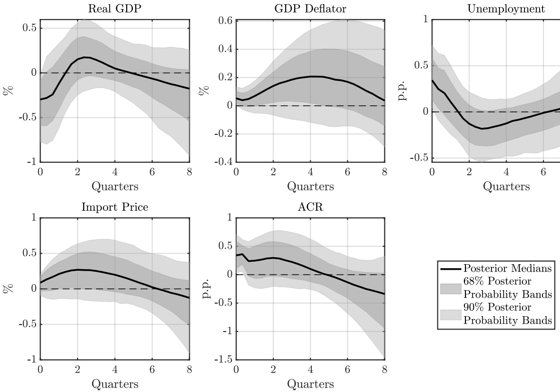


Figure 17: Using ACR.

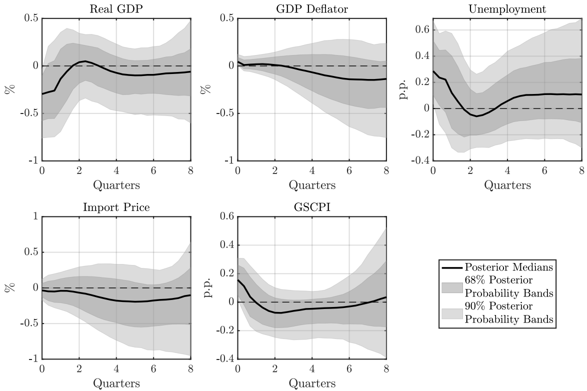


Figure 18: Using GSCPI.

# FEVD for Real GDP, GDP Deflator, & Unemployment

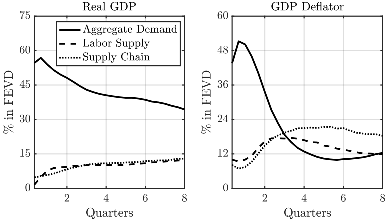


Figure 19: Using ACR.

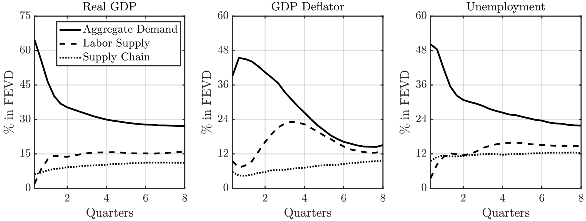


Figure 20: Using GSCPI.

# Quarterly Cumulative Historical Contribution of Each Shock to U.S. Inflation

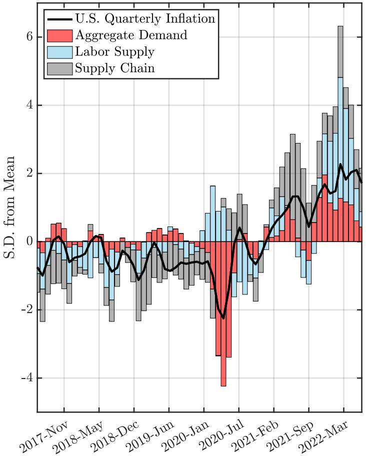


Figure 21: Using ACR.

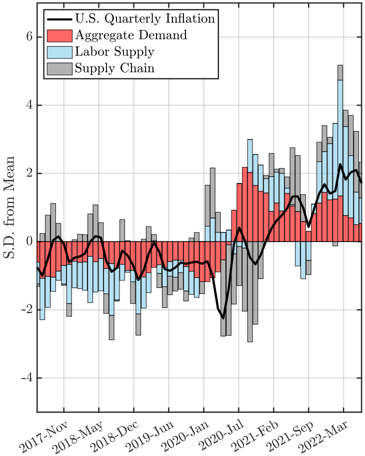


Figure 22: Using GSCPI.[1]

[1] The estimation results are obtained with each variable measured in percent change from the previous period.

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- Theoretically,
  - A contractionary monetary policy shock $\rightarrow$ money supply $\downarrow$.
  - Supply chain disruptions $\rightarrow$ scale parameter of the log-normal distribution of transportation cost $\uparrow$:
    - Mean transportation cost $\uparrow$;
    - Probability that a random draw of transportation cost lies above the reservation level $\uparrow$.

# Effectiveness of Monetary Policy: Theoretical Prediction (cont.)

- At an equilibrium where the product market tightness is sufficiently reactive to the supply chain disruption, **a contractionary monetary policy shock** would induce:
    - A smaller decrease in consumption (or output);
    - Larger decreases in price, product market tightness, and import price;
    - Smaller increases in matching cost and spare capacity (or unemployment).

Partial & Cross Derivatives Back

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  - A smaller decrease in consumption (or output);
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  - Smaller increases in matching cost and spare capacity (or unemployment).
- **Intuition**:
  - The higher spare capacity resulting from supply chain disruptions constrains the supply of goods, thus increasing the sensitivity of prices to movements in demand;
  - As larger shifts in prices are needed to ration the product market, these changes in the relative movements of prices and output increase the effectiveness of monetary policy in stabilizing inflation amid supply chain disruptions.

Partial & Cross Derivatives Back

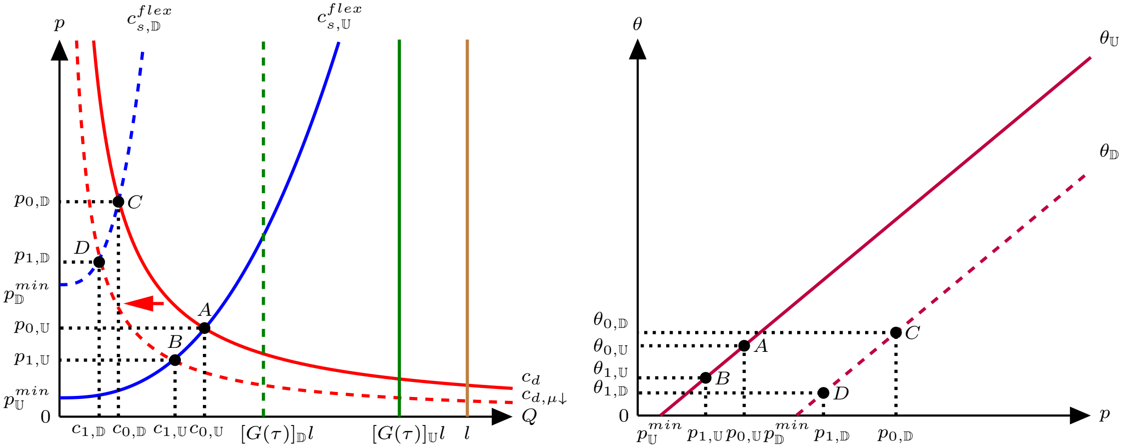


Figure 23: State-Dependent Effects of a Contractionary Monetary Policy Shock: Theoretical Prediction.

# 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 six endogenous variables:
  1. Federal Funds Rate (FFR);
  2. Real GDP;
  3. GDP deflator;
  4. Unemployment;
  5. Import price;
  6. ACR.

Setting Up the TVAR

# Shock and Identification Restrictions

- ***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 $k = 1$.
- Restriction 4 is imposed using the penalty function approach (Uhlig, 2005; Mountford and Uhlig, 2009).

Theoretical Prediction

# Estimation Details

- 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 as in Pizzinelli et al. (2020) and Bratsiotis and Theodoridis (2022).

# IRFs to a Contractionary Monetary Policy Shock

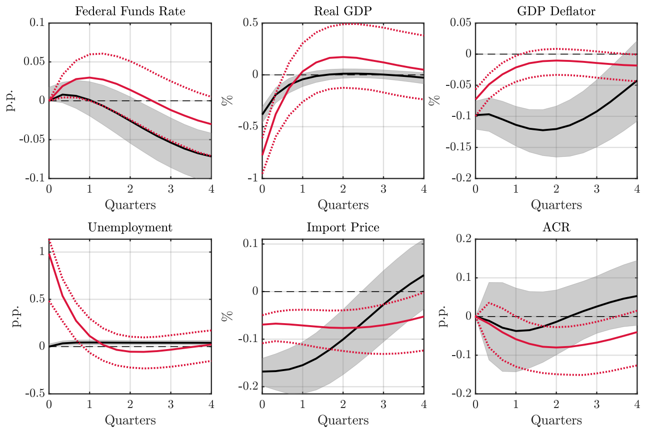


Figure 24: State-Dependent Effects of a Contractionary Monetary Policy Shock: Empirical Validation.[2] LPs

[2] The black solid (red solid) line shows the point-wise posterior medians, and the black shaded area (red dotted lines) depicts the 68% equal-tailed point-wise posterior probability bands for the supply chain disrupted (undisrupted) regime.

# 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 three main results:
  1. Supply chain disruptions generate stagflation accompanied by an increase in spare capacity;
  2. One could not obtain such results using the New York Fed's GSCPI;
  3. Monetary tightening could tame inflation at reduced costs of real activities during times of supply chain disruptions.

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# 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; Karimi-Mamaghan et al., 2020; 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 includes 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., heading of ships during mooring).

# Estimating Port Congestion Using AIS Data and IMA-DBSCAN (cont.)

- With the geographical boundaries of berths and anchorages sketched out, we use information on the geographical coordinates and timestamps recorded in the AIS data to determine the behaviors of each containership at port.
- We define the Average Congestion Rate (ACR) for a port as the ratio of containerships that moor at an anchorage before docking at a berth, relative to the total number of port calls.

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# More Identification Results


Figure A.1: Singapore.

Figure A.2: Rotterdam, Netherlands.


Figure A.3: Ningbo-Zhoushan, China.

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# ACR for the Major Container Ports Worldwide

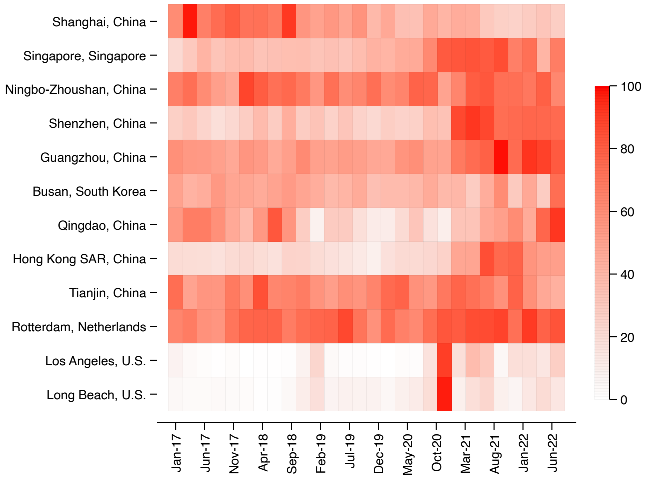


Figure A.4: ACR for the Top 10 Container Ports and the Ports of Los Angeles and Long Beach. Back

# ACR vs. Transportation Cost

- ACR against the China Containerized Freight Index (CCFI), a widely-accepted measure of cross-border transportation costs.
- The series did not track closely with each other before 2020, but shot up together since the onset of the pandemic.

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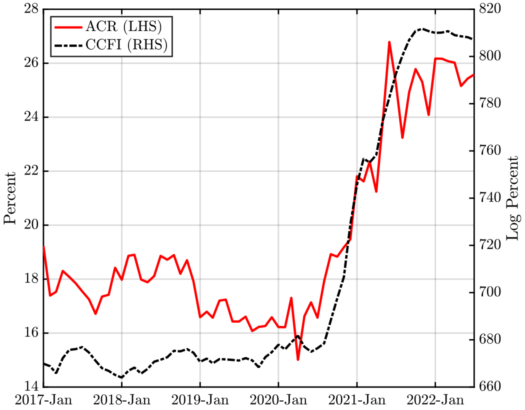


Figure A.5: ACR vs. CCFI.

# U.S. Supply Disruptions Index (SDI)

- Originates from the S&P Global Panjiva dataset of U.S. seaborne import records;
- Identify supply chain disruptions by monitoring regular and active consignee-shipper relationships over quarterly periods; a disruption occurs when a consistently active relationship goes inactive for a quarter and then resumes.

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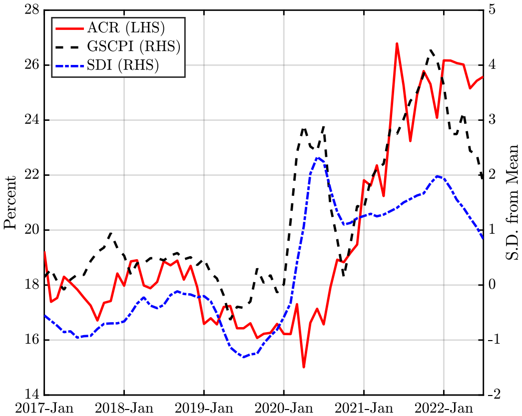


Figure A.6: ACR, GSCPI, & SDI.

# Firms

- Exporters:
  - Produce goods with a capacity determined by labor inputs $l > 0$ that are inelastically supplied by households;
  - Supply goods to importers, yet matching frictions prevent their full capacity from being sold.
- Importers:
  - Purchase goods by visiting exporters, yet not all visits would result in a match due to matching frictions;
  - Sell imported goods to households for a price.

# Matching Process

- The matching function establishes the number of meetings $m$ between exporters and importers:

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

where $x_U$ and $i_U$: the number of unmatched exporters and importers; $\xi > 0$: elasticity of substitution between $x_U$ and $i_U$.

- Product market tightness $\theta$ is defined by:

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

- The tightness determines the probabilities that exporters and importers 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

- Exporters pay an idiosyncratic transportation cost when exporting goods.
- In each period, exporters 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.

# Recursive Value Functions

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

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

where $r(z)$: import price; $z$: transportation cost; $\beta$: discount factor; $z'$: draw of transportation cost at the beginning of the next period.

- The value for an unmatched exporter $X_U$ is:

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

where $f(\theta)$: probability that an exporter meets an importer.

# Recursive Value Functions (cont.)

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

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

where $p$: price of goods.

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

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

where $\rho$: fixed cost to pay per visit; $q(\theta)$: probability that an importer meets an exporter.

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

$$I_U = 0.$$

# Nash Bargaining

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

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

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

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

- The import 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 $\theta$, defined for all $p \in (0, +\infty)$, $\bar{z} \in (0, +\infty)$, and $\theta \in [0, +\infty)$, satisfying:

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

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

# 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 $\theta$, defined for all $\bar{z} \in (0, +\infty)$ and $\theta \in [0, +\infty)$, satisfying:

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

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

# Aggregate Supply

- The aggregate supply in the economy results from the steady-state equilibrium in the international product market, which is defined as:

**Definition 1**

*The steady-state equilibrium in the international product market consists of a price* $p \in (0, +\infty)$, *a reservation transportation cost* $\bar{z} \in (0, +\infty)$, *and a product market tightness* $\theta \in [0, +\infty)$ *such that the conditions for match separation* (1) *and match creation* (2) *simultaneously hold:*

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

# Aggregate Supply (cont.)

## Proposition 1

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

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

*where $G(.)$: log-normal CDF. Hence, $\theta$ 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 importers and exporters that survive separation for a given productive capacity $l$.
- By deriving the equilibrium number of matched exporters and substituting in Equation (3), we define the aggregate supply as:

**Definition 2**

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

$$c_s(p,\bar{z}) = \frac{\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\bar{z})}{1-G(\bar{z})+\left\{1+\left[\frac{1-\eta}{\eta\rho}\left(p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}}G(\bar{z})}l, \tag{4}$$

*for all $(p,\bar{z}) \in (0,+\infty)\times(0,+\infty)$ satisfying:*

$$p-\bar{z}+\beta\int_0^{\bar{z}}G(z')dz' \geq 0. \tag{5}$$

# Flexible-Price Aggregate Supply

- Since $c_s$ is determined by two endogenous variables, infinitely many combinations of $p$ and $\bar{z}$ would yield the same $c_s$, as long as they satisfy the constraint (5).
- For tractability, we specify a pricing mechanism in which $p$ 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 price $p$ defined by:*

$$c_s^{flex}(p) = \frac{\left\{1 + \left[\frac{1-\eta}{\eta\rho}\left(p - \tau + \beta\int_0^\tau G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}} G(\tau)}{1 - G(\tau) + \left\{1 + \left[\frac{1-\eta}{\eta\rho}\left(p - \tau + \beta\int_0^\tau G(z')dz'\right)\right]^{-\xi}\right\}^{-\frac{1}{\xi}} G(\tau)} l, \tag{6}$$

*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 essentially represents the quantity of goods traded that satisfy Equation (4) when $\bar{z} = \tau$.
- Therefore, its dynamics are solely determined by how the equilibrium product market tightness reacts to a price change.

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# Households

- In addition to supplying labor inelastically, the representative household derives utility from consumption $c$ and holding real money balances $m/p$:

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

  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:

$$pc + m \leq \mu,$$

  where $\mu$: 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 all resources are consumed:

**Definition 3**

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

$$c_d(p) = \frac{\chi^{\epsilon}}{1+\chi^{\epsilon}} \frac{\mu}{p}. \tag{7}$$

**Proposition 3**

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

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# Flexible-Price Equilibrium

- The flexible-price equilibrium is defined as an equilibrium in which the reservation transportation cost is an external parameter:

**Definition 4**

*A flexible-price equilibrium parameterized by $\tau > 0$ consists of a price $p$ and a reservation transportation cost $\bar{z}$ such that the flexible-price aggregate supply equals the aggregate demand:*

$$c_s^{flex}(p) = c_d(p), \tag{8}$$

*while the reservation transportation cost is given by the parameter $\tau$, i.e., $\bar{z} = \tau$.*

**Proposition 4**

*For any $\tau > 0$, there exists a unique flexible-price equilibrium parameterized by $\tau$ that features positive price and consumption.*

# Flexible-Price Equilibrium (cont.)

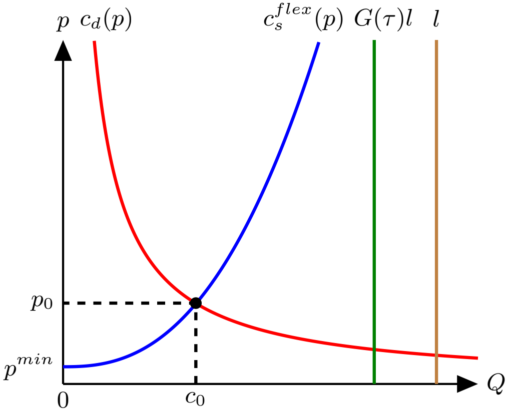


Figure A.7: Flexible-Price Aggregate Supply, Aggregate Demand, and Flexible-Price Equilibrium. Back

# Setting up the SVAR

- Our model is based on Rubio-Ramirez et al. (2010) and Arias et al. (2018):

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

  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 length.

- 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:*

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

*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:*

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

*The cross derivatives that describe the variation in the responses of the endogenous variables ascribed to the supply chain disruption satisfy:*

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

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

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# 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; $\boldsymbol{\omega}_t = [1, t]'$: $2 \times 1$ 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

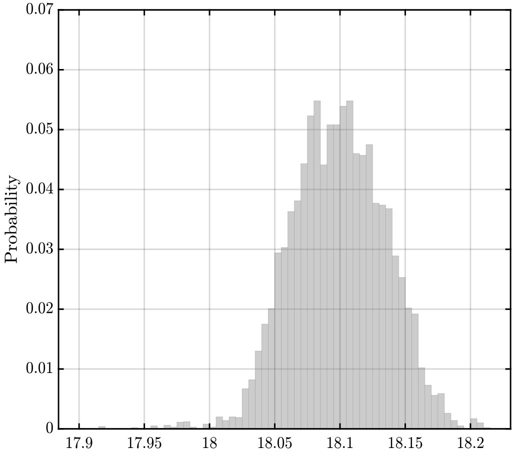


Figure A.8: Posterior Distribution of $\overline{ACR}$.

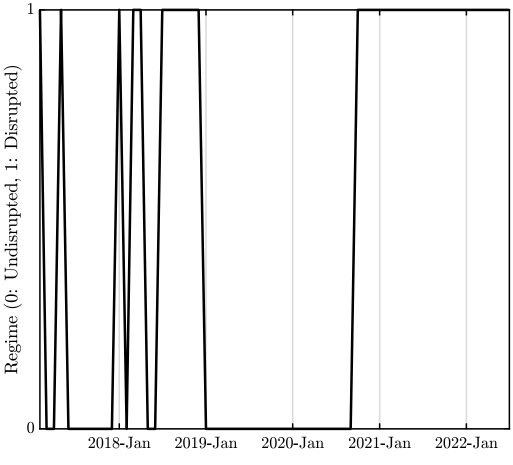


Figure A.9: Regimes Switches.

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# Local Projections (LPs) with Interaction Terms

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

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

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 is above its median level over the sample (18.1%).[1]

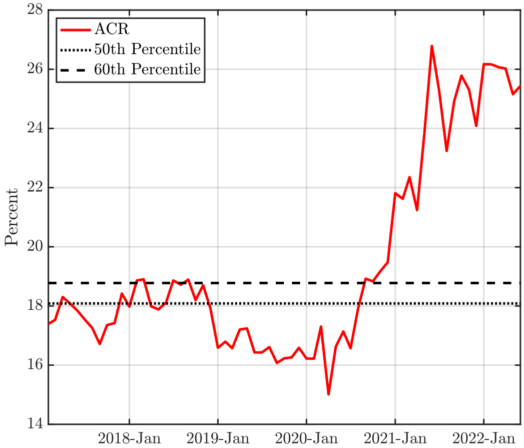


Figure A.10: ACR and Its 50th and 60th Percentiles.

[1] Our results are robust to considering a threshold at the 60th percentile (18.8%).

# Shock and Identification Restrictions

- ***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 horizons $k = 1, 2, 3$. The on-impact response of GDP deflator in p.p. is bounded to be smaller than that of FFR in p.p.

# Estimation Details

- We include two lags in the LPs.
- We compute the identified set of IRFs by numerically solving the quadratic program described in the supplement to Plagborg-Møller and Wolf (2021), using Algorithm 2 of Giacomini and Kitagawa (2021).
- We impose a normalization to the identified set of IRFs so that a contractionary monetary policy shock increases the FFR by 0.05 p.p. on impact in both regimes.

# IRFs to a Contractionary Monetary Policy Shock

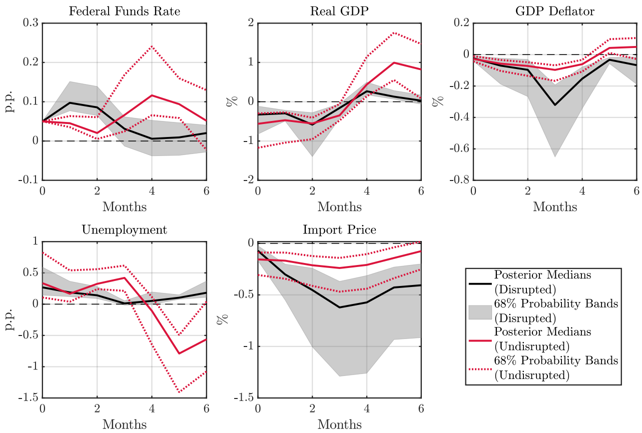


Figure A.11: State-Dependent Effects of a Contractionary Monetary Policy Shock: Using the LPs. Back