

The Economic Impact of COVID-19 in China: Evidence from City-to-City Truck Flows*

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Abstract

We estimate the economic impact of COVID-19 in China using high-frequency, city-to-city truck flow data. We invert a gravity model to recover bilateral trade cost shocks during the outbreak. We find local pandemic severity accounts for <20% of these shocks; the large residual component suggests substantial cross-city and over-time variations in containment policies. Shocks to Wuhan and Beijing had the greatest economic impact, lowering national real income by 1.7% and 1.6%. If all Chinese cities had containment policies that responded to local pandemic severity as those in Hubei did, China's first-quarter real income would have declined by 47%.

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1 Introduction

The ongoing COVID-19 pandemic is not only a public health crisis but also an economic one. The pandemic severely disrupts economic activities through government-mandated shelter-in-place, lock-down orders as well as self-protective social isolation responses. Draconian measures, for instance, were implemented in Wuhan, China’s epicenter of the pandemic, locking down the entire city with 11 million people for more than two months. Despite the growing evidence for the effectiveness of Wuhan-style lockdown in containing the pandemic, the associated economic costs remain obscure to both the scientific community and policymakers. The main challenge is that the effect of containment measures, even if confined to a single locality, will spill over into all the other connected economies through economic linkages and is, therefore, hard to uncover by conventional locality-specific economic statistics.

In this paper, we tackle the problem by using a unique data set on daily, city-to-city truck flows. The data come from G7, one of China’s leading logistical service providers, which tracks real-time GPS information on 1.4 million heavy trucks operating in 336 out of 342 prefecture-level cities.¹ We develop sufficient statistics that recover city-to-city impediments to truck flows from observed truck flow changes. The impediment measures have structural interpretations in gravity-based trade models as iceberg trade costs and can arise due to either voluntary production slowdowns or mandatory lock-downs in the pandemic.

We analyze the impediment measures by exploiting the heterogeneity in the pandemic severity and the asynchronous policy adjustments across Chinese cities. We refer to the changes in the impediment measure as *COVID shocks*, to the extent that they capture the variations of the severity of the pandemic as well as individual and policy responses across cities and over time. We find that local pandemic severity can only account for less than 20% of the estimated COVID shocks. For instance, after controlling for the severity of COVID-19 outbreaks, the residual component in COVID shocks to Beijing and Guangzhou is 0.13 log points higher and 0.21 log points lower than the national average, respectively, suggesting the intense preventive responses in Beijing and the correspondingly lax measures in Guangzhou. Overall, we find COVID shocks to a city largely manifest through adding costs to the outflows of goods from the city, as opposed to the inflows of goods to the city.

Using our sufficient statistics approach, we find the COVID shocks reduced China’s real income by 19.4% in the first quarter of 2020 while increased by 3.1% in the second quarter. The economic impact is highly heterogeneous across cities: in the first-quarter, real income declined in 272 out of 315 cities, and Wuhan experienced a drop of 60.4%; on the other hand, 43 cities actually experienced real income gains. At the province level, our estimates of real income losses correlate strongly to the official GDP statistics in both quarters.

We exploit the network nature of city-to-city trade and analyze the spillover effect of city-level

¹Time-series aggregate statistics of the data have been used for descriptive analysis on China’s economic responses to COVID-19 by both academics (e.g., [Chen et al. \(2020a, 2020b\)](#)) and market analysts (e.g., [CICC, 2020](#)). This paper is the first attempt to explore the network features of the data.

COVID shocks on the real income in other cities and in the nation as a whole. We find COVID shocks to Wuhan and Beijing had the largest national impact, knocking 1.7% and 1.6% off China's real income in the first quarter, respectively. Wuhan had a large national impact because it experienced substantial COVID shocks; by contrast, Beijing had a large national impact because of its inherent importance in the truck flow network.

Finally, we estimate the relationship between COVID shocks and local pandemic severity, and we conduct various counterfactual analysis. We find enormous economic costs of implementing Wuhan-style lockdown at the national level: if all Chinese cities had containment policies that responded to local pandemic severity in the same way as those in Hubei province, where Wuhan is the capital city, China's first-quarter real income would have declined by 47.3%.

Methodologically, we extend the first-order sufficient statistics in [Kleinman et al. \(2020\)](#) to recover trade cost shocks from over-time changes in trade flows, and we derive sufficient statistics that map from trade cost shocks to welfare changes. Unlike the standard [Head and Ries \(2001\)](#) method, which recovers the *levels* of trade costs from bilateral trade *expenditures* under the assumption that trade costs are symmetric, our sufficient statistics instead invert the over-time *changes* in the *quantity* of bilateral trade into *changes* in trade costs that fully rationalize the data. The trade cost shocks we recover are therefore asymmetric. The asymmetry is an important feature of our analysis, as it enables us to study how trade costs relate to the pandemic severity and containment measures in the source and destination cities of truck flows.

There is a fast-growing literature on the economic impacts of COVID-19 through trade linkages (see, for example, [Maliszewska et al.\(2020\)](#), [Bonadio et al.\(2020\)](#), [Eppinger et al.\(2020\)](#) and [Hsu et al.\(2020\)](#) among many others). Due to limited data on international trade after the outbreak of COVID-19, that literature, to the best of our knowledge, has to simulate economic losses caused by COVID-19. A unique feature of this paper is to use the bilateral truck flow data that measures actual trade flows between Chinese cities. We estimate, rather than simulate, the severity of a COVID-19 shock in a trade model.

The paper is organized as follows. Section 2 summarizes several basic features of the truck flow data. We present our methodology in Section 3. Empirical analyses of COVID-19 shocks and counterfactual exercises on their welfare implications are conducted in Section 4 and 5, respectively. Section 6 concludes.

2 Data

The city-to-city truck flow data, constructed by the logistical service provider, measures the number of trucks that depart from a city identified as the place of loading and arrive at another city identified as the place of discharge. Because trucking is the primary mode of domestic freight transport in China,² truck flows are highly correlated with economic activities. In Figure 1, we show that city-level truck outflows correlate strongly to city-level GDP in 2018 (correlation 0.9) and also to night

²Highway accounts for 73% of the total freight in China in 2019 by official statistics.

light intensity (correlation 0.86).

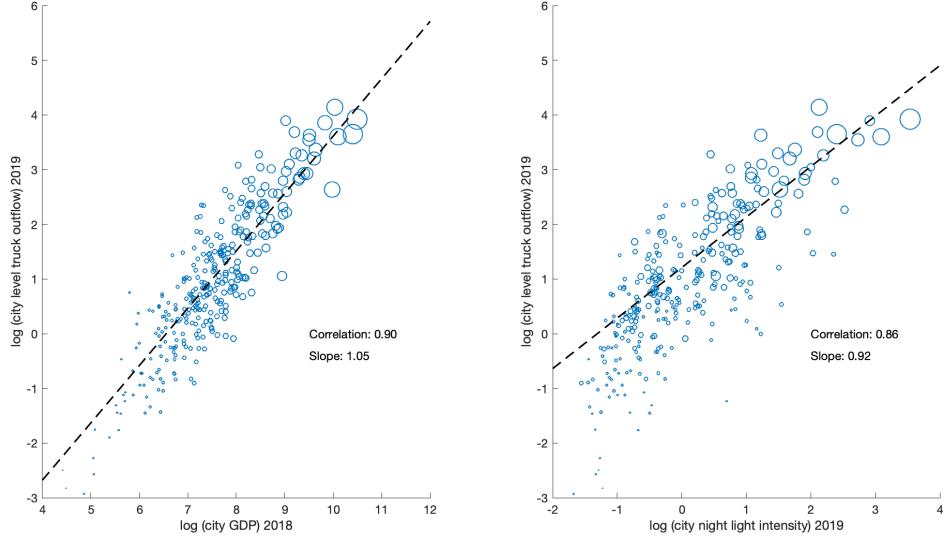


Figure 1: Truck Outflow, GDP and Night Light³

Our truck flow data have two unique advantages over the conventional economic statistics. First, the data capture not only city-specific economic activities but also city-to-city economic flows; the network nature of our data is central to our analysis.⁴ Second, the data is high frequency and can capture the instantaneous economic responses. These features enable us to map out the evolution of city-to-city, bilateral trade flow as COVID-19 and containment measures unfolded over-time, and we are therefore able to assess the associated economic impact of these events at an unparalleled granularity.

Our sample consists of 315 prefecture-level cities.⁵ On average, truck outflows declined, year-on-year, by 15.3% in the first quarter of 2020 and increased by 8.5% in the second quarter (see Figure 2 for visualization). The pattern is consistent with the systematic, national-wide lockdown measures in the first quarter and a swift recovery of economic activities in the second quarter, when cities reopened. The geographic heat maps also reveal substantial variation in the impact of COVID-19 across cities. Most notably, Wuhan, the epicenter of COVID-19 outbreak, experienced the most significant drop (-58%) in truck outflows in the first quarter.

³The nightlight data is from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), which uses average radiance composite images produced by the Earth Observations. These images are produced in 15 arc-second geographic grids with radiance value spanning from 0 to 60. We use the average radiance value of all observations in a city as the city-level nightlight intensity.

⁴Since freight trucks are seldom used for within-city shipments, we set year-on-year changes of truck flows within a city to be the changes on all routes connected to the city. Our measure is highly correlated with the changes in visits to office buildings and shopping malls according to mobile phone location data in Chen et al. (2020a, 2020b) (correlation 0.66 for 2020q1).

⁵We exclude cities in Tibet and Xinjiang provinces from our analysis, as these two regions have few trade linkages to the rest of China.

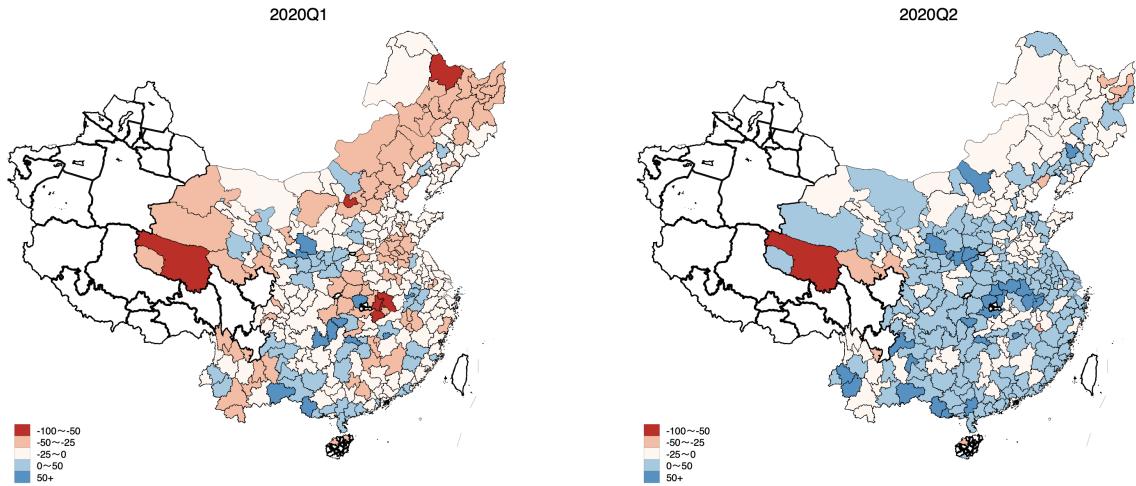


Figure 2: City-Level Year on Year Changes in Truck Outflow (in Percentage)

Figure 3 shows the time-series of truck flows as the COVID-19 outbreak unfolded between January 10th and June 30th. The thin solid line captures the daily, total truck flows for China as a whole (year-on-year relative to 2019). The thick solid line shows the number of confirmed COVID-19 cases (7-day moving average), which started to surge in late January.⁶ China soon implemented a draconian, nation-wide lockdown policy. The lockdown significantly restricted economic activities, and truck flows evidently collapsed. As COVID-19 passed its peak in February, Chinese cities asynchronously started to phase out the lockdown policy, and truck flows gradually recovered. By April, new COVID-19 cases almost disappeared, and economic activities fully recovered. The dotted curves represent truck flows and new COVID-19 cases for Hubei province, where the COVID-19 outbreak was especially severe. The corresponding decline in truck flow in January was also especially drastic, and the subsequent recovery was more gradual in Hubei than in the rest of China.

3 Methodology

Our methodology starts from the standard [Armington \(1969\)](#) model of trade, and we derive linear sufficient statistics that map changes in bilateral trade flows to changes in trade costs and real income. Our results extend those in [Kleinman et al. \(2020\)](#), which derive linear sufficient statistics of productivity changes on real income. In subsequent sections we perform analysis and policy counterfactuals based on our sufficient statistics and the recovered trade costs.⁷

⁶Because we exploit cross-city and over-time variation with city and time fixed effects, our analysis is not affected by under-reporting of COVID cases at the city or time level)

⁷Although we choose the Armington formulation for simplicity, our results hold for any international trade model with an import demand system characterized by a single trade elasticity $\theta > 0$.

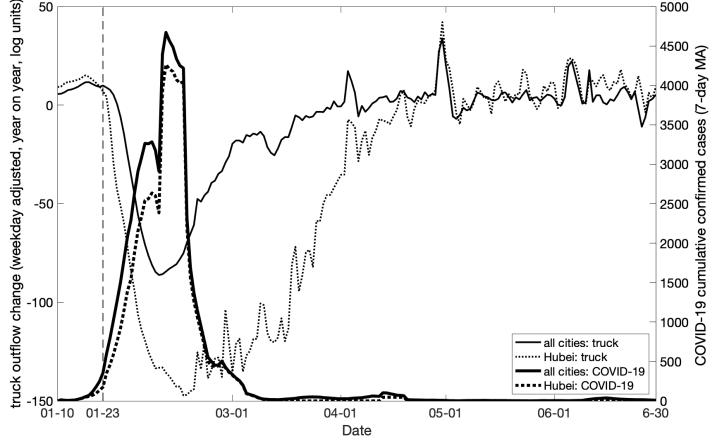


Figure 3: Truck Outflow and Severity of COVID-19 Outbreak: Daily

3.1 Setup

Each city $n \in \{1, \dots, N\}$ in China is modeled as an open economy endowed with a representative consumer who supplies ℓ_n units of labor inelastically to produce a city-specific good with productivity z_n . Each consumer has a taste for variety, with utility function

$$u_n = \left[\sum_{i=1}^N Q_{ni}^{\frac{\theta}{\theta+1}} \right]^{\frac{\theta+1}{\theta}}, \quad (1)$$

where Q_{ni} is the quantity of good i consumed in city n , and $\theta + 1$ is the elasticity of substitution across goods. The terms "welfare", "real income", and "utility" are often used interchangeably in the literature. To avoid confusion, we will refer to u_n as "real income".

Cities trade with one another subject to iceberg-type proportional trade cost τ_{ni} for sending good produced in i ("good i " in short) to city n . The model predicts a gravity relationship for city-to-city bilateral trade flows:

$$\underbrace{Q_{ni} w_i \tau_{ni} / z_i}_{\text{city } n\text{'s expenditure on good } i} = \underbrace{w_n \ell_n}_{\text{city } n\text{'s income}} S_{ni}, \quad S_{ni} \equiv \frac{(w_i \tau_{ni} / z_i)^{-\theta}}{\sum_{k=1}^N (w_k \tau_{nk} / z_k)^{-\theta}}, \quad (2)$$

where w_i is the cost of labor (wage rate) in city i , and $w_i \tau_{ni} / z_i$ is its unit cost; S_{ni} is the expenditure share of consumer n on good i . An equilibrium is the set of quantities and wage rate $\{Q_{ni}, w_i\}_{i,n=1}^N$ that satisfies the expenditure share relationship in (2) as well as the trade-balance condition (3) below, which states that the total income of city i is equal to the sum of expenditure on good i by all other cities:

$$w_i \ell_i = \sum_{n=1}^N w_n \ell_n S_{ni} \quad (3)$$

The trade-balance condition implies that cities within China do not trade with the rest of the world. This is motivated by our focus on the city-to-city trade within China and by China's small overall trade imbalance in recent years (only 1.5% of GDP in 2019). For expositional ease, we refer to goods-producing cities as *exporters* and goods-buying cities as *importers*.

Our baseline model abstracts away from nontradable sectors, which we incorporate in Appendix B.4 and show our conclusions are quantitatively robust under the assumption that city-level productivity shocks apply equally to tradable and nontradable sectors. Our model also abstracts away from labor mobility, because inter-city migration is limited in the short run.

3.2 COVID Shocks, Trade Flow, Income, and Welfare

We use the system of equations (1), (2), and (3) to derive sufficient statistics that connect trade flow changes to trade cost and productivity changes as well as welfare changes, extending the results in Kleinman et al. (2020). Unlike the standard Head and Ries (2001) method, which recovers the *levels* of trade costs from bilateral trade *expenditures* under the assumption that trade costs are symmetric, our sufficient statistics instead invert the over-time *changes* in the *quantity* of bilateral trade into *changes* in trade costs that fully rationalize the data. The trade cost shocks we recover are therefore asymmetric. The asymmetry is an important feature of our analysis, as it enables us to study how trade costs relate to the pandemic severity and containment measures in the source and destination cities of truck flows. In subsequent sections, we use the recovered shocks and our sufficient statistics to estimate the economic impact of COVID and perform counterfactual analysis.

Because a productivity change in city i is isomorphic to a uniform change in the shipping cost from i to all of its trading partners (including city i itself), we define $d \ln B_{ni} \equiv d \ln \tau_{ni} - d \ln z_i$ as the composite change in trade cost and productivity in the rate at which labor in city i produces goods consumed by city n . We refer to $d \ln B_{ni}$ simply as "COVID" shocks, and we interpret these shocks as reduced-form, catch-all terms that summarize any impediments to the production and flow of goods during the pandemic, including both the public health impact of the pestilence as well as policy response such as lockdown and social isolation measures.

We stack bilateral truck flows Q_{ni} , expenditure shares S_{ni} , and COVID shocks B_{ni} into $N \times N$ matrices \mathbf{Q} , \mathbf{S} , and \mathbf{B} respectively. Let $\boldsymbol{\pi}$ be the vector of nominal income ($\pi_n \equiv w_n \ell_n$), and let \mathbf{T} be the income share matrix whose i -th entry $T_{in} \equiv S_{ni} \pi_n / \pi_i$ is the share of income in city i derived from selling to n . Both \mathbf{S} and \mathbf{T} are stochastic matrices with row sums equal to one, and the income vector $\boldsymbol{\pi}'$ is the dominant left-eigenvector of \mathbf{S} and \mathbf{T} matrices, as equation (3) can be written in matrix form as $\boldsymbol{\pi}' \mathbf{S} = \boldsymbol{\pi}'$, which also implies $\boldsymbol{\pi}' \mathbf{T} = \boldsymbol{\pi}'$.

Proposition 1 Starting from an equilibrium with expenditure share \mathbf{S} and income share \mathbf{T} , consider a matrix of COVID shocks $d \ln \mathbf{B}$ that generate observed changes in trade flows $d \ln \mathbf{Q}$.

1. Welfare changes in city n is:

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

2. The matrix of COVID shocks is

$$d \ln \mathbf{B} = -\frac{1}{\theta+1} d \ln \mathbf{Q} - \frac{\theta}{\theta+1} d \ln \mathbf{u} \mathbf{1}' + d \ln \boldsymbol{\pi} \mathbf{1}' - \mathbf{1} d \ln \boldsymbol{\pi}',$$

where $\mathbf{1}$ is an all-one vector, $d \ln \boldsymbol{\pi}$ is the vector of nominal income changes

$$d \ln \boldsymbol{\pi} = -\frac{\theta}{\theta+1} (\mathbf{I} - \mathbf{T} + \mathbf{1} \boldsymbol{\pi}')^{-1} (\mathbf{T} d \ln \mathbf{u} + d \ln \mathbf{b}),$$

\mathbf{I} is the identity matrix, and $d \ln \mathbf{b}$ is a vector whose i -th entry $d \ln \mathbf{b}_i \equiv -\sum_{n=1}^N \mathbf{T}_{in} d \ln \mathbf{Q}_{ni}$ is the average change in truck flow leaving city i , weighted by i 's income share derived from each market n .

Using the pre-COVID trade flow matrices (\mathbf{S} and \mathbf{T}) and observed year-on-year trade flow changes during the outbreak ($d \ln \mathbf{Q}$), Proposition 1 enables us to recover the matrix of COVID shocks ($d \ln \mathbf{B}$)—which reflect a combination of trade cost and productivity changes—and the resulting changes in real income ($d \ln \mathbf{u}$) across cities.

We leave the proof to the appendix. Intuitively, when trade cost from i to n increases due to COVID shock $d \ln \mathbf{B}_{ni}$, city n lowers its demand for good i and raises demand for other goods. This partial equilibrium substitution effect lowers the income in city i and its production cost, thereby causing further rounds of substitution, through which the effect of $d \ln \mathbf{B}_{ni}$ affects prices, consumption, and real income in other cities $k \notin \{n, i\}$. The full, general equilibrium effect of COVID shocks sums across all rounds of propagation and is disciplined by the model in Section 3.1. Proposition 1 provides linear sufficient statistics for these general equilibrium effects of COVID shocks. In subsequent sections, we use the recovered shocks and our sufficient statistics to estimate the economic impact of COVID-19. Because the linear mapping between $d \ln \mathbf{B}$ and $d \ln \mathbf{Q}$ is invertible, Proposition 1 also enables us to perform counterfactual analysis and study the impact of hypothetical COVID shocks.

Even though our linear sufficient statistics are only exact for small shocks, Kleinman et al. (2020) show that linearized counterfactuals in this class of trade models almost coincide with the nonlinear solution (e.g. see Dekle et al. 2008, and Caliendo et al. 2017) even for large shocks. Hence, the linear formulas in the Proposition are suitable for studying the economic impact of COVID-19.

4 Analysis of the COVID Shocks

We apply Proposition 1 to recover bilateral COVID shocks based on the year-on-year trade flow changes at each time in the year 2020 relative to 2019. We recover these shocks at quarterly frequency as we analyze the cross-sectional determinants of COVID shocks in Section 4.1, and we recover the shocks at the daily frequency in Section 4.2 to trace the outbreak over time and during recovery. To apply Proposition 1, we adopt $\theta = 4$, the standard value of trade elasticity from the literature. Appendix D shows our estimates of the COVID shocks are highly correlated within an extended range of θ between 2 and 20.

4.1 Cross-Sectional Determinants of COVID shocks

We first recover the COVID shocks for the first quarter (Q1) of 2020 to analyze the cross-sectional determinants of the COVID shocks. Through the lens of our model, these COVID shocks completely rationalize the year-on-year changes in trade flows; they therefore capture any impediments to the production and flow of goods during the pandemic, including both the public health impact of the pestilence as well as policy response such as lockdown and social isolation measures.

Table 1: Regressions of COVID Shocks

	(1)	(2)	(3)
log(covid cases of exporter)		0.0682*** (0.00214)	
log(covid cases of importer)		0.00167 (0.00148)	
Exporter FE	YES	NO	NO
Importer FE	NO	YES	NO
Observations	30,412	30,412	30,412
R-squared	0.571	0.126	0.188

Standard errors are in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Dependent variables in column (1)-(3) are model deduced bilateral shocks $d \ln B_{ni}$ of all the city pairs; $\log(\text{covid cases of exporter})$ is the logarithm of cumulative confirmed cases in exporting city for the first quarter of 2020; $\log(\text{covid cases of importer})$ is the logarithm of cumulative confirmed cases in importing city for the first quarter of 2020.

Figure 4 scatter-plots the bilateral COVID shocks against year-on-year changes in truck flows. Although COVID shocks strongly correlate with the route-level changes in truck flow, there are still substantial variations in COVID shocks that are orthogonal to truck flow changes. These residual variations represent the general equilibrium forces inherently present in a trading network: because consumers adjust their expenditure and sourcing decisions in response to COVID shocks, the trade flow between the city-pair (n, i) is affected not only by $d \ln B_{ni}$ but also by COVID shocks that hit any other city-pairs. Our approach disciplines these general equilibrium forces through the trade model, and we are therefore able to extract structural interpretations, such as changes in real income, from the changes in trade flows.

We analyze the cross sectional determinants of COVID shocks by correlating them to observables. We begin by regressing $d \ln B_{ni}$ for 2020Q1 separately on exporter and importer fixed effects. The R^2 of these regressions are reported in columns (1) and (2) of Table 1. There is a stark contrast: exporter fixed effects account for 57.1% of the variations in $d \ln B_{ni}$, whereas importer fixed effects can only account for 12.6%.

Column (3) replaces exporter and importer fixed effects with the total number of confirmed COVID-19 cases in the exporter and importer city in the first quarter of 2020. The COVID shocks are significantly correlated with the outbreak severity in the exporter city but uncorrelated with the severity in the importer city. The R^2 of this regression is low: local outbreak severity explains only 19% of the variation in COVID shocks.

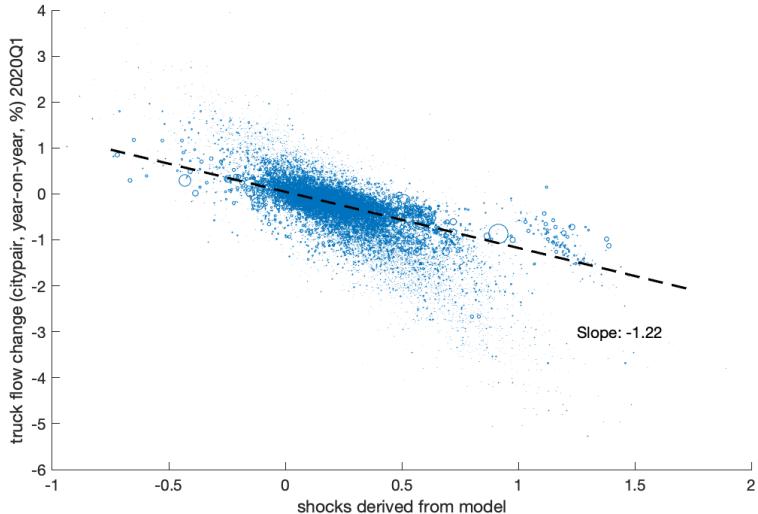


Figure 4: Comparison between Truck Flow Change and Trade Cost Shocks

Note: The size of each point is drawn proportionally to the truck flows along the route in 2019Q1.

Taken together, these regressions show that about 60% of the estimated shocks in 2020Q1 can be explained by the exporter-level variations but only less than 20% can be explained by the exporter's pandemic severity. These results are suggestive that the policy response adopted by local governments—rather than the COVID-19 outbreak itself—may have had the greatest impact on cross-city trade in China. Such policy measures include not only the draconian lockdown that were widely adopted between February and March in China but also other preventative and isolation measures such as the strictly enforced quarantines for traveling across regions. Note that a strong explanatory power of exporter fixed effects could arise from policy measures adopted by either by exporter-cities for outgoing shipments or importer-cities for incoming shipments; our results are consistent with both interpretations but cannot distinguish the two.

Motivated by the dominant role of exporter fixed-effects, we collapse COVID shocks to the exporting city and plot again the city's COVID-19 cases in Figure 5. The significant residual variation in exporter-specific COVID shocks that are orthogonal to local pandemic severity is indicative of the stringency of local containment measures. As expected, Wuhan has a large residual component, 0.44 log points above the fitted line. The residual component for Beijing is also positive but much closer to the fitted line. Among the top ten largest cities by 2018 GDP, to which both Beijing and Wuhan belong, the residual component is all negative for the other eight cities. Guangzhou has the smallest residual component, 0.21 log points below the fitted line, indicating much milder containment measures in Guangzhou.

Wuhan is not the only city in Hubei that adopted stringent lockdown policies. 11 out of 14 Hubei cities, the triangles in Figure 5, are above the fitted line. In Table 2, we show the COVID shocks are over four times as sensitive to local pandemic severity in Hubei than in the rest of China, suggesting

that containment measures in Hubei were much more responsive to local pandemic severity than those in the other cities.

Table 2: Regression of Exporter-Specific Shock

	Full sample (1)	Hubei (2)	Non-Hubei (3)	Full sample (4)	Hubei (5)	Non-Hubei (6)
log(covid cases of Q1)	0.0646*** (0.0187)	0.167*** (0.0203)	0.0359*** (0.0114)			
log(covid cases before 0206)				0.0622*** (0.0210)	0.218*** (0.0277)	0.0313*** (0.0117)
Constant	-0.0466 (0.0723)	-0.729*** (0.214)	0.0634 (0.0400)	-0.00915 (0.0720)	-0.973*** (0.245)	0.0953** (0.0368)
Observations	294	14	280	292	14	278
R-squared	0.316	0.750	0.110	0.260	0.749	0.079

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Dependent variables in all the columns are model deduced exporter-specific shocks $d \ln b_i$, where columns (1) and (4) are for all the cities in our sample; columns (2) and (5) are for cities in Hubei province and columns (3) and (6) are for cities outside Hubei province; $\log(\text{covid cases of Q1})$ is the logarithm of cumulative confirmed cases in the city for the first quarter of 2020; $\log(\text{covid cases before 0206})$ is the logarithm of cumulative confirmed cases in the city in two weeks after Wuhan's lockdown; $D\text{-hubei}$ is a dummy variable which is equal to 1 when city is in Hubei province, otherwise it is 0.

The number of COVID-19 cases may endogenously respond to local containment measures. As a robustness check, we replace the number of all COVID-19 cases in the first quarter in all the regressions with the number of cases before February 6, within two weeks after Wuhan's lockdown and are therefore unaffected by later containment measures. The results are very robust and reported in Table A.1 in the Appendix and Column (4)-(6) in Table 2.

4.2 COVID Shocks during the Recovery

Most Chinese cities adopted strict containment measures within two weeks after Wuhan's lockdown; yet, the easing of the containment measures was gradual, asynchronous, and depended on the severity of the outbreak in each region. We exploit the asynchronous nature of regional reopening in China in order to shed light on how policy measures affected the estimated COVID shocks.

As a proxy for the timing of reopening in each region, we use the date on which each province downgraded the Public Health Emergency Response Level (PHER henceforth) from level 1 to any levels above (PHER-1 is akin to the state-level public health emergency in the United States).⁸ Figure 6 shows the cumulative share of cities in our sample that have downgraded PHER over time. Gansu was the first province to downgraded PHER, from level 1 to level 3, on February 21st. More than 80% cities had downgraded PHER by early March.

⁸PHER downgrading is a good proxy for lockdown easing in most provinces. The only exception is Hubei, which maintained PHER-1 long after the lockdown. Our empirical results are robust to excluding Hubei.

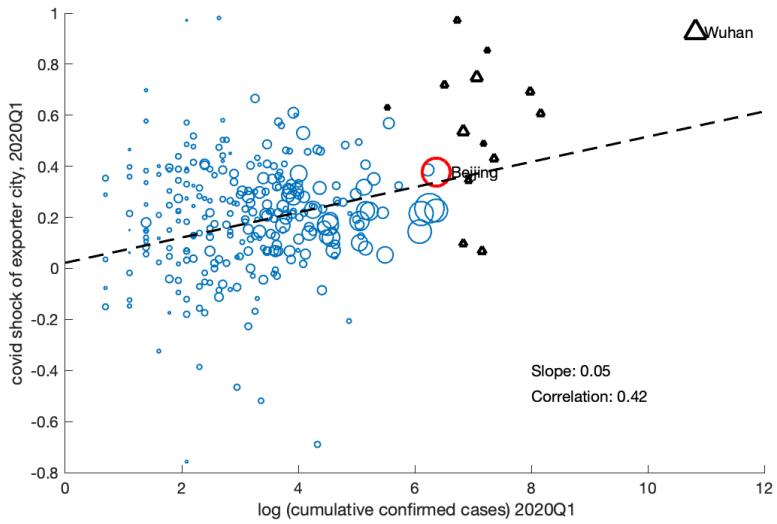


Figure 5: COVID Shock and COVID-19 Cases: City Level

Notes: Triangles denote cities in Hubei province; and circles represent cities outside Hubei.

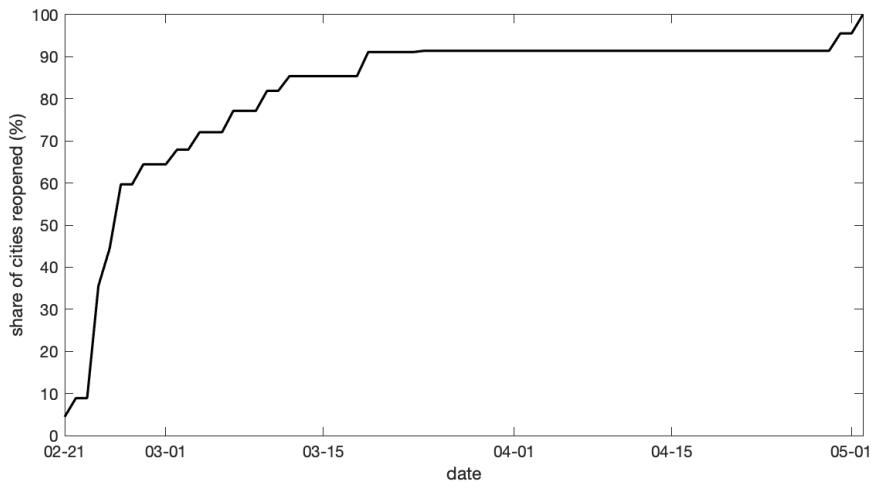


Figure 6: Cumulative Share of Reopened Cities over Time (%)

We run the following regression:

$$d \ln B_{ni,t} = \sum_{j \in \{\text{exporter, importer, both}\}} \beta_j D_{ni,t}^j + \gamma_i \cdot t + \eta_n \cdot t + \delta_{ni} + \nu_t + \epsilon_{ni,t}, \quad (4)$$

where $D_{ni,t}^j$ is a set of dummies indicating whether the exporter (and not the importer), importer (and not the exporter), or both cities along the route (n, i) has downgraded PHER at time t . We also control exporter time trend, $\gamma_i \cdot t$, importer time trend, $\eta_n \cdot t$, city-pair fixed effect, δ_{ni} , and day fixed effect ν_t . The sample period is from February 14th, one week before the first downgrading of PHER, to May 1st, one day before the downgrading of Hubei province.

The regression results are shown in Table 3. The routes in which both cities kept PHER-1 are the control group in all the specifications. We find that, relative to the control group, COVID shocks are significantly correlated with unilateral downgrading of PHER by exporters (column (1)) or bilateral downgrading (column (3)) but uncorrelated with unilateral downgrading by importers (column (2)). Column (4), our preferred specification, shows that a unilateral downgrading of PHER by exporters can reduce COVID shocks by 3.2 log points, more than 3 times the effect of a unilateral downgrading of PHER by importers. The regression also shows that PHER downgrading by both trading partners has a similar effect (3.1 log points) on COVID shocks to the unilateral downgrading by the exporters. These findings are consistent with our cross-sectional analysis earlier, that exporter-specific factors are much more important than importer-specific factors in accounting for COVID shocks.

Table 3: Regression Results for Downgrading PHER

	(1)	(2)	(3)	(4)
<i>D-exporter</i>	-0.0214*** (0.00410)			-0.0323*** (0.00339)
<i>D-importer</i>		-0.00924 (0.00581)		-0.00716** (0.00358)
<i>D-both</i>			-0.0370*** (0.00381)	-0.0305*** (0.00349)
Day Fixed Effect	YES	YES	YES	YES
Exporter Time Trend	YES	NO	YES	YES
Importer Time Trend	NO	YES	YES	YES
City-Pair Effect	YES	YES	YES	YES
N	682805	682805	1813230	2341724

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Economic Implications

In this section we quantify the economic implications of the COVID shocks. First, we compute city-level real income changes in the first and second quarter of 2020, and we compare our results

to the official statistics disclosed by the Chinese government. We then decompose the real income response in every city into components due to COVID shocks to each of its trading partners. Finally, we aggregate and calculate the impact of each city's COVID shocks on the national real income, and we decompose the aggregate impact into local and spillover components.

5.1 Real Income Changes in Each City

We apply Proposition 1 and calculate city-level changes in real income from trade flow changes (see Table 4 and Figure 7 for summary statistics). We find that, for the first quarter of 2020, the median city experienced a decline of 19.7% in real income. The effect is highly heterogeneous within China: Wuhan (and its neighbors) experienced a big decline (-60.4%), whereas real income actually improved for 13.7% of cities. Our results also show that, by the second quarter of 2020, the Chinese economy has almost fully rebounded from COVID, and the median city's second-quarter real income is only 0.7% less than 2019.

Table 4: Summary Statistics of Real Income Change

	Mean	Max	Min	Std	P10	P25	P50	P75	P90
2020Q1	-17.6%	113.3%	-62.5%	21.4%	-38.8%	-30.7%	-19.7%	-7.0%	4.7%
2020Q2	1.6%	144.8%	-73.6%	24.6%	-21.8%	-12.9%	-0.7%	13.6%	29.0%

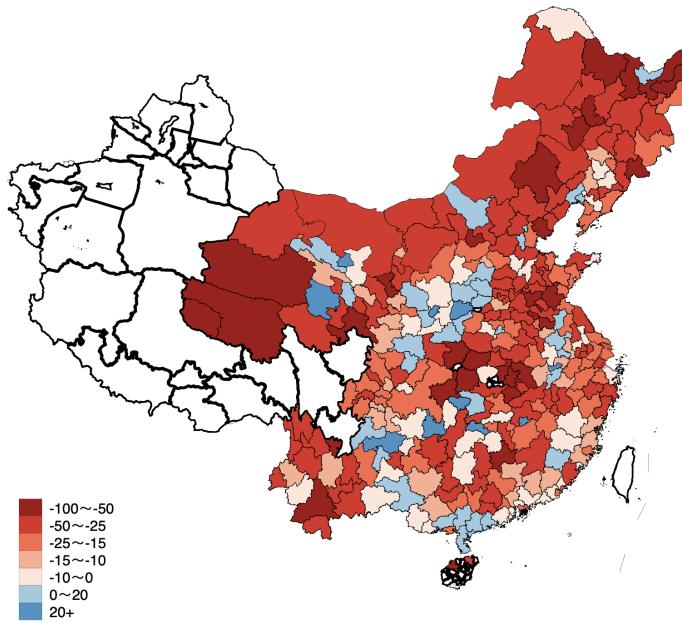


Figure 7: City-Level Year-on-Year Output Changes Implied by the Model (in Percentage, 2020Q1)

Figure 8 shows that our estimates of real income losses collapsed to the province level correlates

closely to the official statistics, with a correlation of 0.34 for the first quarter and 0.42 for the second. Despite the strong correlation, there are important differences in the *levels* of real income loss between our estimates and the official statistics for the first quarter: the nation as a whole experienced a real income decline of 19.4% according to our estimates, compared with a decline of 6.8% according to the official statistics. The dispersion of real income losses across provinces for 2020Q1 is also significantly higher under our estimates than in the official statistics. For the second quarter, our estimate of national real income growth (+3.1% year-on-year) is much closer to the officially reported GDP growth of 3.2%.

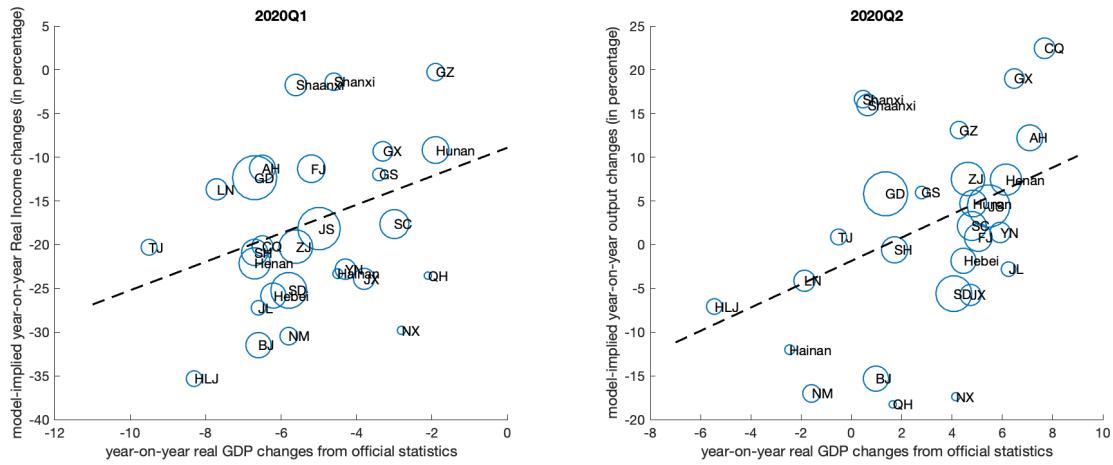


Figure 8: Estimated Real Income Change and Official Statistics

Note: The weighted correlation in this figure is 0.34 for 2020Q1 and 0.42 for 2020Q2.

There are two potential explanations for the discrepancy in the first quarter. First, while truck flows is the primary mode of freight transport, it remains possible that the truck flow response to COVID-19 and containment measures differ across industries and types of goods, and our analysis misses this heterogeneity because of our data do not contain industry-level information. The second possibility is that the official statistics may indeed be an unreliable measure of real income losses. Quarterly GDP statistics have often been subsequently revised because of limited information at the time of release, and the pandemic could have further disrupted data collection and reduced the precision of the quarterly statistics.⁹

⁹Another possibility is that the official statistics may be prone to manipulations because of political and social stability concerns. However, the magnitude of GDP misreporting between 1 and 2 percent in the past can hardly explain the discrepancy of 13% in the first quarter (Chen et al., 2019).

5.2 Decomposing Real Income Changes

The real income losses $d \ln \mathbf{u}_k$ reported in Section 5.1 account for the entire matrix of bilateral COVID shocks and can be re-written as

$$d \ln \mathbf{u}_k = \sum_{n,i=1}^N \frac{\partial \ln \mathbf{u}_k}{\partial \ln \mathbf{B}_{ni}} d \ln \mathbf{B}_{ni},$$

where the partial derivative $\partial \ln \mathbf{u}_k / \partial \ln \mathbf{B}_{ni}$ captures the sensitivity of real income in city k to trade cost shocks to route (n, i) . When $k = n$ ($k = i$), the partial derivative captures the importer's (exporter's) real income sensitivity to route-specific COVID shock; when $k \notin \{n, i\}$, the partial derivative captures the general equilibrium effect that propagate through the trade network across cities. Proposition 1 enables us to calculate the entire set of partial derivatives for any n, i, k as functions of the pre-shock bilateral trade flows. We now use these partial derivatives to decompose the real income losses due to different components of the COVID shocks.

Motivated by our earlier finding, that exporter-specific components explain two-thirds of the variations in the COVID shocks, we decompose the welfare impact into components due to exporter-specific outgoing shocks. Specifically, we compute $d \ln \mathbf{u}_k^i \equiv \sum_{n=1}^N \frac{\partial \ln \mathbf{u}_k}{\partial \ln \mathbf{B}_{ni}} d \ln \mathbf{B}_{ni}$ for every city-pair (k, i) , and we visualize the decomposition in the left of Panel A in Figure 9. The object $d \ln \mathbf{u}_k^i$ can be interpreted as the impact of outgoing COVID shocks from city i on the real income of city k , taking into account the general equilibrium effects while shutting down COVID shocks that apply to goods shipping from any cities besides i . By construction, $d \ln \mathbf{u}_k = \sum_{i=1}^N d \ln \mathbf{u}_k^i$.

The chord diagram in the left of Figure 9 Panel A shows the bilateral welfare exposures $d \ln \mathbf{u}_k^i$. For visual ease, we collapse the city-pair level exposures to province-pair level, and we show the 30% largest exposures (in absolute value) across province-pairs in China. Provinces are arranged around a circle, where the size of the inner segment for each province shows its overall outward exposure (the effect of its outgoing COVID shocks on other provinces), and the gap between the inner and outer segments shows its overall inward exposure (the effect of COVID shocks from other provinces upon it). Arrows emerging from the inner segment for each province show the bilateral impact of its outgoing COVID shocks on the real income of other provinces.

Evident from the figure, COVID shocks in Hubei, Shandong, and Jiangsu provinces have significantly lowered the real income in many other regions; on the flip side, Gansu and Shanghai are negatively affected by shocks from many other regions. Note that shocks in region i can significantly reduce the real income in region k either because region i was severely affected by COVID shocks (such as Hubei) or because region k is particularly *sensitive* to shocks to i , i.e., the partial derivatives are large in absolute values. The right chord diagram in Figure 9 Panel A neutralizes the effects arising from large COVID shocks and isolates the *sensitivity* component; specifically, its arrows show $\sum_{n=1}^N \frac{\partial \ln \mathbf{u}_k}{\partial \ln \mathbf{B}_{ni}}$ for the same set of province-pairs (i, k) . Comparing the left and right panels of the figure, the most salient feature is the fact that Hubei's influence on the rest of China is significantly smaller in the right panel. This implies that Hubei's COVID shocks had a large effect

primarily because of the size of these shocks, whereas the two other salient provinces, Shandong and Jiangsu, had large effects primarily because of their inherent importance in the trade network.

5.3 National Real Income and Exporter-Specific COVID Shocks

We now collapse the real income response along dimension k and examine the impact of COVID shocks in each city i on the national real income, $d \ln \mathbf{u}^{agg,i} \equiv \sum_{k=1}^N \pi_k d \ln \mathbf{u}_k^i$. Once again, due to linearity, the national welfare decline due to the outgoing COVID shocks from each city i adds up to the aggregate decline in national real GDP due to the entire matrix of COVID shocks.

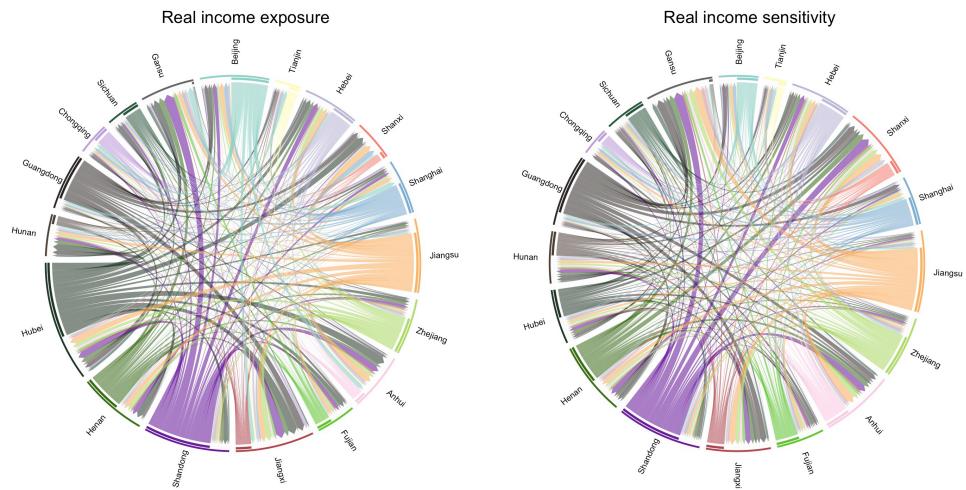
Panel B in Figure 9 represents $d \ln \mathbf{u}^{agg,i}$ on a heap map. As expected, COVID shocks to Wuhan have the largest effect, knocking 1.7% off the aggregate real income in the first quarter. The second largest effect came from Beijing, where COVID shocks reduce the aggregate real income by 1.6%. We have shown that COVID shocks in total reduce China's first-quarter real income by 19.4%. Our numbers suggest that COVID shocks to Wuhan and Beijing alone account for 7.3 percent and 6.8 percent of the aggregate real income losses, respectively, far bigger than the two cities' GDP share of 1.6 percent and 3.6 percent (based on 2018 official GDP data).

The largest effect of Wuhan's COVID shocks is hardly surprising. As the epicenter of the pandemic, Wuhan's COVID cases account for 61% of China's total cases in the first quarter. The large output losses by Beijing's COVID shocks is disproportionate to its COVID-19 cases, which only account for 0.7% of China's total cases in the first quarter. Compared with Beijing, Shanghai has a larger GDP and similar COVID cases. But the national impact of COVID shocks to Shanghai is lower than those to Beijing by a third. The different effects of COVID shocks to Beijing and Shanghai are mainly driven by the residual component in the COVID shocks, which is 0.13 and -0.07 log points for Beijing and Shanghai, respectively.

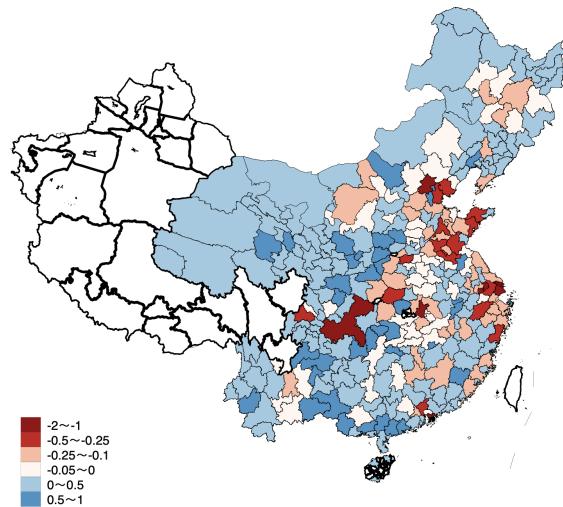
The left panel of Panel C in Figure 9 reports $d \ln \mathbf{u}^{agg,i}$ for the top ten largest cities by 2018 GDP. The blue bar in the right panel reports each city's contribution to the national real income decline (i.e., each bar shows $d \ln \mathbf{u}^{agg,i} / \sum_{j=1}^N d \ln \mathbf{u}^{agg,j}$). The yellow and grey bars plot the city's share of COVID-19 cases and GDP, respectively. Guangzhou stands out once again: the city's COVID-19 cases are only slightly lower than Beijing's; yet, the contribution of Guangzhou's COVID shocks to the decline of the aggregate real income is substantially smaller than its GDP share. This is, again, mainly explained by the small residual component in the COVID shocks to Guangzhou.

5.4 Local and Spillover Effects

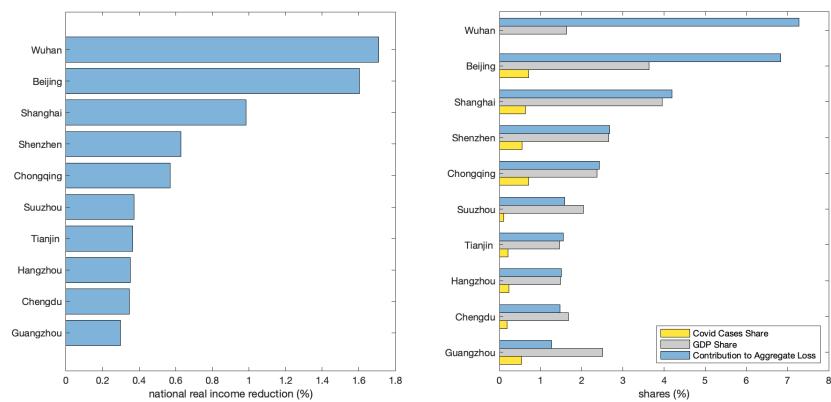
The effect of a city-specific COVID shock on national real income can be decomposed into two components: The effect on the real income of the city itself (local effect, i.e. $\pi_i d \ln \mathbf{u}_i^i$) and the effect on the real income of the other cities (spillover effect, i.e. $\sum_{k \neq i} \pi_k d \ln \mathbf{u}_k^i$). Overall, the spillover effect accounts for 8.0% of the economic losses caused by COVID shocks. The magnitude of the spillover effect also varies a lot across cities. Figure 10 plots the proportion of the spillover effect for the top ten cities with the largest GDP in 2018. The spillover effects of Tianjin and Wuhan account



Panel A: Bilateral Impact of City-Level COVID Shocks on Real Income



Panel B: Impact of City-Level COVID Shocks on National Real Income



Panel C: The National Impact of Shocks to the Worst-Hit Cities

Figure 9: Economic Impact of COVID Shocks

for nearly 8% of the aggregate losses by their COVID shocks. Guangzhou is, again, on the other side of the spectrum. The COVID shocks to the city inflicted more local losses than aggregate losses, implying positive spillovers to the other regions.

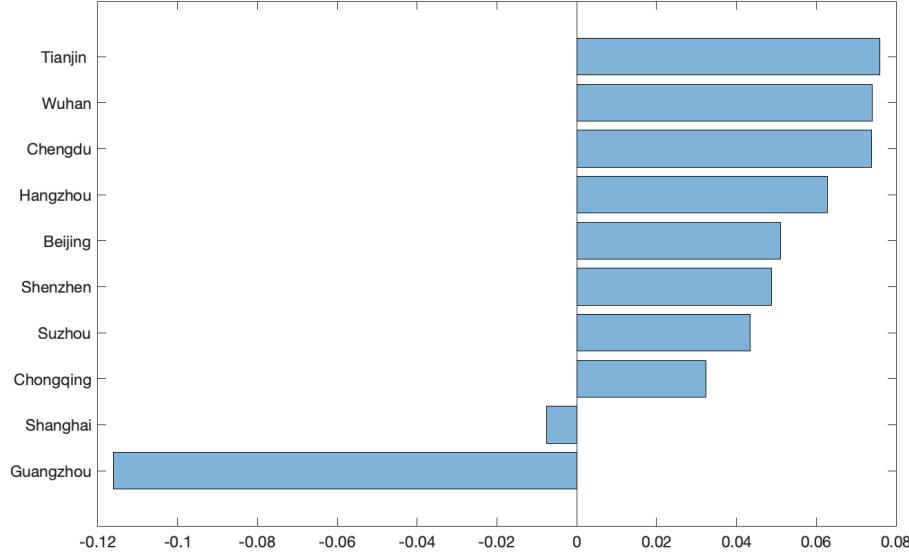


Figure 10: Share of Spillover Effect (TOP 10 Cities)

5.5 Counterfactuals

Finally, we conduct counterfactual analysis by examining the economic impact of *hypothetical* COVID shocks. We consider two scenarios. First, we suppose all the cities were hit by COVID shocks of equal magnitude as those in Wuhan. The effect would have been catastrophic: the national real income would have declined by 66.5%, over three times as large as the effect China actually experienced in the first quarter of 2020.

Because most cities outside of Hubei reported fewer than 100 COVID-19 cases, it is perhaps unrealistic for them to adopt the same stringent level of containment measures as those in Hubei did. A second and perhaps more realistic scenario is what if all cities in China had containment policies that responded to local pandemic severity in the same way as those in Hubei did. To answer this, we estimate the relationship between city-level COVID shocks and the pandemic severity using the sample of cities in Hubei, and we use the estimated relationship to predict COVID shocks as functions of local pandemic severity for cities outside of Hubei.¹⁰ We find that these predicted COVID shocks would have lowered the national real income by 47.3%, still about 2.5 times as large as the effect that China actually experienced. The result suggests that adopting Wuhan-style lockdown nationally, even if fine-tuned to the scale of local outbreak, would still have led to catastrophic economic losses.

¹⁰See Column (2) of Table 2.

6 Conclusion

This study develops sufficient statistics based on high-frequency, city-to-city truck flow data to assess the economic impact of COVID-19 in China. Our methodology can be applied to estimate the economic losses of region-specific containment policies with varying degrees of stringency. Our approach supplements existing studies that focus on the public health aspect of containment measures and therefore contributes to a more holistic cost-benefit analysis of policy response to COVID-19.

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Appendix

A Supplementary Tables for Robustness

Table A.1: Robustness Regressions of COVID Shocks

	(1)	(2)	(3)
log(covid cases of exporter before 0206)		0.0662*** (0.00241)	
log(covid cases of importer before 0206)		0.000964 (0.00162)	
Exporter FE	YES	NO	NO
Importer FE	NO	YES	NO
Observations	30,412	30,412	30,412
R-squared	0.571	0.126	0.1533

Standard errors are in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Dependent variables in column (1)-(3) are model deduced bilateral shocks $d \ln B_{ni}$ of all the city pairs; $\log(\text{covid cases of exporter before 0206})$ is the logarithm of cumulative confirmed cases in the exporting city two weeks after Wuhan's lockdown; $\log(\text{covid cases of importer before 0206})$ is the logarithm of cumulative confirmed cases in importing city two weeks after Wuhan's lockdown.

B Derivation of Proposition 1

B.1 Armington Model

We use Armington model with trade costs. There are N cities and each city produce a unique variety of goods with the following production function

$$q_n = z_n \ell_n$$

where z_n and ℓ_n are the TFP and labor endowment in city n , respectively. For each city, total labor endowment ℓ_n is exogenously given and labor do not move across cities. Given wage rate w_n , unit cost of producing goods in city n is

$$c_n = z_n^{-1} w_n \quad (\text{B.1})$$

The representative household has a CES preference over goods from all the cities,

$$u_n = \left[\sum_{i=1}^N Q_{ni}^{\frac{\theta}{\theta+1}} \right]^{\frac{\theta+1}{\theta}} \quad (\text{B.2})$$

where Q_{ni} is goods produced in city i and sold in city n and $\theta + 1$ is constant substitute elasticity of different goods ($\theta > 0$). And the price index for final consumption in city n is

$$p_n = \left[\sum_{i=1}^N (\tau_{ni} w_i / z_i)^{-\theta} \right]^{-\frac{1}{\theta}} \quad (\text{B.3})$$

where $\tau_{ni} w_i / z_i$ is the price of goods from region i to region n ; and $\tau_{ni} > 1$ is the iceberg trade cost from region i to region n .

As a result, the expenditure share of household in city n on goods i is

$$S_{ni} = \frac{X_{ni}}{\sum_k X_{nk}} = \frac{(\tau_{ni} w_i / z_i)^{-\theta}}{\sum_{k=1}^N (\tau_{nk} w_k / z_k)^{-\theta}} \quad (\text{B.4})$$

where $X_{ni} = (\tau_{ni} w_i / z_i) Q_{ni}$ is the nominal trade flow from city i to n .

In addition, trade balance requires, for each city n

$$\sum_i X_{ni} = \sum_i X_{in}$$

Goods market clearing condition requires

$$\sum_i \tau_{in} Q_{in} = q_n$$

Labor market clearing condition requires

$$w_n \ell_n = \sum_{i=1}^N X_{ni} = \sum_{i=1}^N w_i \ell_i S_{in} \quad (\text{B.5})$$

B.2 Notations

Besides the expenditure share S_{ni} , we define

$$T_{ni} \equiv S_{in} w_i \ell_i / w_n \ell_n \quad (\text{B.6})$$

as the income share of city n derived from market i .

We define

$$d \ln B_{ni} \equiv d \ln \tau_{ni} - d \ln z_i \quad (\text{B.7})$$

as the composite trade cost shock from region i to region n because productivity shock $d \ln z_i$ is not separable from trade cost shock $d \ln \tau_{ni}$, acting as a negative trade cost shock.

We stack bilateral truck flow, expenditure share, income share and COVID shocks into $N \times N$ matrices \mathbf{Q} , \mathbf{S} , \mathbf{T} and \mathbf{B} respectively. Let $\boldsymbol{\pi}$ be the vector of nominal income ($\boldsymbol{\pi}_n \equiv w_n \ell_n$).

B.3 Proof of Proposition 1

Taking total differentiation on Equation (B.2), real income change in city n is

$$d \ln \mathbf{u}_n = \sum_{i=1}^N S_{ni} d \ln \mathbf{Q}_{ni} \quad (\text{B.8})$$

Real trade flow change can be written as

$$d \ln \mathbf{Q}_{ni} = d \ln \mathbf{S}_{ni} + d \ln \boldsymbol{\pi}_n - d \ln \boldsymbol{\pi}_i - d \ln \mathbf{B}_{ni}$$

Since $d \ln \mathbf{T}_{in} = d \ln \mathbf{S}_{ni} + d \ln \boldsymbol{\pi}_n - d \ln \boldsymbol{\pi}_i$, then we have

$$\sum_{n=1}^N \mathbf{T}_{in} d \ln \mathbf{Q}_{ni} = -d \ln \mathbf{b}_i \quad (\text{B.9})$$

where $d \ln \mathbf{b}_i \equiv \sum_{n=1}^N \mathbf{T}_{in} d \ln \mathbf{B}_{ni}$ is average outgoing cost shock from city i .

Taking total differentiation of Equation (B.1), (B.4) and (B.5) and putting them together, we have

$$(\theta + 1) d \ln \boldsymbol{\pi}_n = \theta \left(\sum_i \mathbf{T}_{ni} \sum_k \mathbf{S}_{ik} d \ln \mathbf{B}_{ik} - d \ln \mathbf{b}_n \right) + \theta \sum_{i,k} \mathbf{T}_{ni} \mathbf{S}_{ik} d \ln \boldsymbol{\pi}_k + \sum_i \mathbf{T}_{ni} d \ln \boldsymbol{\pi}_i \quad (\text{B.10})$$

In addition, regional welfare change can also be written as

$$d \ln \mathbf{u}_i = d \ln \boldsymbol{\pi}_i - d \ln \mathbf{p}_i = d \ln \boldsymbol{\pi}_i - \sum_k \mathbf{S}_{ik} d \ln \boldsymbol{\pi}_k - \sum_k \mathbf{S}_{ik} d \ln \mathbf{B}_{ik} \quad (\text{B.11})$$

Taking Equation (B.11) into (B.10) and re-arranging in matrix format, we have

$$d \ln \boldsymbol{\pi} = -\frac{\theta}{\theta + 1} (\mathbf{I} - \mathbf{T} + \mathbf{1}\boldsymbol{\pi}')^{-1} (\mathbf{T} d \ln \mathbf{u} + d \ln \mathbf{b}) \quad (\text{B.12})$$

Note that $\boldsymbol{\pi}_n \mathbf{S}_{ni} = \boldsymbol{\pi}_i \mathbf{T}_{in}$, and that both \mathbf{S} and \mathbf{T} are row-stochastic matrices with $\boldsymbol{\pi}'$ being the unique left-eigenvector with an associated eigenvalue of one: $\boldsymbol{\pi}' = \boldsymbol{\pi}' \mathbf{S} = \boldsymbol{\pi}' \mathbf{T}$. One can therefore obtain \mathbf{T} from \mathbf{S} and vice versa. Kleinman et al. (2020) give a detail description on the role of $\boldsymbol{\pi}$.

Total differentiating Equation (B.4), we have

$$d \ln \mathbf{S}_{ni} = -\theta(d \ln \mathbf{B}_{ni} + d \ln \boldsymbol{\pi}_i) + \theta \sum_k \mathbf{S}_{nk} (d \ln \mathbf{B}_{nk} + d \ln \boldsymbol{\pi}_k)$$

Then the bilateral real trade flow change is

$$\begin{aligned} d \ln \mathbf{Q}_{ni} &= d \ln \mathbf{S}_{ni} + \underbrace{d \ln \boldsymbol{\pi}_n - d \ln \boldsymbol{\pi}_i - d \ln \mathbf{B}_{ni}}_{\text{terms of trade}} \\ &= -(\theta + 1)(d \ln \mathbf{B}_{ni} + d \ln \boldsymbol{\pi}_i) + \theta(d \ln \boldsymbol{\pi}_n - d \ln \mathbf{u}_n) + d \ln \boldsymbol{\pi}_n \end{aligned}$$

In matrix notation,

$$d \ln \mathbf{Q} = -(\theta + 1) \underbrace{(d \ln \mathbf{B} + \mathbf{1} d \ln \boldsymbol{\pi}')}_{\text{cost of import}} + \theta \underbrace{(d \ln \boldsymbol{\pi} - d \ln \mathbf{u}) \mathbf{1}'}_{\text{importer price index}} + \underbrace{d \ln \boldsymbol{\pi} \mathbf{1}'}_{\text{importer income}} \quad (\text{B.13})$$

Thus

$$d \ln \mathbf{B} = -\frac{1}{\theta + 1} d \ln \mathbf{Q} - \frac{\theta}{\theta + 1} d \ln \mathbf{u} \mathbf{1}' + d \ln \boldsymbol{\pi} \mathbf{1}' - \mathbf{1} d \ln \boldsymbol{\pi}' \quad (\text{B.14})$$

Now we could recover $d \ln \mathbf{B}$ from $d \ln \mathbf{Q}$ as the following:

1. Use quantity change $d \ln \mathbf{Q}$ to recover welfare change $d \ln \mathbf{u}$ (Equation B.8) and average outgoing cost shocks $d \ln \mathbf{b}$ (Equation B.9);
2. Use welfare change $d \ln \mathbf{u}$ and average outgoing cost shocks $d \ln \mathbf{b}$ to recover incoming change $d \ln \boldsymbol{\pi}$ (Equation B.12);
3. Finally, combine $d \ln \mathbf{Q}$, $d \ln \boldsymbol{\pi}$ and $d \ln \mathbf{u}$ to recover $d \ln \mathbf{B}$ from Equation (B.14).

B.4 Extension: Add Nontradables

Our analysis can be easily extended to incorporate nontradables such as services. Let β_n denote city n 's expenditure share on nontradables; consumer utility function is

$$\mathbf{u}_n^{adj} = \left[\sum_{i=1}^N \mathbf{Q}_{ni}^{\frac{\theta}{\theta+1}} \right]^{\frac{\theta+1}{\theta}(1-\beta_n)} (\mathbf{Q}^*)_n^{\beta_n}, \quad (\text{B.15})$$

where \mathbf{Q}_n^* is final consumption of nontradable goods. Under the assumption that truck flows only capture tradable goods and that city-level productivity shocks apply equally to tradable and nontradable sectors, the real income change $d \ln \mathbf{u}_n^{adj}$ in the presence of nontradables is

$$d \ln \mathbf{u}_n^{adj} = (1 - \beta_n) d \ln \mathbf{u}_n + \beta_n d \ln \mathbf{B}_{nn}, \quad (\text{B.16})$$

where $d \ln \mathbf{u}_n$ is the real income change calculated from Proposition 1, and $d \ln \mathbf{B}_{nn}$ is the proportional change in the cost of production for good n consumed within the city itself.

To measure nontradable expenditure share β_n , we use each province's tertiary sector share of value-added in 2019 from official statistics. Table B.1 provides some summary statistics.

We calculate city-level real income changes using B.16 and find them to be almost identical to $d \ln \mathbf{u}_n$, our baseline estimates without accounting for nontradables (c.f. Figure B.1)

Table B.1: Summary Statistics for the Share of Nontradable

Mean	P10	P25	P50	P75	P90
51.7%	48.0%	50.1%	51.3%	53.0%	55.1%

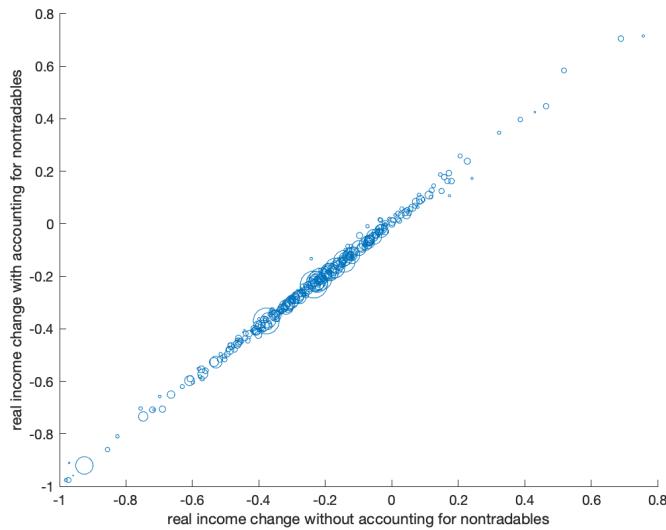


Figure B.1: Real Income Change Comparison: with and without Accounting for Nontradables

C Estimation of Expenditure Share Matrix

The city-to-city expenditure share matrix is not directly observable. We adopt two approaches to estimate the matrix. The first approach is to apply the gravity model to estimate city-to-city trade flows by China's regional input-output table in 2012, the most recent one published by China's National Bureau of Statistics. Some more recent non-official regional IO tables are also used for robustness check. The second approach is to use city-to-city trade flows in [Gao et al. \(2020\)](#) and [Luo \(2020\)](#), which are directly constructed from China's value-added invoice data.¹¹ The estimated economic impacts are highly correlated across different approaches.

The gravity model assumes that the trade flow between two cities, (X_{ij}), is a function of the total supply of the exporter, (E_j), the total demand of the importer, (M_i), and the impedance of transportation costs, for which the distance between two regions is often used as a proxy (D_{ij}).¹² The standard gravity model is as follows:

$$X_{ij} = G^{\beta_0} \frac{(E_j)^{\beta_1} \times (M_i)^{\beta_2}}{(D_{ij})^{\beta_3}},$$

where G is a constant term. The equation in logarithmic form is:

$$\ln X_{ij} = \beta_0 + \beta_1 \ln E_j + \beta_2 \ln M_i + \beta_3 \ln D_{ij}.$$

Due to limited information on exports and imports at the city level, we make the following assumptions:

$$\ln E_j = \alpha_0 + \alpha_1 \ln GDP_j,$$

$$\ln M_i = \gamma_0 + \gamma_1 \ln GDP_i.$$

The gravity model becomes:

$$\ln X_{ij} = \eta_0 + \eta_1 \ln GDP_j + \eta_2 \ln GDP_i + \eta_3 \ln D_{ij},$$

where $\eta_0 = \beta_0 + \beta_1 \alpha_0 + \beta_2 \gamma_0$, $\eta_1 = \beta_1 \alpha_1$, $\eta_2 = \beta_2 \gamma_1$ and $\eta_3 = \beta_3$.

We now use the data at the provincial level to estimate the coefficients $\{\eta_0, \eta_1, \eta_2, \eta_3, \alpha_0, \alpha_1, \gamma_0, \gamma_1\}$, which will be used to back out city-to-city trade flows. The province-to-province trade flow data and provincial GDP are from [Liu et al. \(2018\)](#). The distance between two provinces is proxied by the distance between their capital cities. The regressions results are reported in the following table:

¹¹See [Gao et al. \(2020\)](#) for a detailed description that connects China's value-added invoice data to the regional IO table.

¹²See more discussions about the gravity model in [Carrère et al. \(2020\)](#).

Table C.1: Regression of gravity model

	(1) $\ln X_{pq}$	(2) $\ln E_q$	(3) $\ln M_p$
$\ln GDP_q$	1.003*** (0.0192)	1.069*** (0.0191)	
$\ln GDP_p$	0.726*** (0.0184)		1.003*** (0.0177)
$\ln D_{pq}$	-0.124*** (0.0293)		
Constant	-10.57*** (0.378)	0.289 (0.182)	0.954*** (0.168)
Observations	917	31	31
R-squared	0.835	0.991	0.991

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

We use the results in Column (1) and (2) to back out city-to-city trade flow, X_{ij}

$$X_{ij} = \begin{cases} \exp(\hat{\eta}_0 + \hat{\eta}_1 \ln GDP_j + \hat{\eta}_2 \ln GDP_i + \hat{\eta}_3 \ln D_{ij}) & , \text{ if } i \neq j \\ \exp(\hat{\alpha}_0 + \hat{\alpha}_1 \ln GDP_j) - \sum_{n \neq j} X_{nj} & , \text{ if } i = j \end{cases}$$

Note that the within-city trade flow of city j is estimated by its total exports minus the sum of its between-city exports. The estimated X_{ij} gives the expenditure share matrix used in the paper. The summary statistics of the first-quarter real income changes are reported again in Table C.2 (the same as Table 4).¹³

We then apply the same method to the 2012 and 2015 regional IO tables constructed by Ou et al. (2019) (CEADS2012) and Zheng et al. (2020) (CEADS2015).¹⁴ The results are reported in the second and third rows. The fourth row summarizes the results using the city-to-city trade flows constructed by value-added invoice tax data in 2018 (Luo, 2020).

Table C.2: Statistics of Real Income Change in 2020Q1 under Different Expenditure Share Matrixes

	Mean	Max	Min	Std	P10	P25	P50	P75	P90	Correlation with Benchmark
Benchmark	-17.6%	113.3%	-62.5%	21.4%	-38.8%	-30.7%	-19.7%	-7.0%	4.7%	1.00
CEADS2012	-18.9%	95.2%	-62.2%	19.5%	-39.8%	-30.9%	-20.4%	-8.1%	2.0%	0.96
CEADS2015	-16.0%	106.7%	-62.4%	22.0%	-38.2%	-29.0%	-19.2%	-6.4%	8.0%	0.93
TAX2018	-17.5%	138.5%	-62.6%	23.0%	-41.3%	-31.9%	-21.0%	-7.8%	8.8%	0.85

¹³One may also use Column (1) and (3) to back out X_{ij} and the expenditure share matrix. The results are similar.

¹⁴CEADS2012 and CEADS2015 are from <http://www.ceads.net/data/input-output-tables>.

D Robustness: Other Trade Elasticities

Our analysis assumes trade elasticity $\theta = 4$, a standard value in the literature. This appendix computes COVID shocks $d \ln \mathbf{B}$ under alternative values of trade elasticity $\theta \in [2, 20]$. We show COVID shocks are highly correlated across these alternative specifications, thereby validating the robustness of our analysis to different values of the trade elasticity.

Table D.1: Statistics of $d \ln \mathbf{B}$ under Different Trade Elasticities

θ	Correlation with benchmark $d \ln \mathbf{B}$	Mean	Median	Std
2	0.9529	0.1783	0.1643	0.2696
3	0.9919	0.1898	0.1816	0.2419
4	1.0000	0.1967	0.1910	0.2298
5	0.9958	0.2013	0.1969	0.2239
6	0.9874	0.2046	0.2008	0.2209
7	0.9778	0.2071	0.2036	0.2194
8	0.9684	0.2090	0.2058	0.2186
9	0.9597	0.2105	0.2073	0.2182
10	0.9518	0.2118	0.2088	0.2180
11	0.9447	0.2128	0.2101	0.2181
12	0.9383	0.2137	0.2109	0.2181
13	0.9326	0.2145	0.2116	0.2183
14	0.9274	0.2152	0.2121	0.2185
15	0.9227	0.2157	0.2127	0.2186
16	0.9185	0.2162	0.2131	0.2188
17	0.9147	0.2167	0.2136	0.2190
18	0.9112	0.2171	0.2139	0.2192
19	0.9080	0.2175	0.2142	0.2194
20	0.9050	0.2178	0.2145	0.2196