Production Networks and Firm-level Elasticities of Substitution

Brian Cevallos Fujiy [1] Devaki Ghose [2] Gaurav Khanna [3]

[1]University of Michigan

[2]World Bank, DECRG

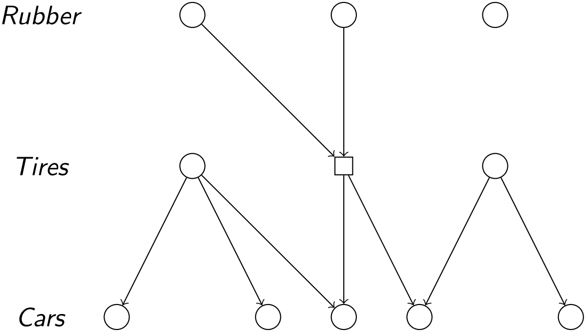
[3]UCSD

Introduction

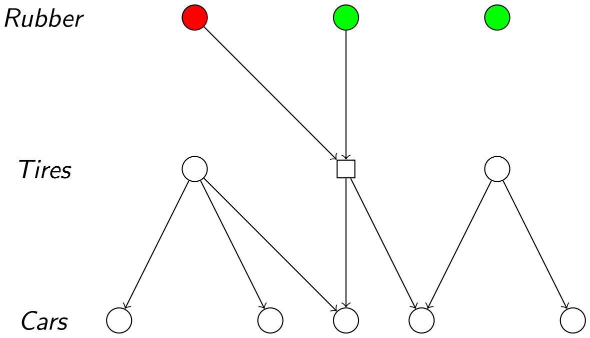
- Being able to substitute across suppliers after shocks
  - Key for resilience of supply chains

- Developing countries hit hard due to Covid-19 lockdowns
  - India: -7.3% GDP growth during 2020/21

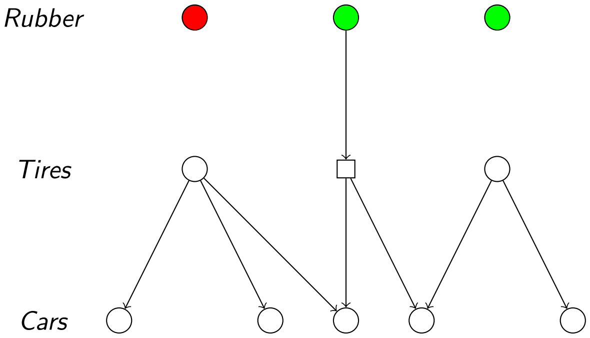
Toy example



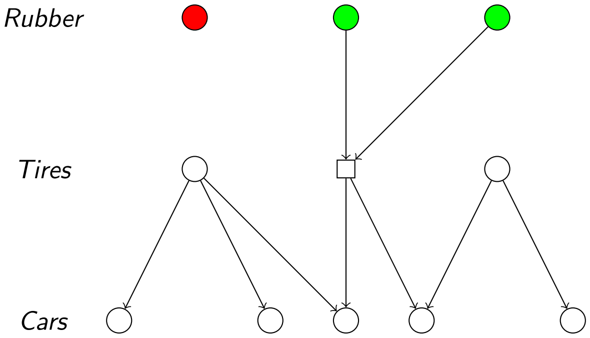
Toy example



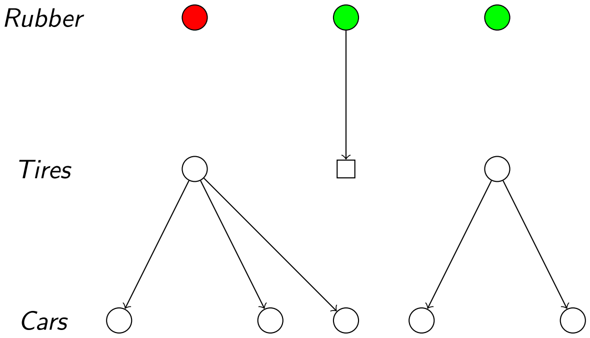
Toy example



Toy example



Toy example



This paper

1. **Provide one of the first causal estimates of firm-level elasticities of substitution across suppliers of the same product**
2. Quantify importance of these elasticities in the propagation of shocks through firm networks

Paper in one slide

Data

- Real-time firm-to-firm transaction data for a large Indian state

Identification Strategy

- Supply shock: India's sudden lockdown policy due to Covid that made inputs costly to produce and transport for some producers

Paper in one slide

Data

- Real-time firm-to-firm transaction data for a large Indian state

Identification Strategy

- Supply shock: India's sudden lockdown policy due to Covid that made inputs costly to produce and transport for some producers

Empirical results

- Elasticities ≈ 0.38
- High levels of complementarity across suppliers

Model

- Extended production network model *a la* Baqaee and Farhi (2019)

Literature

Propagation of shocks through supply chains

- (Baqaee and Farhi, 2019, 2020; Barrot and Sauvagnat, 2018; Carvalho et al., 2021; Peter et al., 2020; Boehm et al., 2019; Atalay, 2017)
- *Contribution:* Estimate novel firm-level elasticities of substitution across suppliers

Covid-19

- (Bonadio et al., 2021; Baqaee and Farhi, 2020; Cakmakli et al., 2021; Demir and Javorcik, 2020; Gerschel et al., 2020; Heise et al., 2020; Lafrogne-Roussier et al., 2021)
- *Contribution:* Use spatial variation of Covid-19 lockdowns to estimate elasticities

Trade

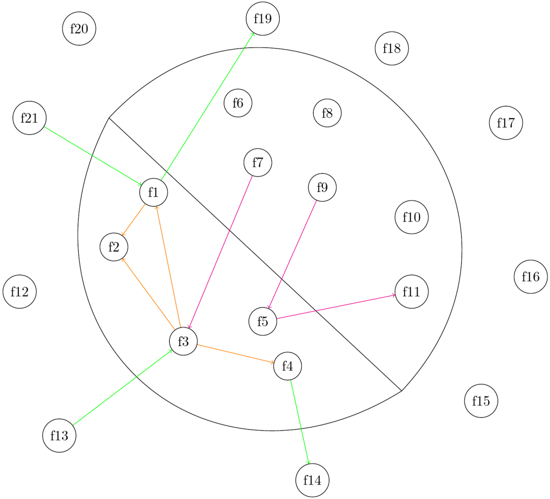
- (Behrens et al., 2013; Giovanni and Levchenko, 2009; Bricongne et al., 2012; Baldwin and Tomiura, 2020; Baldwin, 2009)
- *Contribution:* Effect of large negative shocks (Covid lockdowns) on internal trade

Data

Firm-to-firm trade

- Daily establishment level transactions for large Indian state, April 2018-October 2020
  - population 2x Chile, 7x Costa Rica, 3x Belgium
- Values, quantities, implied unit values, district, 8-digit HSN

Firm-to-firm trade

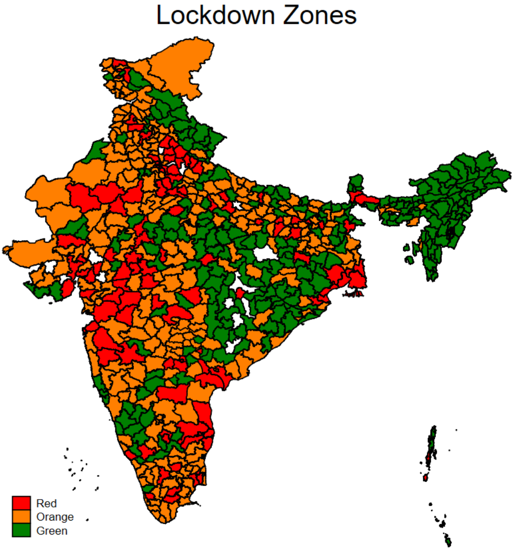


Data

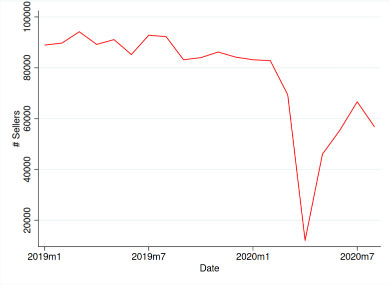
Lockdowns

- On March 25th 2020, nation-wide lockdown policies
- Unexpected and of indeterminate duration a-priori
- District classification: *Red* (severe), *Orange* (mid), *Green* (mild)
- Implementation of lockdown done by Indian states

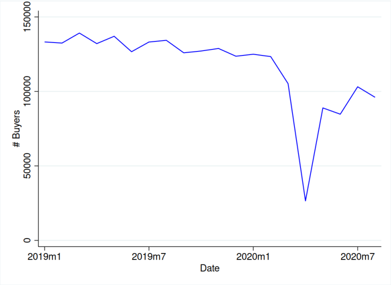
Lockdown in India



Summary statistics

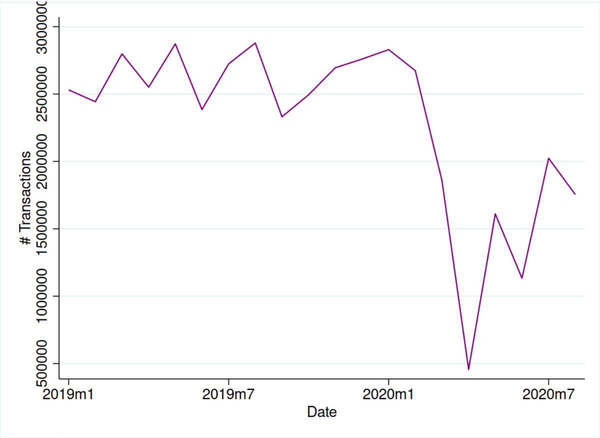


(a) Number of sellers per month



(b) Number of buyers per month

Summary statistics: Total number of transactions



Event study using the lockdown as treatment

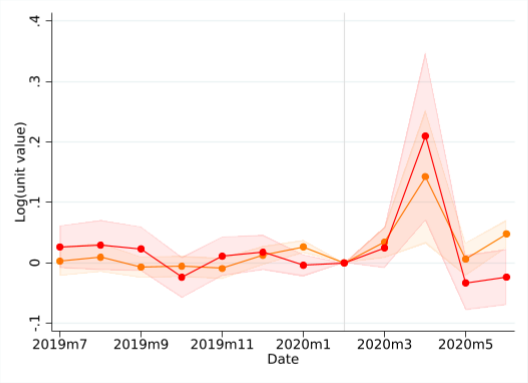
Seller-level regressions:

$$Y_{si,t} = \iota_i + \iota_{o_{(s)}} + \iota_t + \sum_{t \neq -1} \beta_t Red_{o_{(s)}} + \sum_{t \neq -1} \gamma_t Orange_{o_{(s)}} + X\delta + \epsilon_{si,t}$$

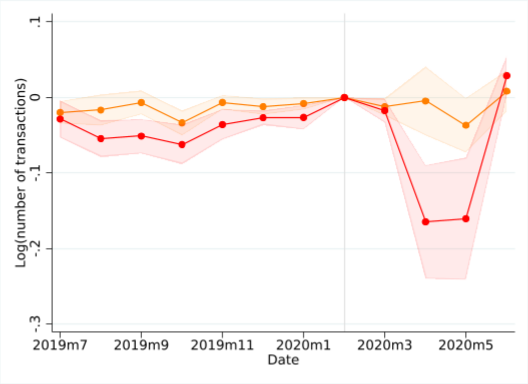
where

- $Y_{si,t}$ are average unit values and number of transactions
- Seller s from origin o
- 2-digit HSN i
- in month t, and $t = -1$ is February 2020 (baseline)
- Omitted group: Green zone

Fact 1: unit values went up during lockdown



Fact 2: number of transactions went down during lockdown



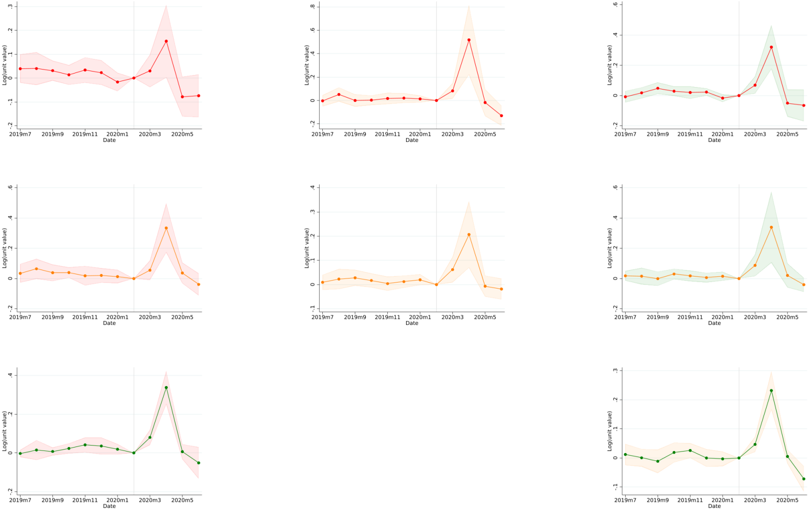
Seller-buyer regressions:

$$Y_{si,b,t} = \delta_{o_{(s)}} + \delta_{d_{(b)},t} + \delta_i + \beta \log \ dist_{od} + X\delta$$
$$+ \sum_{(x,z)\in\Omega} \sum_{t\neq -1} \beta_t^{xz} \left(\gamma^x_{o_{(s)}} \times \gamma^z_{d_{(b)}} \right) + \epsilon_{si,b,t}$$

where

- where $Y_{si,t}$ are average unit values and number of transactions
- From seller s in origin o to buyer b in destination d
- 2-digit HSN i
- Month t, and $t = -1$ is February 2020
- $\Omega = \{RR, RO, RG, OR, OO, OG, GR, GO\}$

Fact 3: rise in unit values proportional to exposure



Fact 4: drop in transactions proportional to exposure

Model

- Setup:
  - Set of firms N
  - Set of industries J
- Final consumption of household:

$$Y = \left(\sum_{j=1}^{J} \sum_{n=1}^{N_j} \omega_j^0 y_{nj}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

- Firm n in industry j produces using labor l_n and a composite of intermediate inputs x_{nj}:

$$y_{nj} = A_n \left(w_{nl} \left(l_n \right)^{\frac{\alpha-1}{\alpha}} + \left(1 - w_{nl} \right) \left(x_{nj} \right)^{\frac{\alpha-1}{\alpha}} \right)^{\frac{\alpha}{\alpha-1}}$$

Model

- First nest:

$$x_{nj} = \left(\sum_{i=1}^{I} \phi_{ij} \left(x_{i,nj} \right)^{\frac{\zeta-1}{\zeta}} \right)^{\frac{\zeta}{\zeta-1}}$$

- Second nest:

$$x_{i,nj} = \left(\sum_{m=1}^{N_m} \mu_{mi,nj}^{\frac{1}{\epsilon}} x_{mi,nj}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}$$

Estimation

- Estimating equation from the model we take to the data:

$$\log\left(\frac{\widehat{PM}_{si,bj,t}}{\widehat{PM}_{i,bj,t}}\right) = (1-\epsilon)\log\left(\frac{\widehat{p}_{si,bj,t}}{\widehat{\tilde{p}}_{i,bj,t}}\right) + \omega_{d_{(b)},t} + \omega_{o_{(s)}} + X\beta + \epsilon_{si,bj,t},$$

where $\widehat{x}_t = \frac{x_t}{x_{t-1}}$

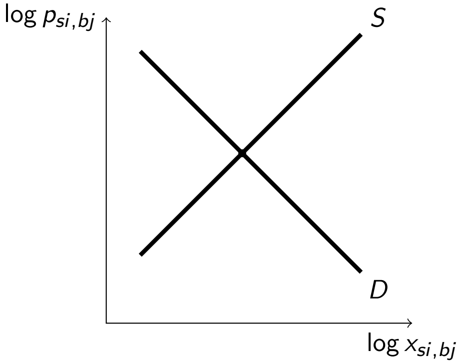
Estimation

- Estimating equation from the model we take to the data:

$$\log\left(\frac{\widehat{PM}_{si,bj,t}}{\widehat{PM}_{i,bj,t}}\right) = (1-\epsilon)\log\left(\frac{\widehat{p}_{si,bj,t}}{\widehat{\tilde{p}}_{i,bj,t}}\right) + \omega_{d_{(b)},t} + \omega_{o_{(s)}} + X\beta + \epsilon_{si,bj,t},$$

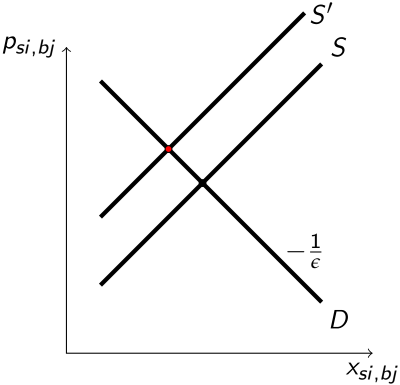
where $\widehat{x}_t = \frac{x_t}{x_{t-1}}$

Identification strategy



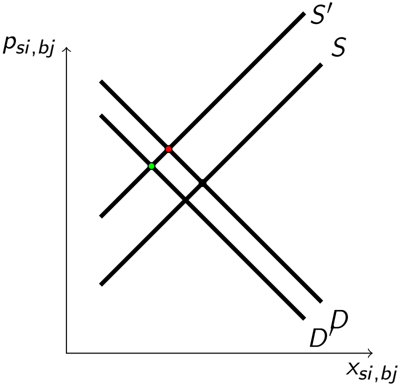
$$\log\left(\frac{p_{si,bj}}{p_{s'i,bj}}\right) = -\left(\frac{1}{\epsilon}\right)\log\left(\frac{x_{si,bj}}{x_{s'i,bj}}\right) + \left(\frac{1}{\epsilon}\right)\log\left(\frac{\mu_{si,bj}}{\mu_{s'i,bj}}\right)$$

Identification strategy



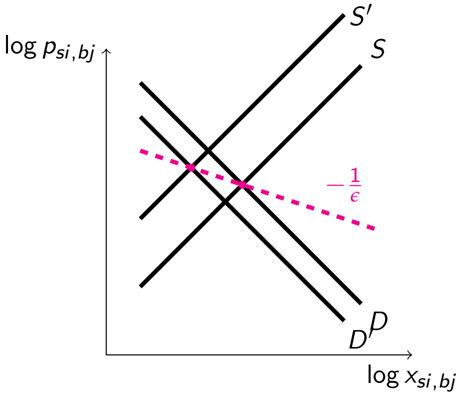
$$\log\left(\frac{p_{si,bj}}{p_{s'i,bj}}\right) = -\left(\frac{1}{\epsilon}\right)\log\left(\frac{x_{si,bj}}{x_{s'i,bj}}\right) + \left(\frac{1}{\epsilon}\right)\log\left(\frac{\mu_{si,bj}}{\mu_{s'i,bj}}\right)$$

Identification strategy



$$\log\left(\frac{p_{si,bj}}{p_{s'i,bj}}\right) = -\left(\frac{1}{\epsilon}\right)\log\left(\frac{x_{si,bj}}{x_{s'i,bj}}\right) + \left(\frac{1}{\epsilon}\right)\log\left(\frac{\mu_{si,bj}}{\mu_{s'i,bj}}\right)$$

Identification strategy



$$\log\left(\frac{p_{si,bj}}{p_{s'i,bj}}\right) = -\left(\frac{1}{\epsilon}\right)\log\left(\frac{x_{si,bj}}{x_{s'i,bj}}\right) + \left(\frac{1}{\epsilon}\right)\log\left(\frac{\mu_{si,bj}}{\mu_{s'i,bj}}\right)$$

Identification strategy

- Sources of variation:

$$\log\left(p_{si,bj,t}\right) = \log\left(p_{si,t}\right) + \log\left(\tau_{sb,t}\right)$$

Identification strategy

- Sources of variation:

$$\log\left(p_{si,bj,t}\right) = \log\left(p_{si,t}\right) + \log\left(\tau_{sb,t}\right)$$

- Variation in $p_{si,t}$ (Seller-level instrument):

$$log(\widehat{p}_{si,bj,t}) = \beta^R Red_{o_{(s)}} Lock_t + \beta^O Orange_{o_{(s)}} Lock_t$$
$$+ \omega_{d_{(b)},t} + \omega_{o_{(s)}} + X\beta + \epsilon^{\nu}_{si,bj,t}$$

Identification strategy

- Sources of variation:

$$\log\left(p_{si,bj,t}\right) = \log\left(p_{si,t}\right) + \log\left(\tau_{sb,t}\right)$$

- Variation in $p_{si,t}$ (Seller-level instrument):

$$log(\widehat{p}_{si,bj,t}) = \beta^R Red_{o_{(s)}} Lock_t + \beta^O Orange_{o_{(s)}} Lock_t + \omega_{d_{(b)},t} + \omega_{o_{(s)}} + X\beta + \epsilon^{\nu}_{si,bj,t}$$

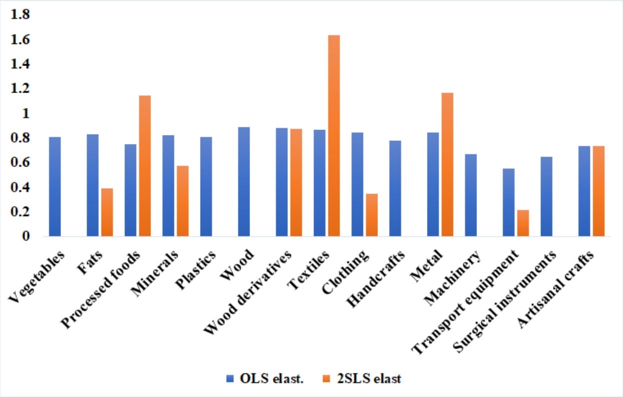
- Variation in $\tau_{sb,t}$ (Seller/buyer level instrument):

$$log(\widehat{p}_{si,bj,t}) = \beta^R Red_{o_{(s)} d_{(b)}} Lock_t + \beta^O Orange_{o_{(s)} d_{(b)}} Lock_t + \omega_{d_{(b)},t} + \omega_{o_{(s)}} + X\beta + \epsilon^{\nu}_{si,bj,t}$$

Estimated elasticity of substitution across suppliers

	OLS	(2)	(3)	(4)	(5)
$\log\left(\frac{\hat{p}}{\hat{\bar{p}}}\right)$	0.230	0.622	0.622	0.616	0.622
	(0.006)	(0.214)	(0.234)	(0.132)	(0.217)
Obs	4449449	4449449	4449449	3213758	4449449
K-PF		17.026	16.958	114.7503	16.958
J-stat		3.082	2.906	2.929	2.906
ϵ	0.770	0.377	0.377	0.383	0.377
Instrument I		Y	Y	Y	Y
Instrument II				Y	
Clustering	o-d	o-d	o	o-d	bootstrap o

Elasticities by industry



Effect of HS Aggregation

Shock propagation through network

- Negative productivity shock to firm j changes prices of other producers (indirect exposure)
- If suppliers are complements, then j becomes a bottleneck
- This affects all firms directly and indirectly related to j

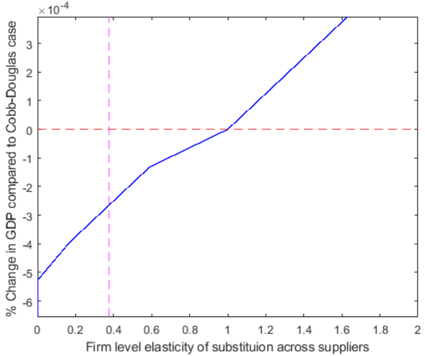
Extent of shock propagation

Baqaee and Farhi (2020) show that extent of shock propagation depends on

1. the degree of complementarity between suppliers
2. the direct and indirect exposure to the shock, measured by the Leontieff inverse
3. the size of exposed suppliers

Preliminary simulation with sample

- Production network data from March 2019-February 2020
- Randomly sample less than 1% of this data (6569 firms)
- Shock randomly chosen firms



Conclusion

- We leverage **variation in input prices** following the Covid-19 lockdown
- Provide one of the first estimates of **elasticities of substitution across suppliers** within the same industry
- Inputs are highly **complementary**:
  - But heterogeneity across industries
- Negative shocks to linked firms can have large negative effects on the aggregate economy

Thank You

References I

Enghin Atalay. How important are sectoral shocks? *American Economic Journal: Macroeconomics*, 9(4):254–80, 2017.

Richard Baldwin and Eiichi Tomiura. Thinking ahead about the trade impact of Covid-19. *Economics in the Time of Covid-19*, 59, 2020.

Richard E Baldwin. *The great trade collapse: Causes, consequences and prospects*. CEPR, 2009.

David Baqaee and Emmanuel Farhi. Nonlinear production networks with an application to the Covid-19 crisis. Technical report, National Bureau of Economic Research, 2020.

David Rezza Baqaee and Emmanuel Farhi. The macroeconomic impact of microeconomic shocks: beyond Hulten's Theorem. *Econometrica*, 87(4):1155–1203, 2019.

References II

Jean-Noël Barrot and Julien Sauvagnat. Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, 131(3):1543–1592, 2018.

Kristian Behrens, Gregory Corcos, and Giordano Mion. Trade crisis? What trade crisis? *Review of Economics and Statistics*, 95(2):702–709, 2013.

Christoph E Boehm, Aaron Flaaen, and Nitya Pandalai-Nayar. Input linkages and the transmission of shocks: Firm-level evidence from the 2011 Tōhoku earthquake. *Review of Economics and Statistics*, 101 (1):60–75, 2019.

References III

Barthélémy Bonadio, Zhen Huo, Andrei A Levchenko, and Nitya Pandalai-Nayar. Global supply chains in the pandemic. *Journal of International Economics*, page 103534, 2021.

Jean-Charles Bricongne, Lionel Fontagné, Guillaume Gaulier, Daria Taglioni, and Vincent Vicard. Firms and the global crisis: French exports in the turmoil. *Journal of International Economics*, 87(1): 134–146, 2012.

Cem Cakmakli, Selva Demiralp, Sebnem Kalemli-Ozcan, Sevcan Yesiltas, and Muhammed Yildirim. The economic case for global vaccinations: An epidemiological model with international production networks. Technical report, National Bureau of Economic Research, 2021.

References IV

Vasco M Carvalho, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi. Supply chain disruptions: Evidence from the great east japan earthquake. *The Quarterly Journal of Economics*, 136(2): 1255–1321, 2021.

Banu Demir and Beata Javorcik. Trade finance matters: evidence from the Covid-19 crisis. *Oxford Review of Economic Policy*, 2020.

Elie Gerschel, Alejandra Martinez, and Isabelle Mejean. Propagation of shocks in global value chains: the coronavirus case. *Notes IPP*, (53), 2020.

Julian di Giovanni and Andrei A Levchenko. Trade openness and volatility. *The Review of Economics and Statistics*, 91(3):558–585, 2009.

References V

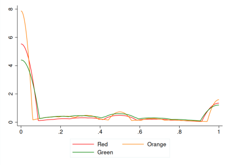
Sebastian Heise et al. How did chinaâs covid-19 shutdown affect us supply chains? Technical report, Federal Reserve Bank of New York, 2020.

R Lafrogne-Roussier, Julien Martin, and Isabelle Méjean. Supply shocks in supply chains: Evidence from the early lockdown in china. Technical report, Mimeo, CREST, 2021.

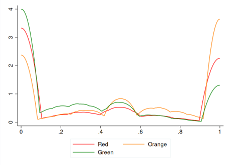
Alessandra Peter, Cian Ruane, et al. The aggregate importance of intermediate input substitutability. *Princeton University, memo*, 2020.

Stephen J Redding and David E Weinstein. Measuring aggregate price indices with taste shocks: Theory and evidence for CES preferences. *The Quarterly Journal of Economics*, 135(1):503–560, 2020.

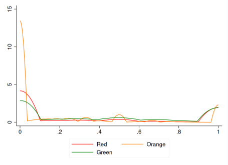
Pre-treatment



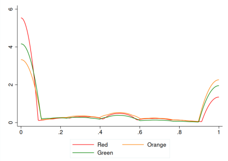
(s) Sellers in Red



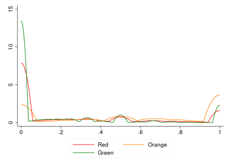
(t) Sellers in Orange



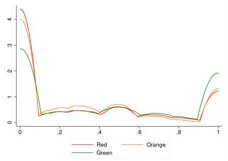
(u) Sellers in Green



(v) Buyers in Red

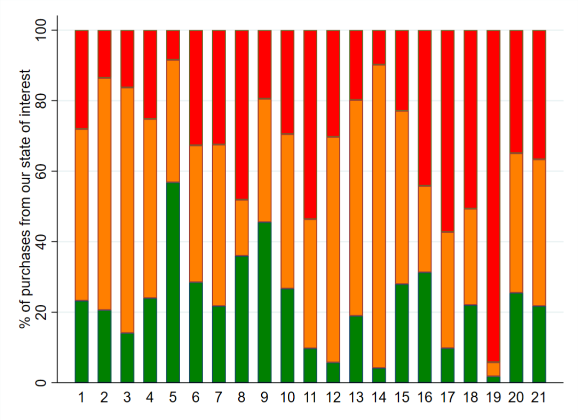


(w) Buyers in Orange



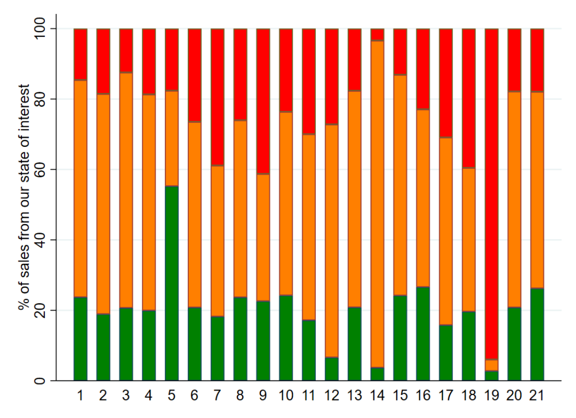
(x) Buyers in Green

Distribution of zones and industries



Back

Distribution of zones and industries



Back

Estimation

- Estimating equation from the model:

$$\log\left(\frac{PM_{si,bj}}{PM_{i,bj}}\right) = (1-\epsilon)\log\left(\frac{p_{si,bj}}{p_{i,bj}}\right) + \log\left(\mu_{si,bj}\right),$$

where $PM_{si,bj} \equiv p_{si,bj}x_{si,bj}$

- Problems:
  1. Unobservable productivity shocks: $p_{i,bj} = \left(\sum_{s'}\left(p_{s'i,bj}^{1-\epsilon}\mu_{s'i,bj}\right)\right)^{\frac{1}{1-\epsilon}}$
  2. Endogeneity concerns: Demand shocks induced by Covid-19 lockdowns

Unobservable productivity shocks

- Based on Redding and Weinstein (2020), we assume buyer shocks across industries are time-invariant
- Then:

$$\hat{p}_{i,bj,t}^{1-\epsilon} = \frac{\hat{\tilde{p}}_{si,bj,t}^{1-\epsilon}}{\hat{\tilde{s}}_{si,bj,t}}$$

where $\widehat{x}_t = \frac{x_t}{x_{t-1}}$, $\tilde{p}_{i,bj,t} \equiv \prod_s p_{si,bj,t}^{\frac{1}{N_{i,bj,t}}}$ is a geometric mean across suppliers of unit values, $\tilde{s}_{i,bj,t} \equiv \prod_s s_{si,bj,t}^{\frac{1}{N_{i,bj,t}}}$ is a geometric mean across suppliers of expenditure shares, $s_{si,bj,t} \equiv \frac{PM_{si,bj,t}}{PM_{i,bj,t}}$, and $N_{i,bj,t}$ is the number of suppliers that firm sourced from in time t.

Effect of HS Aggregation

	(1)	(2)	(3)	(4)	(5)
$\log\left(\frac{\hat{p}}{\hat{\hat{p}}}\right)$	0.713	0.713	0.531	0.600	0.713
	(0.313)	(0.329)	(0.158)	(0.438)	(0.362)
Obs	5478629	5478629	3945976	3945976	5478629
K-PF	8.817	8.608	81.811	12.634	8.608
J-stat	0.054	0.065	0.549	2.930	0.065
ϵ	0.286	0.286	0.468	0.399	0.286
Instrument I	Y	Y	Y	Y	Y
Instrument II			Y	Y	

Back

Effect of HS Aggregation

	(1)	(2)	(3)	(4)	(5)
$\log\left(\frac{\hat{p}}{\hat{\hat{p}}}\right)$	0.418	0.418	0.507	0.644	0.418
	(0.281)	(0.305)	(0.128)	(0.362)	(0.206)
Obs	3870856	3870856	2799889	2799889	3870856
K-PF	28.169	31.042	25.610	17.814	31.042
J-stat	2.379	1.868	2.562	5.536	1.868
ϵ	0.581	0.581	0.492	0.355	0.581
Instrument I	Y	Y	Y	Y	Y
Instrument II			Y	Y	

Back