The Economic Cost of Lockdown in China: Evidence from City-to-City Truck Flows

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Motivation

- Economic cost of non-pharmacological interventions
- Challenges:
    - Policy response depending on the severity of the pandemic
    - Effect of policy vs. individual response
    - Economic spillovers

Zero COVID Policy in China between the End of Wuhan Lockdown and Emergence of Omicron

- Very effective (almost zero infection rate)
- Uniform implementation (minimizing policy endogeneity)
- Small and local outbreaks (limiting self-preventive measures by fear)
- Monthly city-to-city truck flow data (high-frequency and network)

Truck FLow

- Representativeness
  - 73% of China's total freight is by trucks
  - Truck flows are highly correlated with GDP and Night Lights.

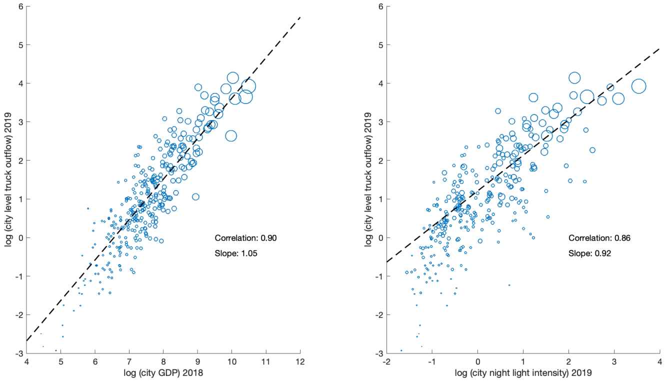


Figure 1: Truck Outflow, GDP and Night Lights

Measuring City-Level Lockdowns

- To accurately measure the timing and duration of lockdowns, we compile a data set of city-level lockdowns in China.
- The first step is to manually collect local government announcements for the three most well-known lockdowns after 2020 Q1: Shijiazhuang, Yangzhou and Xi'an.
  - Local governments seldom used the word of *fengcheng*(封城), "locking down the city" in Chinese.
  - Three keywords frequently appear in the official announcements: (1) closed-off management in all areas (全域封闭管理); (2) traffic controls in all roads (所有道路交通管制); (3) public transport out of service (全部停运).

Measuring City-Level Lockdowns

- We then scrape the first 50 results by searching the triplet of year, month and city with new COVID cases and one of the three keywords on Baidu.
    - Drop the irrelevant web pages
    - Select official announcements on lockdown
- We distinguish city-level (**full-scale**), district-level (**partial**) and community-level (**minimum**) lockdown.

Lockdowns and Truck Flows

- We find 16 full-scale lockdowns in 16 cities, with average duration 24 days; and 22 partial lockdowns in 18 cities, with average duration 19 days.

Table 1: Lockdowns after Q1 2020

Panel A: Citywide Lockdowns After Q1 2020		
Number of City	Average City COVID Cases	$\mathrm{d}\ln \bar{q}_t^h$
16	329 (74.9)	-48.08%

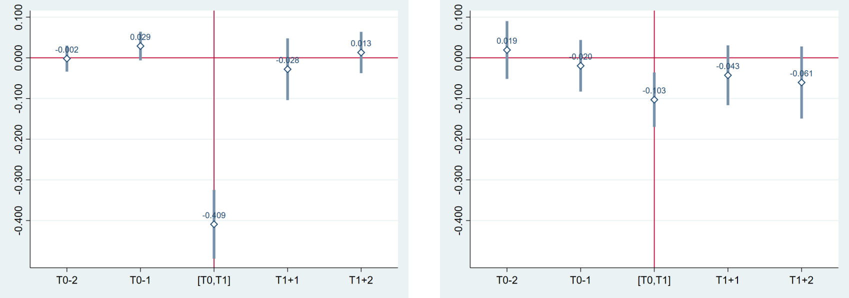
Panel B: Partial Lockdowns After Q1 2020		
Number of City	Average City COVID Cases	$\mathrm{d}\ln \bar{q}_t^l$
18	108 (24)	-21.23%

Panel C: Other community Lockdowns After Q1 2020		
Number of City	Average City COVID Cases	$\mathrm{d}\ln \bar{q}_t^m$
111	38 (6.2)	-2.93%

Reduced-Form Approach

- City-pair lockdown dummies, $D^k_{ni,t}$: $k \in \{h, l, m\}$ stands for full-scale ($k = h$), partial ($k = l$) and minimum lockdown ($k = m$), respectively.
    - For $n \neq i$, $D^h_{ni,t}$ is a city-pair dummy that equals one if at least one of the cities has full-scale lockdown in the period.
- Construct a sample with no overlaps of lead-lag lockdown effects.

Reduced-Form Approach: Event Study



(a) full-scale lockdown (b) partial lockdown

Figure 3: Event Study

Reduced-Form Approach: TWFE

- We adopt a two-way fixed effect regression to estimate the effect of lockdown on $d \ln q_{ni,t}$, for $n \neq i$.

$$d \ln q_{ni,t} = \sum_k \alpha^k D^k_{ni,t} + \delta_{ni} + \nu_t + \eta_{ni} t + \epsilon_{ni,t},$$

- Add $\ln(1 + \text{Case}_{ni,t})$, where Case is the number of new COVID cases in the city pair.

- Replace the dummy variable $D^k_{ni,t}$ with $\hat{D}^k_{ni,t}$, the proportion of days with type-k lockdown in the month.

- Robust estimates by de Chaisemartin and D' Haultfœuille (2020)

Reduced-Form Approach

Table 2: Effect of Lockdown on Truck Flow, Panel Regression

	(1)	(2)	(3)	(4)	(5)
		D^k_{ni}		$\hat{D}^k_{ni}$	
Full-Scale Lockdown	-0.4096	-0.4175	-0.3507	-0.8940	-0.7697
	(0.0415)	(0.0418)	(0.0376)	(0.0656)	(0.0667)
Partial Lockdown	-0.0911	-0.0958	-0.0396	-0.2183	-0.1052
	(0.0258)	(0.0257)	(0.0268)	(0.0624)	(0.0660)
COVID Dummy		-0.0276			
		(0.0064)			
$\ln(1 + \text{Case})$			-0.0229		-0.0205
			(0.0027)		(0.0025)
Time FE	YES	YES	YES	YES	YES
City pair FE	YES	YES	YES	YES	YES
City pair trend	YES	YES	YES	YES	YES
N	206322	206322	206322	206322	206322
R-squared	0.3349	0.3358	0.3380	0.3368	0.3392

Armington Model

- Producer: $Q_n = a_n l_n$
- Consumer: $u_n = \left[\sum_{i=1}^{N} Q_{ni}^{\frac{\theta}{\theta+1}}\right]^{\frac{\theta+1}{\theta}}$
- Market Clear Conditions:
  - Goods market: $\sum_i \tau_{in} Q_{in} = Q_n$
  - Labor market: $w_n l_n = \sum_i X_{ni}$
  - Trade balance: $\sum_i X_{ni} = \sum_i X_{in} + \bar{d}_n$

Model

- Expenditure Share:

$$S_{ni} \equiv \frac{\left(w_i \tau_{ni} / a_i\right)^{-\theta}}{\sum_{k=1}^{N} \left(w_k \tau_{nk} / a_k\right)^{-\theta}}$$

- **Shock to composite cost**:

$$d \ln z_{ni} \equiv d \ln \tau_{ni} - d \ln a_i$$

- Stack Q_{ni}, S_{ni} and z_{ni} into $N \times N$ matrices $\boldsymbol{Q}$, $\boldsymbol{S}$ and $\boldsymbol{Z}$.
- Let $\mathcal{Q}_{N^2 \times 1}$ and $\mathcal{Z}_{N^2 \times 1}$ be the vector form of $\boldsymbol{Q}$ and $\boldsymbol{Z}$.

Model: Proposition 1

Starting from an equilibrium with expenditure share $\boldsymbol{S}$

(1) Let $\boldsymbol{G}$ be an $N^2 \times N^2$ matrix that depends on θ and $\boldsymbol{S}$.

$$d \ln \mathcal{Q} = \boldsymbol{G} d \ln \mathcal{Z}$$

(2) The real income change in city n:

$$d \ln \boldsymbol{u}_n = \sum_{i=1}^{N} S_{ni} d \ln Q_{ni}.$$

Structural Approach

- Parameterize composite cost shocks as

$$d \ln z_{ni,t} = \sum_{k \in \{h,l\}} \left(\beta^k \mathbf{1}(n \neq i) + \gamma^k \mathbf{1}(n = i) \right) D^k_{ni,t} + \varepsilon_{ni,t},$$

- We estimate (β^k, γ^k) by

$$\hat{\Psi} = \arg\min_{\Psi} \sum_{ni,t} W_{ni} \left(d \ln \hat{Q}_{ni,t}(\Psi) - d \ln Q_{ni,t} \right)^2,$$

where $\Psi \equiv \{\beta^h, \gamma^h, \beta^l, \gamma^l\}$ and W_{ni} is city-pair weight.

Structural Approach

- The first-order approach delivers a closed-form solution

$$\hat{\Psi} = \left(\boldsymbol{X}'\boldsymbol{W}\boldsymbol{X}\right)^{-1}\boldsymbol{X}'W\boldsymbol{Y},$$

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{GI}(n \neq i)\mathcal{D}_1 & \boldsymbol{GI}(n = i)\mathcal{D}_1 \\ \vdots & \vdots \\ \vdots & \vdots \\ \boldsymbol{GI}(n \neq i)\mathcal{D}_T & \boldsymbol{GI}(n = i)\mathcal{D}_T \end{bmatrix}, \boldsymbol{Y} = \begin{bmatrix} d\ln \boldsymbol{\mathcal{Q}}_1 \\ \vdots \\ \vdots \\ d\ln \boldsymbol{\mathcal{Q}}_T \end{bmatrix},$$

- $\boldsymbol{G}$: assume $\theta = 4$ and calibrate the expenditure shares to the official provincial input output table in 2012.

Structural Approach

Table 3: Effect of Lockdown on Truck Flow, Structural Estimates

	(1)	(2)	(3)	(4)	(5)
		D^k_{ni}		$\hat{D}^k_{ni}$	
Full-Scale Lockdown ($n \neq i$)	0.2343	0.2381	0.2105	0.5631	0.5138
	(0.0287)	(0.0288)	(0.0273)	(0.0322)	(0.0328)
Full-Scale Lockdown ($n = i$)	0.3742	0.3770	0.3476	0.9507	0.8912
	(0.0734)	(0.0734)	(0.0705)	(0.0776)	(0.0782)
Partial Lockdown ($n \neq i$)	0.0461	0.0493	0.0278	0.1435	0.1035
	(0.0105)	(0.0105)	(0.0104)	(0.0243)	(0.0250)
Partial Lockdown ($n = i$)	0.0740	0.0763	0.0519	0.2486	0.1965
	(0.0223)	(0.0222)	(0.0213)	(0.0524)	(0.0527)
COVID Dummy ($n \neq i$)		0.0091			
		(0.0021)			
COVID Dummy ($n = i$)		0.0115			
		(0.0044)			
$\ln(1 + \text{Case})$			0.0102		0.0087
			(0.0010)		(0.0009)
Time FE	YES	YES	YES	YES	YES
City pair FE	YES	YES	YES	YES	YES
City pair trend	YES	YES	YES	YES	YES
N	419527	419527	419527	419527	419527

Model-Based Accounting

- City n's real income change caused by a type-k lockdown of city i:

$$d\ln \boldsymbol{u}_n^{i,k} \equiv \frac{\partial \ln \boldsymbol{u}_n}{\partial \ln \boldsymbol{z}_{ii}}\gamma^k + \sum_{j\neq i}\left[\frac{\partial \ln \boldsymbol{u}_n}{\partial \ln \boldsymbol{z}_{ji}} + \frac{\partial \ln \boldsymbol{u}_n}{\partial \ln \boldsymbol{z}_{ij}}\right]\beta^k$$

- The aggregate real income change caused by a type-k lockdown in city i:

$$d\ln \boldsymbol{u}_{ag}^{i,k} \equiv \sum_{n=1}^{N} \mu_n d\ln \boldsymbol{u}_n^{i,k}, \tag{1}$$

where μ_n is city n's pre-shock real income share.

Results

- A full-scale lockdown of Shijiazhuang for a month would reduce the local and national real income by 59% and 0.4% in the lockdown period.
- Full-scale lockdown in Shanghai, Beijing and Shenzhen will reduce the national real income by 2.7%, 2.5% and 1.8%, respectively.
- The contribution of the spillover effect varies from 0 to 16 percent.

Decomposition

- Decompose the aggregate effect into local and spillover effects

$$d \ln \boldsymbol{u}_{ag}^{i,k} = \mu_i d \ln \boldsymbol{u}_i^{i,k} + d \ln \boldsymbol{u}_{so}^{i,k}$$

where

$$d \ln \boldsymbol{u}_{so}^{i,k} = \sum_{n \neq i} \mu_n d \ln \boldsymbol{u}_n^{i,k}.$$

Decomposition

- Aggregate effects correlated to the city's size and its position in the network (eigenvector centrality)

Table 4: Economic Size and Network Centrality

	(1) $-d\ln \boldsymbol{u}_{ag}^{i,h}$ (%)	(2) $-d\ln \boldsymbol{u}_{so}^{i,h}$ (%)
GDP	0.2093	0.0145
	(0.0057)	(0.0028)
Centrality	0.0126	0.0106
	(0.0065)	(0.0030)
N	315	315
R-squared	0.9996	0.9888

External Validity

- Wuhan lockdown: Truck flows and GDP fell by 57% and 41% in 2020Q1
- Shanghai:
  - Prediction: A one-month full-scale lockdown on Shanghai would reduce the local truck flows (GDP) by 60%.
  - Actual decline in April: 80% for truck flows and 61% for industrial value added.

Conclusion

- A simple estimate on the economic cost of lockdown
- Potentially larger effect by locking down more cities with longer duration (expectation change, supply chain disruption ...)