The Economic Cost of Locking down like China: Evidence from City-to-City Truck Flows*

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Abstract

Containing the COVID-19 pandemic by non-pharmacological interventions is costly. Using high-frequency, city-to-city truck flow data, this paper estimates the economic cost of lockdown in China, a stringent but effective policy. By comparing the truck flow change in the cities with and without lockdown, we find that a one-month full-scale lockdown causally reduces the truck flows connected to the locked down city in the month by 54%, implying a decline of city's real income with the same proportion in a gravity model of city-to-city trade. We also structurally estimate the cost of lockdown in the gravity model, where the effects of lockdown can spill over to other cities through trade linkages. Imposing full-scale lockdown on four largest cities for one month would reduce the national real GDP by 8.6%, of which 11% is contributed by the spillover effects.

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1 Introduction

Many countries implemented non-pharmacological interventions such as stay-at-home mandate (lockdown) in the ongoing COVID-19 pandemic. The stringency and effectiveness of the interventions vary across countries. On the one hand, there is compelling empirical evidence that lockdown has a limited effect on the spread of coronavirus or death in Europe and North America.[1] On the other hand, lockdown appears to be more effective in flattening the curve of COVID-19 in the Asia-Pacific region, where the pandemic led to more aggressive policy responses before the emergence of Omicron.[2] China's zero-COVID policy was particularly effective. Hale et al. (2022a), for example, document that the first stay-at-home order was followed by a more than 90% decline in the number of confirmed new cases in China. The pattern was less dramatic in other Asia-Pacific countries and even reversed in the US, Canada and most European countries. It is hardly surprisingly that a communicable disease can be contained by sufficiently strict non-pharmacological interventions. The question is how much cost a country would have to pay for locking down like China.

Lockdown causes short-term losses of goods and services as well as various more persistent social costs. However, even the narrowly defined economic cost of a lockdown remains largely obscure to both the scientific community and policymakers. The main challenge is two-fold. First, it is hard to isolate the effect of policy intervention in a pandemic, in which other factors like fear-driven individual choices also contribute to economic losses (see, e.g., Goolsbee and Syverson, 2021). Moreover, since policy responds to the severity of the pandemic, endogeneity is an impediment to causal inference. Second, the effect of policy intervention, even if confined to a single locality, will spill over into all the other connected areas through economic linkages (see, e.g., Baqaee and Farhi, 2020; Bonadio et al., 2020). Such policy spillovers are hard to uncover by conventional locality-specific economic statistics.

Interestingly, China's draconian lockdowns themselves provide an ideal opportunity to tackle the identification issue. Since the epidemic broke out in Wuhan, the Chinese authority has developed a policy package that aims at zero local transmission of COVID cases. Lockdown plays a central role. A new COVID case immediately activates local lockdown, which may escalate to full-scale citywide lockdown within several days. The fact that most lockdowns were speedily implemented in response to even the smallest outbreak minimizes the endogeneity of policy responses. Moreover, the swift and stringent lockdowns are effective. Local outbreaks had all been very small until Omicron emerged. This bounds the effect of self-preventive measures by fear of infection. The power of China-style lockdown is yet to be tested by Omicron.[3] But

[1] See, for example, Berry et al. (2021); Bendavid et al. (2021); Atkeson et al. (2020) and a dozen more empirical studies reviewed by Allen (2022).

[2] See, e.g., Ahn (2021) and Tang and Li (2021), for evidence from the Asia-Pacific region.

[3] The three most severe local outbreaks before Omicron came are Shijiazhuang, Yangzhou and Xi'an. The

its success with less transmissible variants of COVID-19 already makes the question highly valuable: How much cost do we have to pay to contain COVID by lockdown?

To deal with the second challenge, we employ a unique data set on monthly city-to-city truck flows. The data are from one of China's leading logistical service providers, which tracks real-time GPS information on 1.8 million (20% of China's) long-haul trucks in 2020.[4] The truck flow data has two advantages over the conventional economic statistics. First, the data is high frequency and can capture instantaneous truck flow changes, which can be one-to-one translated into real income changes in a gravity model of city-to-city trade. Second, 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. These features enable us to map out the real income change in response to lockdowns, from which we can further back out the spillover effect of a lockdown through the trade linkage.

We collect and compile a new data set on city-level lockdowns in China. The sample period starts from April 2020, when the Wuhan lockdown ended, to January 2022. The cities experiencing citywide or main urban district lockdown are classified as full-scale lockdowns, while the cities with some counties or districts locked down as partial lockdowns. We find that full-scale and partial lockdowns were imposed on 16 and 18 cities, with an average duration of 24 and 19 days, respectively. 32 out of the 34 cities were locked down for only once.

Our empirical analysis starts with an event study approach. We provide evidence for parallel trends and against anticipatory effects. We then employ a two-way fixed effects regression that compares the truck flow between the cities of which at least one is in lockdown and the truck flow between the cities of which neither is in lockdown. A one-month full-scale lockdown reduces the truck flow connecting to the city in the month by 59%. The effect of a partial lockdown is 20%.

While all the COVID outbreaks after 2020 Q1 in our sample period were small, self-preventive measures driven by fear might still contribute significantly to the collapse of truck flow in full-scale lockdowns. Goolsbee and Syverson (2021) find the effect of shelter-in-place (S-I-P) order on consumer traffic to be small in the US. Moreover, the effect of fear appears to be strongly correlated with the number of local COVID deaths. To control for individual responses to the severity of local COVID outbreak, we add the number of COVID cases to the regression. The estimated effect of full-scale lockdown reduces marginally to 54%. If both

three cities were locked down in an average of 7 days after the first new case was found, with an average of only 111 COVID cases recorded (11.6 per million). The ongoing Omicron outbreak in Shanghai, which recorded several thousand new cases a day at the end of March, is the most severe local outbreak since the Wuhan lockdown. However, the daily new cases, most of which were asymptomatic and detected in mandatory mass testing, are still an order of magnitude less than the peak in Hong Kong, where no lockdown or mass testing was implemented.

[4]Time-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., 2021a) and market analysts (e.g., CICC, 2020).

consumer traffic and truck flow can measure local real income, our results would indicate that full-scale lockdown in China inflict much larger damage to the local economy than S-I-P order in the US.

The reduced-form estimation, despite simple and highly transparent, is potentially flawed because it does not consider the spillovers of lockdown and their feedback through the intercity economic network. The high frequency city-to-city truck flow data allow us to structurally estimate the Armington model, in which a lockdown affects the between- and within-city cost of producing and selling goods, which in turn affect each city's production. Our estimation suggests that a full-scale lockdown increase the between- and within-city cost by 67% and 144%, respectively. Consistent with the results from reduced-form approach, the effects of a partial lockdown are much smaller.

The trade linkages transmit the effects of lockdown to the other cities. The advantage of the structural approach is that we can estimate the aggregate effect of a lockdown and decompose it into the local and spillover effects. For example, our model suggests that putting Shijiazhuang, a city with 11 million population, into full-scale lockdown cause a 0.2% drop in the national real income. After adjusting the proportion of lockdown days in a month, we find that locking down Shijiazhang for one month would reduce the national real income by 0.4%. Imposing one-month full-scale lockdown on a big city like Beijing would knock 2.5% off China's real income in the month. The aggregate effect of locking down a city is primarily determined by its economic size. However, the city's position in the trade network plays a larger role in the spillover effect, which accounts for about 10% of the aggregate effect. We find that the eigenvector centrality of a city given the trade matrix can account for 43% of the variations in the spillover effect of lockdown across cities. Finally, we find enormous economic costs of implementing full-scale lockdown at the national level. If the government put all Chinese cities into full-scale lockdown for one month, the real income would decline by 53%.

Methodologically, we extend the first-order sufficient statistics in Kleinman et al. (2020) to obtain a closed-form formula that recovers productivity and trade cost shocks from over-time changes in trade flows. The first-order approach greatly reduces the computational cost of structural estimation. We also derive sufficient statistics that map from the 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.

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 can estimate, rather than simulate, the effects of lockdown shock in a trade model.

It should also be noted that our analysis has a few obvious caveats. First of all, our city-to-city truck flow data do not disaggregate flows by industry. The monthly official statistics by city and industry are nonexistent in China. Therefore, we cannot distinguish the heterogeneous effects of lockdown across industries (e.g., Dingel and Neiman, 2020), nor can we study the implications of the associated sectoral reallocation that have been extensively analyzed in the recent literature (e.g., Krueger et al., 2020; Gottlieb et al., 2022). Second, the same data limitation prevents us from analyzing the effect of lockdown transmitted through both input-output and trade linkages, an important channel studied in the recent COVID literature on international trade. The third caveat is that the contingency of lockdown might affect expectation and lead to intertemporal adjustments (e.g., Guerrieri et al., 2020) that are entirely absent in our study.

We contribute to the literature assessing the economic impact of COVID-19 and lockdown policies. Since the literature has been expanding rapidly, it is hard to give a comprehensive review. Many studies look into consumption expenditure change during the lockdown period in the first half of 2020 relative to the same period in the previous year. Cross-country comparison of the results provides some rough estimates of economic losses caused by lockdown outside China. As noted in Andersen et al. (2020), if we use Sweden as a counterfactual of no lockdown, where consumption expenditure fell by 25% between March 11 and April 5, most of the 27% consumption expenditure decline in Denmark between March 11 and May 3 would be attributed to the virus itself, rather than the mandate lockdown orders. This echos the finding in Goolsbee and Syverson (2021) that individual responses account for most of the decline in consumer traffic in the US. The quarterly GDP data are also informative. Italy implemented relatively strict lockdown policies among European countries. The difference in the GDP change in 2020 Q2 between Sweden and Italy implies lockdown in Italy reduce its quarterly GDP by 5.7%. Allen (2022) also uses Sweden as a counterfactual to argue that the effect of Canadian lockdowns on GDP in 2020 Q2 is 5.1%. To the extent that truck flows are proportional to GDP, our estimates suggest that a one-month full-scale lockdown in China reduce GDP by 17.6% in the quarter. The economic losses caused by Chinese lockdowns are three times as large as those caused by Italian and Canadian lockdowns.[5]

[5] The literature has also looked into employment and electricity consumption. See, for example, Montenovo et al. (2020), Forsythe et al. (2020), Adams-Prassl et al. (2020) and Buechler et al. (2022). There are other aspects of the economic consequences of COVID-19 and lockdown policies. Coibion et al. (2020) analysed how the timing of local lockdowns causally affects households' spending and macroeconomic expectations. Altig et al. (2020) constructs several indicators to measure the economic uncertainty in reaction to the pandemic and its economic fallout. Hensvik et al. (2021) explore real-time data on vacancy postings and job ad views on Sweden's largest online job board. Brodeur et al. (2021) use Google Trends data to show the effect of the

Our paper is also related to the research on the economic impact of COVID in China. Most papers focus on the first wave of the pandemic in the first quarter of 2020. While the first wave and the associated aggregate economic impact are larger by an order of magnitude, the virus swept almost all cities and local policies responded to the severity of the epidemic, making the identification much harder. Fang et al. (2020), Chen et al. (2021) and Ai et al. (2022) employ the DiD strategy to disentangle the effect of lockdown on mobility, consumption expenditure and electricity consumption, respectively, by comparing the lockdown and pre-lockdown periods in 2019 and 2020. He et al. (2020) and Pei et al. (2021) quantify the impact of lockdown on city's air pollution and year-on-year growth rate of exports by comparing locked down and non-locked down cities in 2020 Q1. Our identification is also based on the comparison between locked down and non-locked down cities. However, we explore a sample period with no major COVID-19 outbreak even in the locked down cities. This bounds the endogenous individual and policy responses to severe outbreaks, which might differ between locked down and non-locked down cities when the virus swept across the country. The data set we compile on city-level lockdowns in China also complements to the province-level indices constructed by Hale et al. (2022b).

Finally, our work also relates to the literature that jointly models the economic decisions and epidemics to quantify the economic costs and benefits of different policies (e.g., Eichenbaum et al., 2021; Krueger et al., 2020; Auray and Eyquem, 2020; Atkeson, 2020; Alvarez et al., 2020; Aum et al., 2021). The focus of our model is entirely on city-to-city trade that maps truck flows to real income. On the empirical side, we provide an estimate of economic cost associated with sufficiently strict lockdown that can swiftly contain the spread of COVID-19.

The paper is organized as follows. Section 2 summarizes several basic features of China's lockdown policy as well as the truck flow data. The reduced-form approach and its results are provided in Section 3. We present the model in Section 4. Section 5 shows the structural approach and its results. Section 6 reports the economic costs of lockdown in the structurally estimated model. Section 7 concludes.

2 Basic Facts

2.1 China's COVID Policy

The first COVID-19 outbreak in Wuhan prompted the Chinese government to implement draconian policies including locking down essentially all the cities in Hubei province, of which

pandemic and lockdown on mental health. The heterogeneous impacts of lockdowns are investigated by (e.g., Palomino et al., 2020; Bartik et al., 2020; Chetty et al., 2020). Other studies on consumption and employment include (e.g., Diewert and Fox, 2020; Alexander and Karger, 2020; Birinci et al., 2021).

Wuhan is the capital city. The strict measures were effective. By April 2020, new COVID cases almost disappeared. Since then, the Chinese authority has developed and implemented a policy package that aims at zero local transmission of COVID cases, which is often referred to as zero-COVID policy. Notwithstanding sporadic local outbreaks, there has been no nationwide outbreak. The solid line in Figure 1 plots the number of monthly new confirmed cases in log unit.[6] The average number of new confirmed cases since April 2020 is about two orders of magnitude smaller than that in the first quarter of 2020. As of the end of 2021, China's total COVID cases per million people are 73, among the lowest worldwide.[7]

China's zero-COVID policy is mainly based on non-pharmacological interventions. Some immediate policy responses, such as testing, contact tracing and quarantine, are commonly adopted elsewhere, though the reaction of the Chinese government is often perceived faster and better implemented than many other countries (Lazarus et al., 2020). Some preemptive measures are also tighter and more persistent. For example, strict border controls, together with at least two-week hotel quarantine for cross-border travelers, has been in place since the pandemic spread to other countries. Yet, the defining feature of China's zero-COVID policy is its determination to extinguish nascent outbreaks by draconian lockdown measures to even the slightest local outbreak. We summarize the guidelines for lockdown policy issued by the State Council according to an official explanatory document.[8]

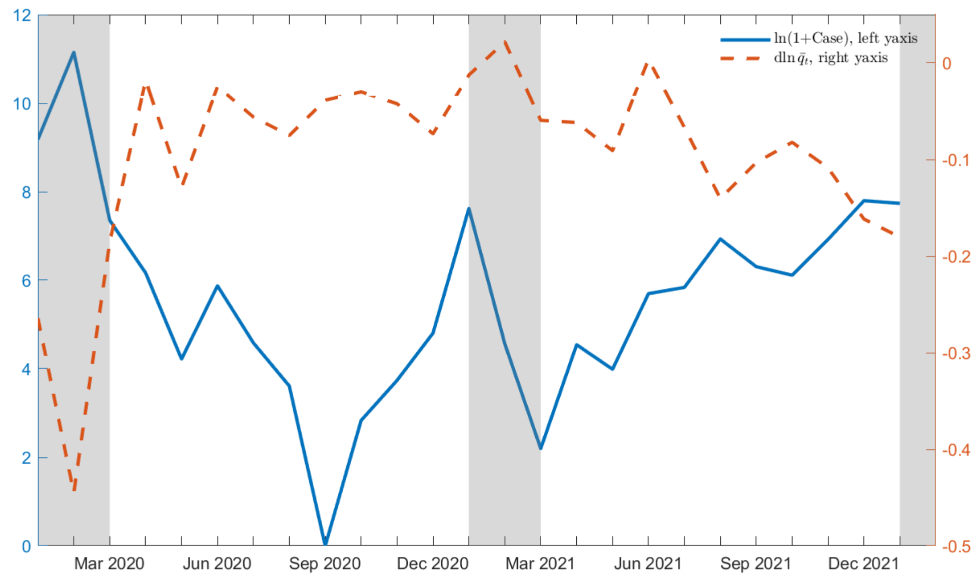
Lockdown starts at community. The Chinese government classifies the communities recording positive but less than or equal to ten COVID cases in the past 14 days as "median-risk" zone. Those recording more than ten COVID cases are classified as "high-risk" zone. The median- and high-risk zones are "sealed" ("*fengkong*" in Chinese). All residents in the zones have to stay at home and be tested multiple times, and all vehicles, unless delivering necessities, are prohibited from entering the zones. According to the standards in Hale et al. (2020), median- and high-risk zones can be coded with the highest scale in all the categories for closures and containment. The restrictions, supposedly enforced by 24-hour patrols, are much stricter than those in Europe and North America. For instance, "staying at home" in China literally means no single step out of your door during the entire lockdown period, while the British version of "stay-at-home" order allows shopping for basic necessities and one form of out-door exercise a

[6] We use the information released by local Health Commissions, collected by DingXiangYuan (`https://ncov.dxy.cn/`). Note that only locally transmitted cases with symptom are counted as new confirmed cases. At the national level, the asymptomatic cases that are tested positive but have never developed symptom account for 68% of total asymptomatic cases in our sample period, less than a fifth of the total confirmed cases. Many local governments do not report the asymptomatic cases.

[7] COVID cases can be underestimated for various reasons. Because our empirical analysis will exploit cross-route and over-time variation with route and time fixed effects, the results will not be affected by under-reporting of COVID cases at the aggregate level.

[8] We cannot find the original document issued by the State Council. The explanatory document we use is from Chengdu Health Commission and publicly available at `https://www.sc.gov.cn/10462/10464/13722/2021/11/10/d0c69ea270c643578fa1fbc77e4a2272.shtml`.

Figure 1: New COVID Cases and Total Truck Flow Change



Note: The solid line is the log of new COVID cases in the month (left axis). The dashed line (right axis) is the aggregate detrended truck flow change, $d\ln\bar{q}_t$, which is defined in the text. The grey shaded areas represent the first quarter.

day.

The county or district to which the locked down community belongs are also affected, even no cases recorded elsewhere in the area. Lockdown-like restrictions are imposed on the "controlled" ("*guankong*") zones – i.e., the communities which the COVID infected individuals travelled to in two days before they are confirmed and are likely to cause local transmission. In particular, the residents in the controlled zones cannot leave home except for purchasing necessities every two or three days. The communities other than the "sealed" and "controlled" zones in the county or district are all "guarded" ("*fangfan*"). The residents cannot leave the guarded zone unless for necessary trips such as seeking medical treatment, which requires a certificate of negative test result within 48 hours. Other measures for the guarded zones include encouraging working from home, restricting group gathering, closing indoor public places, and limiting restaurant dining.

We refer to lockdowns imposed on communities in a city as minimum lockdowns. The measures will escalate into locking down counties or districts in the city, referred to as partial lockdown, if there is evidence for community transmission. In the worse scenario, referred to as full-scale lockdown, the entire city or main urban district is locked down. The conditions for escalation are mainly determined by the severity of COVID outbreak. Dr. Fu Gao, the head of China's CDC, provides an example of Shijiazhuang in an article for which he is the correspondence author (Chen et al., 2021b).[9] There are exceptions. For instance, Langfang was locked down alongside Shijiazhuang in January 2021. However, the decision for Langfang is perhaps based more on its proximity to Beijing (64 km) than on the severity of the outbreak (only one case recorded).

COVID policies adapt to the evolving transmissibility and lethality of the virus. The recent outbreak of Omicron forced governments in many countries to adjust their policy interventions. Several Chinese officials have soften the language when describing lockdowns in their campaign slogans, from "zero COVID" to "dynamic clearance". Yet, there has not been any measurable relaxation in China's lockdown policies during the time frame of this study. The average stringency index in Hale et al. (2022b) in the second half of 2021 is actually slightly higher than that in the first half. Therefore, we simply assume the stringency of lockdown to be time-invariant.

2.2 Measuring Lockdowns

To accurately measure the timing and duration of lockdowns, we collect and compile a novel data set of Chinese lockdowns. Fang et al. (2020) and He et al. (2020) identify lockdown for each Chinese cities in 2020 Q1. However, no systematic measures of city-level lockdowns are available after the first quarter of 2020, and in particular the data are not published by China's official statistics.[10] To fill the blank, we compile a monthly city-level lockdown index to distinguish the scale of lockdown. This subsection describes the collection methodology and presents some summary statistics.

We start with full-scale lockdowns, where the entire city or main urban district is locked down. A well-known example is that Wuhan, where the COVID epidemic first broke out, locked down the entire city with 11 million people for more than two months. The lockdown measures that can be found in government announcements include suspension of all traffics, closed-off management for all residential buildings and no leaving from the city (see, e.g., Fang et al. (2020) and Pei et al. (2021)). We use web scraping to compile a new data set on full-scale lockdowns between April 2020 and January 2022. 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. While the announcements are all about lockdown,

[9] Shijiazhuang, the capital city of Hebei province, recorded the first case on January 2, 2021. The first round of mass testing for the city, which was conducted from 6 to 9 January, detected 354 cases. The whole city was locked down on January 7 according to news reports.

[10] China's CDC frequently updates the list of median- and high-risk zones at the community level, according to the number of new locally transmitted COVID cases. However, there are few economic data available at the same granular level. Hale et al. (2022b) create a composite index for China's COVID policy responses at the provincial level.

local governments seldom used the word of *fengcheng*, meaning "locking down the city" in Chinese. Instead, our reading detects three keywords that frequently appear in the official announcements: (1) closed-off management in all areas; (2) traffic controls in all roads; (3) public transport out of service. We then scrape the first 50 results by searching year, month, city name and the three keywords on Baidu, where the year, month and city refer to the month in the year when the city recorded new COVID cases. The scraped web pages are manually processed through two more steps. The first is to drop the irrelevant web pages, including those with inconsistent timing and location and those on traffic controls caused by non-COVID considerations (e.g., extreme weather conditions). The second is to select official announcements on lockdown in the remaining web pages. This procedure identifies 16 cities on which full-scale lockdown was imposed once after 2020 Q1. No cities experienced the most draconian lockdown for more than once. The average duration of full-scale lockdowns are 24 days.

A less draconian response is to lock down a county or district in a city (e.g., partial lockdown). We replace city name in the above procedure with county/district name and repeat the procedure for all the counties and districts in the city. We find 22 partial lockdowns in 18 cities. Two cities experienced partial lockdown for more than once. The average duration of partial lockdowns are 19 days.

The starting date of each full-scale or partial lockdown can be extracted from government announcements. The lockdowns are on average imposed 3 days after recording the first new case. The end of lockdown is not always openly announced. We can find the ending date for 32 out of all the 38 full-scale or partial lockdowns. For the 32 lockdowns with ending dates, the lockdowns are on average lifted 7 days before the "clearance" day – i.e., the first day when no new case is recorded over the past 14 consecutive days. For the remaining 6 lockdowns, we assume they all end 7 days before the "clearance" day.

Locking down communities (i.e., minimum lockdown) is the mildest response. According to the mandate of the State Council, minimum lockdown should be immediately implemented in the cities recording new cases. The periods in which a city records positive new COVID cases but has no partial or full-scale lockdown are regarded as minimum lockdown periods.[11]

Table 1 summarizes our findings. The appendix provides the full list of the 34 cities on which full-scale or partial lockdown were imposed. Not surprisingly, the scale of lockdown relates to the severity of COVID outbreak. The average number of new cases per million people is 74.9, 24 and 6.2 in the cities with full-scale, partial and minimum lockdown, respectively.

[11]Since it is hard to measure the actual duration of a minimum lockdown, which might vary across regions and over time, we assume that the Chinese government uniformly locks down all the communities with new COVID cases in the past two weeks.

Table 1: Lockdowns after Q1 2020

Number of City	Average City COVID Cases	$\mathrm{d}\ln \bar{q}_t^h$
Panel A: Citywide Lockdowns After Q1 2020		
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%

Note: Average COVID cases are the new COVID cases in the lockdown period. The number in parenthesis is the ratio of new COVID cases to the city population (per million). $\mathrm{d}\ln \bar{q}_t^k$ measures the average truck flow change in the cities with type-k lockdown relative to that without lockdown. $k \in \{h, l, m\}$ stands for full-scale lockdown ($k = h$), partial lockdown ($k = l$) and minimum lockdown ($k = m$), respectively. See the text for more detailed definition.

2.3 Truck Flows

The city-to-city truck flow data comes from real-time truck GPS records of 1.8 million trucks operating in 336 out of 342 prefecture-level cities.[12] Specifically, the truck flow data measures the number of round-trip trucks that depart from a city identified as the place of loading and arrive at another city identified as the place of discharge. The city-to-city truck flow is symmetric by construction. Because trucking is the primary mode of domestic freight transport in China,[13] truck flows are highly correlated with economic activities. Figure A1 in the appendix shows that cross-sectionally city-level truck outflows correlate strongly to city-level GDP in 2018 (correlation 0.9) and also to night light intensity (correlation 0.86).

This paper employs the truck flow data covering 315 cities from January 2019 to January 2022.[14] The logistical service provider does not monitor within-city truck flows. Truck flows are regularly updated on 60% of all the $315 \times 314/2 = 49,455$ between-city pairs. The city pairs with truck flow data are closer to each other and richer than those without.[15] To control for the effects of the growth trend of the economy and the expansion of the logistical service provider, we filter out the route-specific trend component in the time series of log truck flow.[16] Denote

[12] See Alder et al. (2021) for a detailed description of the real-time GPS data.

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

[14] We exclude cities in Tibet and Xinjiang, as these two regions have much fewer trade linkages to the rest of China.

[15] The difference is 35% less and 55% more in the between-city distance and total GDP, respectively.

[16] We use linear detrending. Using HP filter gives essentially the same results.

by $\ln q_{ni,t}$ the detrended log truck flow from city i to n at period t. To control for the seasonal effects, we take difference of the detrended log truck flow between the current period and the same period in 2019. The difference is referred to as the log change in truck flow and denoted by $\mathrm{d}\ln q_{ni,t}$. The aggregate truck flow change is measured by $\mathrm{d}\ln \bar{q}_t \equiv \sum_{n,i} \omega_{ni} \,\mathrm{d}\ln q_{ni,t}$, where ω_{ni} is the weight measured by the city-pair's total truck flows in 2019.

Figure 1 shows that, in the time series, the aggregate truck flow change correlates negatively to new COVID cases (correlation -0.68). The negative correlation remains significant (correlation -0.42 with p-value 0.08) after removing data from the first quarter, a time window that contains the Chinese New Year (January 25 in 2020, February 12 in 2021 and February 1 in 2022), a major festival during which economic activities, COVID policies, and the outbreaks themselves may operate differently from the rest of the year.

To link city-level lockdown measures to the city-to-city truck flows, we construct city-pair lockdown dummies, $D^k_{ni,t}$, where $k \in \{h, l, m\}$ 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. Similarly, $D^l_{ni,t}$ equals one if at least one city has partial lockdown and no full-scale lockdown is imposed on any of the cities in the period. Likewise, $D^m_{ni,t}$ is the dummy variable for minimium lockdown, which equals one if any city in the pair records new COVID cases and none of the cities have full-scale or partial lockdown. For $n = i$, $D^h_{ii,t}$, $D^l_{ii,t}$ or $D^m_{ii,t}$ becomes a city dummy, which equals one if the city experiences full-scale, partial and minimum lockdown, respectively.

The decline of truck flows in the lockdowns is evident. Denote by $\mathrm{d}\ln \bar{q}^k_t$ the weighted average truck flow change for the city pairs with $D^k_{ni,t} = 1$ relative to that for $D^k_{ni,t} = 0\ \forall k$. Table 1 shows that $\mathrm{d}\ln \bar{q}^k_t$ for $k = h$ (full-scale lockdown) declined by 48%. The decline is 21% and 3% for $k = l$ and $k = m$ (partial and minimum lockdown), respectively.

In what follows, we will treat minimum lockdowns as no lockdown. This is based on the observations that the number of COVID cases and the disruption of truck flows are both small in minimum lockdowns. Section 3.1 will check the robustness of our results by estimating separately the effect of minimum lockdowns.

2.4 Normal and Lockdown Periods

Let $D_{ni,t} = D^h_{ni,t} + D^l_{ni,t} > 0$ be the lockdown dummy that equals one if at least one city has full-scale or partial lockdown at period t. We define a period $[N_0, N_1]$ as "normal" if there are no lockdowns in the broader time window from 2 months before to 2 months after the period – i.e., $D_{ni,t} = 0\ \forall t \in [N_0 - 2, N_1 + 2]$. We define $[T_0, T_1]$ as a "lockdown" period if there are lockdowns during $[T_0, T_1]$, but no lockdowns in the 4 months prior to T_0 and 4 months after T_1. We work with the sample that consists of all the lockdown periods, extended by 2 months forward and backward, and all the normal periods. This drops about 1.5% city-pair-month observations. As will be shown in the event study below, the restriction guarantees that there are no overlaps of lead-lag effects in the sample. Our sample has 2068 city-pair-month lockdowns. We do not distinguish the city pairs with one or both cities locked down since only 28 observations have both cities locked down.

3 Reduced-Form Approach

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

$$\mathrm{d}\ln q_{ni,t} = \sum_{k\in\{h,l\}} \alpha^k D^k_{ni,t} + \delta_{ni} + \nu_t + \eta_{ni} t + \epsilon_{ni,t}, \tag{1}$$

where we control city-pair fixed effect, δ_{ni}, time fixed effect, ν_t, and city-pair-specific time trend, $\eta_{ni}t$. $\epsilon_{ni,t}$ is an error term, which has zero mean and can be serially correlated. Since $q_{ni,t} = q_{in,t}$, the regression does not distinguish between exporter and importer. Each observation is a city pair and weighted by ω_{ni} (the city pair's total truck flows in 2019).

Equation (1) estimates the effect of type-k lockdown, α^k, by comparing the cities with type-k lockdown and those without lockdown in the same month. Identifying α^k requires two key assumptions. First, the average truck flows with and without lockdown would have followed parallel trends in the absence of lockdown. Second, lockdown has no causal effect prior to its implementation (no anticipatory effect). Both assumptions would be satisfied if lockdown is solely activated by random local COVID outbreaks.[17] Moreover, the parallel trends would still hold if the selection bias remains the same between the periods with and without lockdown. This can be checked by comparing trends of truck flows in the pre-lockdown period, which will be examined in Section 3.1.

Different from the canonical DiD specification, (1) has staggered treatments (lockdowns). In addition, they are not an absorbing state. The implications of staggered and non-absorbing treatments have been studied in the recent literature (see, e.g., de Chaisemartin and D'Haultfœuille, 2020). We also need homogeneous treatment effects (i.e., constant β^k across routes and over time) for the OLS estimator to be unbiased. The recent literature addresses some limitations of the OLS estimator with staggered treatment and heterogeneous effects. We adopt a new method and find the results to be very robust. The details are provided in Section A.2.

We can allow $n = i$ in (1) by inferring $\mathrm{d}\ln q_{ii,t}$ from (11), which assumes within-city truck flow to be a weighted average of between-city truck flow change. However, by construction, the

[17]The decision of lockdown may be affected by other factors. However, we do not find any correlation between lockdown and city's economic or population size (see Figure A2 in the appendix).

unweighted OLS estimate of the coefficient of $D^k_{ii,t}$ will be identical to that of $D^k_{ni,t}$ for $n \neq i$. While the reduced-form regression cannot distinguish the within- and between-city effects, they can be separately estimated in the structural approach.

3.1 Results

Before estimating the model, we first check our identification assumptions by generalizing (1) to an event-study approach.

$$\mathrm{d}\ln q_{ni,t} = \sum_{j=1}^{\bar{J}} \sum_{k} \alpha^k_{-j} PRE^{k,j}_{ni,t} + \alpha^k_0 D^k_{ni,t} + \sum_{j=1}^{\bar{J}} \sum_{k} \alpha^k_j POST^{k,j}_{ni,t} + \delta_{ni} + \nu_t + \eta_{ni} t + \epsilon_{ni,t}. \quad (2)$$

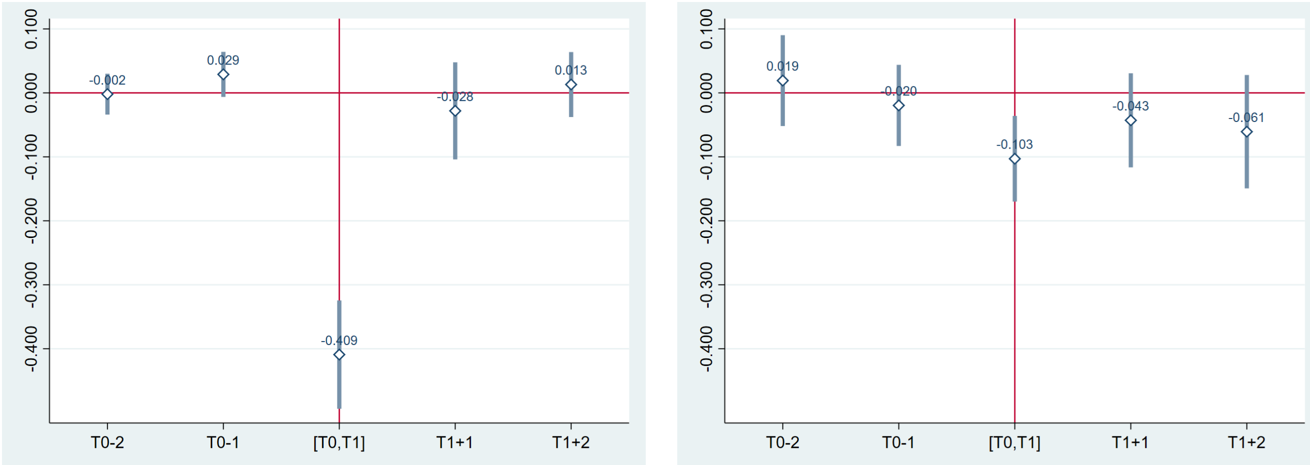
Here, $PRE^{k,j}_{ni,t}$ is a dummy that equals 1 if t is j months before the beginning of the next type-k lockdown. Analogously, $POST^{k,j}_{ni,t}$ is a dummy that equals 1 if t is j months after the end of the previous type-k lockdown.

The estimated α^k_0 will capture the difference between truck flows in type-k lockdowns and those in normal periods. The estimated α^k_{-j} or α^k_j will capture the difference between truck flows in j months prior to or after type-k lockdowns and those in normal periods, respectively. We use the leads to verify the presence of pre-trends. The lags, if statistically significant, would suggest some persistent effects after the lockdown ends. $\underline{J}$ is set to 2 so that there are no lead-lag effects of other lockdowns in the 2 months prior to or after the lockdown in our sample.[18]

The results are reported in Figure 2. There is no evidence for pre-trends since the estimated α^k_{-j} are statistically insignificant. The estimates of α^k_0 are significant and quantitatively sizable. Imposing full-scale lockdown on city i will reduce the truck flows connected to the city by 0.41 log points or 34%. The effect of a partial lockdown is 10%. The estimates of α^k_1 and α^k_2 become insignificant and much smaller than that of α^k_0. These estimates suggest that lockdown has no persistent effect on truck flows. We cluster standard errors at the city-pair level. Similar results can be found in Figure A3 if we cluster standard error at both city n and i (Cameron et al., 2011).

[18] Recall that we only keep the lockdowns that are at least four months away from the other lockdowns in the sample.

Figure 2: Event Study



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

Note: The figure plots the estimated α_j^h (left panel) and α_j^l (right panel) in (2), together with their 95% confidence intervals.

We then run the regression (1). The results are reported in the first column of Table 2. Not surprisingly, the estimate of α^k is very close to α_0^k in the event study.

We have been treating cities with minimum lockdown as part of the control group. We can check the validity of our assumption by adding the COVID dummy to the regression. The COVID dummy for a city pair will be equal to one if any city in the pair records new COVID cases and none of the cities have full-scale or partial lockdown. Since minimum lockdown is automatically activated by a new COVID case, the COVID dummy is also a dummy for minimum lockdown in the city pair ($D_{ni,t}^m$). The results are reported in the second Column of Table 2. The effect of minimum lockdown is statistically significant but quantitatively small. It only reduces truck flows by 3%. Moreover, the estimated α^h and α^l remain robust after controlling for minimum lockdown. These results are reassuring. Ignoring minimum lockdown will not significantly bias the estimates on the effects of full-scale and partial lockdown.

Equation (1) assumes that lockdown is the only channel through which the pandemic can affect truck flows. Equation (1) can be extended by allowing truck flows to be affected by individual choices. Specifically, we assume that a more severe COVID outbreak will intensify self-protective measures that suppress economic activities and truck flows.

$$\mathrm{d}\ln q_{ni,t} = \sum_k \alpha^k D_{ni,t}^k + F(s_{ni,t}) + \delta_{ni} + \nu_t + \eta_{ni} t + \epsilon_{ni,t}, \tag{3}$$

where F is an increasing function and $s_{ni,t}$ measures the severity of the pandemic in the city pair (n, i). We assume $F(s_{ni,t}) = b \ln(1 + \text{Case}_{ni,t})$, where "Case" is the number of new COVID cases

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 + 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

Note: The first two rows report the effect of lockdown on truck flows. Standard errors are clustered at city pair and reported in the parenthesis. Each observation is weighted by ω_{ni}, the city-pair's total truck flows in 2019. In Column (1) to (3), we use D^k_{ni} to measure lockdown, which is a dummy that equals one if city pair (n, i) has type-k lockdown. In Column (4) and (5), we use $\hat{D}^k_{ni,t}$, which the represents the proportion of days with type-k lockdown in the month with $D^k_{ni,t} = 1$. COVID Dummy equals one if the city pair has new COVID cases and none of the cities have full-scale or partial lockdown. "Case" refers to the number of new COVID cases in the city pair.

in the city pair.[19] The third column of Table 2 shows that, conditional on lockdown status, a more severe COVID outbreak is indeed associated with a larger decline in truck flows. Moreover, the estimated α^h and α^l drop by 14% and 57%, respectively, after controlling for $F(s_{ni,t})$. Our finding confirms that lockdown should not be the only reason for the disruption to economic activities in lockdown. To the extent that the number of COVID cases correlates to fear of infection and self-protective measures, individual choices may account for a significant part of the decline in truck flows. That being said, the estimated α^h remains quantitatively large. A full-scale lockdown reduces truck flows by 30% on average. In contrast, the effect of COVID severity has the maximum of 16% for Xi'an, which recorded 2052 cases between December 2021 and January 2022. The estimates of partial lockdown become statistically insignificant after controlling for the number of COVID cases. The effects of policy interventions and individual

[19]The results are robust to adding high-order polynomials to $F(s_{ni,t})$. Only the linear term would be significant.

responses to the pandemic may be harder to separate in less stringent lockdown.

We have so far used monthly lockdown dummies to match the monthly truck flow data. The monthly dummies, albeit simple, do not reflect the length of lockdown in a month. The full-scale lockdown in Langfang lasts for only 5 days, while Yangzhou was under full-scale lockdown in the entire month of August 2021. The average days of full-scale and partial lockdown in the lockdown month (not the whole lockdown period) with $D^h_{ni,t} = 1$ and $D^l_{ni,t} = 1$ are 14 and 12, respectively. To provide a more accurate measure of lockdown, we construct a continuous variable, $\hat{D}^k_{ni,t} \in (0, 1]$, which represents the proportion of days with type-k lockdown in the month with $D^k_{ni,t} = 1$. The last two columns of Table 2 show that the estimated coefficient of $\hat{D}^k_{ni,t}$ more than doubles that of $D^k_{ni,t}$. Controlling for COVID cases reduces the effect of full-scale lockdown by 14%. Imposing full-scale lockdown on a city for a whole month would reduce truck flows connected to the city by 77 log points or 54%. A whole month partial lockdown would reduce the truck flows by 10%.

4 Model

The reduced-form approach estimates the local effect of lockdown. To explore the spillover effect, we employ the standard Armington (1969) model of trade. We derive linear sufficient statistics that map changes in bilateral trade flows to changes in trade costs and real income. As is well-known in the trade literature (e.g., Arkolakis et al., 2012), the Armington model is isomorphic to the model in Eaton and Kortum (2004). Our results extend those in Kleinman et al. (2020), which derive linear sufficient statistics of productivity changes on real income. The first-order approach greatly reduces the computational cost of structurally estimating the cost of lockdown. We will perform policy counterfactuals based on our sufficient statistics and the recovered trade costs.[20]

Each city $n \in \{1, ..., N\}$ in China is modeled as an open and perfectly competitive economy endowed with a representative consumer who supplies ℓ_n units of labor inelastically to produce a city-specific good with productivity a_n, or the production function $Q_n = a_n l_n$. Given wage rate w_n, unit cost of producing goods in city n is

$$c_n = w_n / a_n. \tag{4}$$

[20] Although 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 $\theta > 0$.

Each consumer has a taste for variety, with utility function

$$\boldsymbol{u}_n = \left[\sum_{i=1}^{N} Q_{ni}^{\frac{\theta}{\theta+1}} \right]^{\frac{\theta+1}{\theta}}, \tag{5}$$

where Q_{ni} is the trade flows of good i consumed in city n in quantity, 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 $\boldsymbol{u}_n$ 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:

$$\underbrace{Q_{ni} w_i \tau_{ni}/a_i}_{\substack{\text{city } n\text{'s expenditure} \\ \text{on good } i}} = \underbrace{w_n \ell_n}_{\substack{\text{city } n\text{'s} \\ \text{income}}} S_{ni}, \qquad S_{ni} \equiv \frac{(w_i \tau_{ni}/a_i)^{-\theta}}{\sum_{k=1}^{N} (w_k \tau_{nk}/a_k)^{-\theta}}, \tag{6}$$

where w_i is the cost of labor (wage rate) in city i, and $w_i \tau_{ni}/a_i$ 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 (6),[21] which states that the total income of city i is equal to the sum of expenditure on good i by all other cities:

$$w_i \ell_i = \sum_{n=1}^{N} (w_n \ell_n + \bar{d}_n) S_{ni} \tag{7}$$

where we choose the normalization that $\sum_i w_i \ell_i = 1$, and $\bar{d}_n$ is trade deficit, which is exogenously given in our model.[22]

Our model abstracts away from nontradable sectors, since our data do not distinguish truck flows by industry.[23] Our model also abstracts away from labor mobility, because inter-city migration is limited in the short run.

We use the system of equations (5), (6), and (7) to derive sufficient statistics that connect trade cost and productivity changes, trade flow changes as well as welfare changes, extending the results in Kleinman et al. (2020).

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 $\mathrm{d}\ln z_{ni} \equiv \mathrm{d}\ln \tau_{ni} - \mathrm{d}\ln a_i$ as the composite change in trade cost and productivity in the route at which labor in city i

[21] Market clearing holds by Walras law given (6) and (7).

[22] We assume the trade with the rest of the world does not change with the domestic shocks.

[23] The main findings are very robust in a more general model with nontradable sectors under the assumption that city-level shocks apply equally to tradable and nontradable sectors.

produces goods consumed by city n.

We stack bilateral trade flow quantities Q_{ni}, expenditure shares S_{ni}, and composite cost z_{ni} into $N \times N$ matrices $\boldsymbol{Q}$, $\boldsymbol{S}$, and $\boldsymbol{Z}$, respectively. For notational ease, we further let $\boldsymbol{\mathcal{Q}}_{N^2\times 1}$ and $\boldsymbol{\mathcal{Z}}_{N^2\times 1}$ be the vector form of $\boldsymbol{Q}$ and $\boldsymbol{Z}$, respectively.

Proposition 1 *Starting from an equilibrium with expenditure share $\boldsymbol{S}$,*

(1). There is a one-to-one linear mapping from the composite cost shocks vector to the changes in bilateral trade flow quantities vector:

$$\mathrm{d}\ln \boldsymbol{\mathcal{Q}} = \boldsymbol{G}\,\mathrm{d}\ln \boldsymbol{\mathcal{Z}} \tag{8}$$

where $\boldsymbol{G}$ is an $N^2 \times N^2$ matrix that depends only on the trade elasticity θ, the expenditure share matrix $\boldsymbol{S}$.

(2). The real income change in city n:

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

We leave the proof to the appendix. Intuitively, when the composite cost from i to n increases due to lockdowns ($\mathrm{d}\ln z_{ni}$), 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 $\mathrm{d}\ln z_{ni}$ affects prices, consumption, and real income in other cities $k \notin \{n, i\}$. The full, general equilibrium effect of composite cost shocks sums across all rounds of propagation and is disciplined by our trade model. The matrix $\boldsymbol{G}$ in Proposition 1 forms the linear sufficient statistics for these general equilibrium effects of COVID shocks. In subsequent sections, we use Proposition 1 to estimate the economic impact of lockdown policy and perform counterfactual analysis.

Under the assumptions that the composition of goods in trucks and the proportion of road transport in the total city-to-city freight do not change over time, the truck flow change is identical to the trade quantity change – i.e., $\mathrm{d}\ln Q_{ni,t} = \mathrm{d}\ln q_{ni,t}$. Then, the second part of Proposition 1 implies that the weighted average truck flow change on the routes to a city can be interpreted as the city's real income change. Moreover, as will be shown below, our linear sufficient statistics allow a closed-form solution to the structurally estimated lockdown shocks, which greatly reduces computational costs of solving a large system of equations.[24]

[24]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.

5 Structural Approaches

A key advantage of the reduced-form approach is the simplicity of the event-study setting that enables us to estimate the effect of a lockdown in city i on truck flows involving city i. An importantly limitation of the approach is that are unable to estimate the general equilibrium spillover effects on truck flows along routes not involving cities under lockdowns.

We now use the model to estimate the general equilibrium and distributional effects of lockdowns. Conceptually, we structurally estimate the effect of lockdowns in two steps. First, we use the observed year-on-year trade flow quantity changes ($\mathrm{d}\ln \boldsymbol{Q}$) to recover the underlying bilateral cost shocks ($\mathrm{d}\ln \boldsymbol{Z}$), exploiting the invertibility of the linear sufficient statistics $\boldsymbol{G}$ in Proposition 1, where we compute $\boldsymbol{G}$ using the trade elasticity θ and the observed expenditure share matrix $\boldsymbol{S}$ before the pandemic.

Second, we linearly project the recovered composite cost shocks $\mathrm{d}\ln \boldsymbol{Z}$ onto lockdown events to separately estimate the effect of partial and full-scale lockdowns on the within- and between-city trade costs. Specifically, we assume parametrize trade cost shocks as

$$\mathrm{d}\ln z_{ni,t} = \sum_{k\in\{h,l\}} \left(\beta^k \mathbf{1}(n \neq i) + \gamma^k \mathbf{1}(n = i)\right) D^k_{ni,t} + \varepsilon_{ni,t}, \tag{9}$$

where $\mathbf{1}(n \neq i)$ and $\mathbf{1}(n = i)$ are between- and within-city dummies that equal one if $n \neq i$ and $n = i$, respectively. The coefficient β^k captures the impact of lockdowns on between-city composite costs, while γ^k captures the impact on within-city composite costs. Like in our reduced-form approach (equation (3)), the term $F(s_{ni,t})$ can be added to control the severity of the pandemic in the city pair (n, i).

We estimate (β^k, γ^k) by minimizing the weighted sum of squared residuals between the observed and simulated trade flow quantity changes in the general equilibrium. Let $\Psi \equiv (\beta^h, \gamma^h, \beta^l, \gamma^l)$.

$$\hat{\Psi} = \arg\min_{\Psi} \sum_{ni,t} W_{ni} \left(\mathrm{d}\ln \hat{Q}_{ni,t}(\Psi) - \mathrm{d}\ln Q_{ni,t}\right)^2 \tag{10}$$

where $\mathrm{d}\ln Q_{ni,t}$ is the observed trade flow quantity change and $\mathrm{d}\ln \hat{Q}_{ni,t}(\Psi)$ is the simulated trade flow quantity change from our model given the value of Ψ and equation (9), W_{ni} is a city-pair weight.

The first-order approach we adopt enables us to obtain a closed-form solution, where we obtain $\hat{\Psi}$ as coefficients of a weighted regression of changes in trade flow quantities (stacking the matrix $\mathrm{d}\ln \boldsymbol{Q}$ as a vector) on a transformation of the $\boldsymbol{G}$ matrix in Proposition 1 adjusted for lockdown status. We provide details of the closed-form solution in the appendix.

In practice, we proxy $\mathrm{d}\ln Q_{ni,t}$, for $n \neq i$, by change in the truck flow from city i to n ($\mathrm{d}\ln q_{ni,t}$). The city-to-city truck flow data do not measure within-city trade. To proxy

$\mathrm{d}\ln Q_{ii,t}$, we assume the within-city truck flow change to equal the average truck flow change on all routes connected to the city.

$$\mathrm{d}\ln Q_{ii,t} = \frac{\sum_{n\neq i} q^{19}_{ni,t}\,\mathrm{d}\ln q_{ni,t}}{\sum_{n\neq i} q^{19}_{ni,t}}. \tag{11}$$

where $q^{19}_{ni,t}$ denotes the truck flow between city i and city n in the same period t in 2019.[25] Last, we set W_{ni} equal to the weight ω_{ni} in the reduced-form approach.

Equipped with the estimates (β^k, γ^k) for $k \in \{l, h\}$, we can exploit the second part of Proposition 1. We will conduct both an accounting exercise, decomposing the local and spillover effects of lockdowns on the real income of any other city, and a counterfactual exercise, where we predict the real income effects of hypothetical lockdowns of varying stringency. We conduct these exercises in Section 6.

5.1 Results

We now turn to the structural approach. To obtain $\boldsymbol{G}$, we assume $\theta = 4$ and calibrate the expenditure shares to the official provincial input output table in 2012 (see Appendix A.3 for details).[26] Note that the structural approach distinguishes the direction of trade flow. The sample size, therefore, almost doubles that in the reduced-form approach.

The first column in Table 3 reports the structurally estimated β^k and γ^k by (10), assuming the cost specification (9). The between-city composite cost will increase by 26% if there is a full-scale lockdown in the city pair. The within-city trade flow change, $\mathrm{d}\ln Q_{ii,t}$, disciplines the effect of lockdown on the within-city composite cost. This allows the structural approach to identify γ^k. The estimates suggest a 45% increase in the within-city composite cost by a full-scale lockdown. In line with the results in Table 2, the effects of partial lockdown is much milder than full-scale lockdown. The increase in the between- and within composite cost is 5% and 8%, respectively.

[25] The inferred changes are correlated with the changes in the number of visits to office buildings and shopping malls according to mobile phone location data in Chen et al. (2021a) (correlation 0.66 for 2020 Q1).

[26] The results under different values of θ and the expenditure shares implied by alternative IO tables imply similar real income effects. See Table A5 in the appendix.

Table 3: Effect of Lockdown on Composite Cost, Structural Estimates

	(1)	(2)	(3)	(4)	(5)
		D_{ni}^k		$\hat{D}_{ni}^k$	
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

Note: The first four rows report the effect of lockdown on the between- and within-city composite cost. $n \neq i$ and $n \neq i$ refer to between- and within-city. D_{ii}^k and $\hat{D}_{ii}^k$ are the city's lockdown measures. COVID Dummy equals one if the city pair $n \neq i$ ($n = i$) has new COVID cases and none of the cities have full-scale or partial lockdown. The other specifications are the same as those for Table 2.

To make sense of the estimates, we derive a formula on the trade flow quantity changes in a partial equilibrium, where nominal wage is constant and lockdown in city n or i only affects the goods price sold from i to n through the composite cost, but does not affect the other prices.

$$\mathrm{d}\ln Q_{ni,t}^p = -(\theta + 1)\,\mathrm{d}\ln z_{ni,t} \tag{12}$$

where $\mathrm{d}\ln Q_{ni,t}^p$ denotes the trade flow quantity change in the partial equilibrium and $\mathrm{d}\ln z_{ni,t}$ is from equation (9). The estimated β^k and γ^k imply that a type-k lockdown will reduce the between- and within-city trade flows by $(\theta + 1)\beta^k$ and $(\theta + 1)\gamma^k$ percent, respectively, in the partial equilibrium. The effect of full-scale lockdown on the between-city trade flow implied by the estimated β^k in the partial equilibrium is substantially larger than that estimated by the reduced-form approach.[27] The effects of partial lockdown are more similar. Note that a lockdown will affect trade flows through two channels in the general equilibrium that are absent in the partial equilibrium. First, the lockdown will reduce nominal wage in the locked down city and amplify its effects on trade flows. Second, the lower nominal wage will reduce the goods price sold from the city and, therefore, dampen the effects on trade flows. Our results suggest that the second channel dominates the first in full-scale lockdown, implying that the general equilibrium effect moderate economic losses of full-scale lockdown.

As in the reduced-form approach, we add COVID dummy to control for community-level lockdown. The second column of Table 3 shows the results. Again, we find the effects of community-level lockdown to be small an the estimates of β^k and γ^k are robust. We also add $F(s_{ni,t}) = b \ln(1 + \text{Case}_{ni,t})$ to the cost specification and structurally estimate b. The third column of Table 3 shows that the effects of full-scale lockdown become smaller after controlling for the number of COVID cases but remain large and significant. Adding the control has a larger effect on the estimates of partial lockdown, though. Both are consistent with the findings from the reduced-form approach.

As in the reduce-form approach, the estimated coefficients of $\hat{D}^k_{ni,t}$ are much larger (the last two columns of the table). In the next section, we will use the estimates to perform policy counterfactuals of one-month lockdowns.

6 The Economic Cost of Lockdown

In this section we quantify the economic implications of lockdown. We first derive a model-based accounting framework that isolates the effects of locking down a city on itself, any other city and the aggregate economy. The aggregate impacts will be further decomposed into local and spillover components. Finally, we will conduct several counterfactual exercises to illustrate the potential economic damage of a nationwide lockdown.

6.1 A Model-Based Accounting Framework

We apply Proposition 1, equation (9) and estimates in Column 5 of Table 3 to generate the city level real income changes caused by the lockdown of city i (assuming no lockdowns in other

[27] This result is robust to the choice of θ within reasonable range of 2 and 6.

cities). Specifically,

$$\mathrm{d}\ln \boldsymbol{u}_n^{i,k} \equiv \frac{\partial \ln \boldsymbol{u}_n}{\partial \ln \boldsymbol{z}_{ii}}\gamma^k + \sum_{j\neq i}\left[\frac{\partial \ln \boldsymbol{u}_n}{\partial \ln \boldsymbol{z}_{ji}} + \frac{\partial \ln \boldsymbol{u}_n}{\partial \ln \boldsymbol{z}_{ij}}\right]\beta^k, \qquad \forall k = h, l, \tag{13}$$

where $\mathrm{d}\ln \boldsymbol{u}_n^{i,h}$ ($\mathrm{d}\ln \boldsymbol{u}_n^{i,l}$) measures the impact of type-k lockdown in city i on the real income of city n, taking into account the general equilibrium effects while shutting down the effects of lockdown elsewhere that apply to goods shipping from any cities besides i. The partial derivative $\partial \ln \boldsymbol{u}_n / \partial \ln z_{ji}$ captures the sensitivity of real income in city n to the composite cost for route (j, i). When $n = j$ ($n = i$), the partial derivative captures the importer's (exporter's) real income sensitivity to the route-specific composite cost shock; when $n \notin \{j, i\}$, the partial derivative captures the general equilibrium effect that propagate through the trade network across cities.[28] The lockdown of city i affects the composite cost of selling goods to itself, z_{ii}, and to the other cities, z_{ij} with $j \neq i$. So, the first term on the right-hand side of (13) is simply the effect of locking down city i on the city's real income, while the second term captures the general equilibrium effect of the lockdown through its effects on the real income of other cities.

The percentage change of the national real income caused by a type-k lockdown in city i can be presented as a weighted average of the percentage change of local real income across cities:

$$\hat{\boldsymbol{u}}_{ag}^{i,k} \equiv \sum_{n=1}^{N} \mu_n \hat{\boldsymbol{u}}_n^{i,k}, \tag{14}$$

where $\hat{\boldsymbol{u}}_n^{i,k} = \exp(\mathrm{d}\ln \boldsymbol{u}_n^{i,k}) - 1$ and μ_n is city n's pre-shock real income share. Equation (14) can be further decomposed into two components: The effect on the real income of the city itself (local effect) and the effect on the real income of the other cities (spillover effect):

$$\hat{\boldsymbol{u}}_{ag}^{i,k} = \mu_i \hat{\boldsymbol{u}}_i^{i,k} + \hat{\boldsymbol{u}}_{so}^{i,k}. \tag{15}$$

where

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

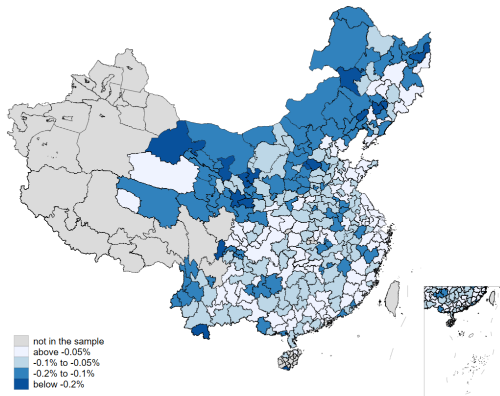
6.2 Results

We use the full-scale lockdown of Shijiazhuang in January and February 2021 as an example. Figure 3 plots its effect on each city ($\hat{\boldsymbol{u}}_n^{i,h}$) in our model, assuming that no other cities are locked down at the same time. The real income of Shijiazhuang would decline by 59%. The real income losses for most of the other cities are negligible, though they can be larger than

[28]Proposition 1 enables us to calculate the entire set of partial derivatives for any n, j, i as functions of the pre-shock bilateral trade flows.

0.2% for 16 cities. At the aggregate level, the lockdown reduces the national real income by 0.4%.

Figure 3: The Effects of Shijiazhuang Lockdown (%)



Note: The figure plots the effect of imposing full-scale lockdown on Shijiazhuang on each city's real come.

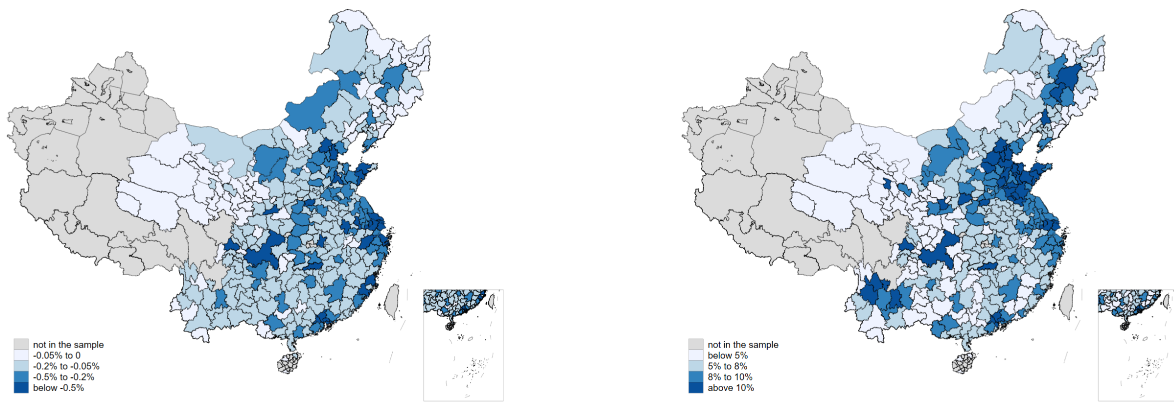
The left panel of Figure 4 plots the effect of imposing a full-scale lockdown in each city for a month on the aggregate real income ($\hat{\boldsymbol{u}}_{ag}^{i,h}, \forall i$). The largest three effects come from Shanghai, Beijing and Shenzhen, where full-scale lockdown will knock 2.7%, 2.5% and 1.8% off the aggregate real income, respectively. We decompose the effect of a full-scale lockdown on the national real income into local and spillover effects. The right panel of Figure 4 plots the contribution of spillover effect to the overall effect ($\hat{\boldsymbol{u}}_{so}^{i,h}/\hat{\boldsymbol{u}}_{ag}^{i,h}$, from equation (15)). The contribution of the spillover effect varies from 0 to 16 percent.

Table 4: Economic Size and Network Centrality

	(1) $-\hat{\boldsymbol{u}}_{ag}^{i,h}$ (%)	(2) $-\hat{\boldsymbol{u}}_{so}^{i,h}$ (%)
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

Note: GDP is the de-meaned city-level GDP in 2019. Centrality is the de-meaned eigenvector centrality associated with the city-to-city trade matrix without diagonal.

Figure 4: The Effect of Full-Scale Lockdown on the National Real Income



(a) Overall effect

(b) Spillover effect

Note: The left panel plots the overall effect of imposing full-scale lockdown on each city on the national real come. The overall effect consists of local and spillover effects. The right panel plots the contribution of the spillover effect to the overall effect.

The effect of locking down a city on the national real income is obviously related to the city's economic size. The first column of Table 4 shows that de-meaned city-level GDP in 2019, which has a standard deviation of 25.7, can account for 96% of the standard deviation in $-\hat{\boldsymbol{u}}_{ag}^{i,h}$, while the city's position in the network, measured by eigenvector centrality, is statistically insignificant. In contrast, the second column shows that the city's eigenvector centrality correlates significantly to its spillover effect on the national income effect. Eigenvector centrality alone accounts for 43% of the variation in $-\hat{\boldsymbol{u}}_{so}^{i,h}$, which is much more comparable to the contribution of 63% by GDP.

7 Conclusion

This paper studies how China's lockdown policy that tries to "nip COVID-19 in the bud" causally affect city-to-city truck flows. Using a DiD design, we find that imposing full-scale lockdown on a city for a month halves the truck flows connected to the city in the month. While locking down one city has a small effect on the national real income in a large economy like China, implementing lockdown on a larger scale might cause significant economic losses. If one-month full-scale lockdown is imposed on China's largest 4 cities (Beijing, Guangzhou, Shanghai and Shenzhen), the four cities would lose their real income by 61% and the national real income would fall by 8.6%, of which 11% is contributed by the spillover effects. The scenario was inconceivable before the emergence of Omicron in China. But at the end of March 2022, as we are finishing the paper, Shenzhen was locked down for a week and Shanghai just escalated partial lockdown to a de facto full-scale lockdown. The aggregate losses would be much larger in the extreme case in which all cities were locked down. The aggregate real income would fall by 53%.

There are many reasons to believe that our estimates only capture the effects of lockdown in the short run. Its effects on expectations, saving and investment decisions in the longer terms are all ignored in the current analysis. Moreover, our estimates alone do not provide evidence for or against immediate lockdown in small COVID outbreaks, a central feature of China's zero-COVID policy. However, they may improve our understanding on the economic cost side of the policy and, therefore, help policymakers to balance the benefits and costs of lockdown.

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A Appendix

A.1 Lockdown Events

Table A1: Full-Scale Lockdowns

City	Starting date	Ending date	Lockdown days	COVID Cases	Δ Truck Flow
Jilin	2020/5/13	2020/6/7	26	44 (12.1)	-37.48%
Shijiangzhuang	2021/1/7	2021/1/29	23	865 (77)	-73.32%
Xingtai	2021/1/12	2021/1/16	5	71 (10)	-74.75%
Langfang	2021/1/12	2021/1/16	5	1 (0.2)	-29.67%
Suihua	2021/1/12	2021/2/6	26	489 (130.2)	-60.93%
Tonghua	2021/1/15	2021/2/21	38	307 (235.6)	-25.50%
Songyuan	2021/1/20	2021/2/3*	15	4 (1.8)	-23.91%
Lu'an	2021/5/18	2021/6/8	22	8 (1.8)	-0.35%
Yangzhou	2021/7/31	2021/9/3	35	570 (125)	-51.52%
Zhuzhou	2021/8/1	2021/8/20	20	29 (7.4)	-20.53%
Zhangjiajie	2021/8/1	2021/8/25	25	67 (44.2)	-126.28%
Jiayuguan	2021/10/23	2021/11/4*	13	5 (15.9)	-12.37%
Zhangye	2021/10/23	2021/11/19	28	15 (13.3)	-5.75%
Heihe	2021/10/28	2021/12/22	56	271 (210.7)	-16.75%
Xi'an	2021/12/23	2022/1/15	24	2052 (158.3)	-75.09%
Anyang	2022/1/10	2022/1/31*	22	464 (84.7)	-60.17%

Note: The definitions are the same as Table 1. The ending date with * is inferred from lockdown ended 7 days prior to the "clearance" day or the end of our sample period (2022/1/31).

Table A2: Partial Lockdowns

City	Starting date	Ending date	Lockdown days	COVID Cases	Δ Truck Flow
Baoding	2020/6/18	2020/7/2*	15	16 (1.4)	-9.35%
Dehong	2020/9/14	2020/9/21	8	0 (0)	6.31%
Dehong	2021/3/30	2021/4/26	28	93 (70.7)	6.12%
Dehong	2021/7/7	2021/7/25	19	88 (66.9)	-17.54%
Fangchenggang	2021/12/22	2022/1/8	18	20 (19.1)	-20.61%
Haerbin	2021/1/18	2021/2/12*	26	146 (14.6)	-13.72%
Haerbin	2021/9/24	2021/10/13*	20	89 (8.9)	-2.95%
Haerbin	2021/12/8	2021/12/17	10	42 (4.2)	-18.39%
Huaian	2021/7/29	2021/8/16	19	12 (2.6)	-12.14%
Hulunbeier	2021/11/27	2021/12/25	29	558 (249.5)	-32.29%
Jingmen	2021/8/7	2021/8/23	17	43 (16.6)	-49.23%
Mudanjiang	2022/1/26	2022/1/31*	6	4 (1.7)	-15.20%
Qiqihaer	2021/1/12	2021/2/7	27	1 (0.2)	-4.75%
Shaoxing	2021/12/11	2021/12/31	21	387 (73.1)	-31.50%
Tianshui	2021/10/27	2021/11/25	30	39 (13.1)	-61.71%
Weinan	2021/12/26	2022/1/9	15	1 (0.2)	-61.08%
Xiangxi	2021/8/1	2021/8/7*	7	0 (0)	-60.18%
Xianyang	2021/12/23	2022/1/20	29	15 (3.8)	-57.95%
Xinyang	2022/1/12	2022/1/16	5	3 (0.5)	-31.64%
Xuchang	2022/1/2	2022/1/31*	30	365 (83.3)	-9.97%
Yan'an	2022/1/3	2022/1/13	11	2 (0.9)	-57.70%
Zhoukou	2021/11/4	2021/11/25	22	18 (2)	-10.40%

Note: The definitions are the same as Table 1. The ending date with * is inferred from lockdown ended 7 days prior to the "clearance" day or the end of our sample period (2022/1/31).

A.2 Robustness Check of DiD results

The recent literature shows that the two-way fixed effects (TWFE) estimator is equal to a weighted sum of the treatment effect in each treated cell, where some weights may be negative. The negative weights are an issue when the treatment effects are heterogeneous across groups or periods. de Chaisemartin and D'Haultfœuille (2020) suggests a diagnosis by checking the weights attached to the TWFE regressions and the absolute value of the coefficient relative to the standard deviation of the weights. If many weights are negative and the ratio is not very large, the TWFE estimator is likely biased. They also propose a new estimator, "DID_M", which is valid even with treatment effect heterogeneity. It estimates the average treatment effect across all the cells whose treatment changes from $t-1$ to t. A test for pretrends is provided.[29]

[29] Goodman-Bacon (2021) and Baker et al. (2022) also propose similar estimators to correct the potential bias of the TWFE regressions.

Table A3: Robustness Check of the Lockdown Effects

	Two-Way Fixed Effects		Joiners' effect in "DID_M"	
	(1)	(2)	(3)	(4)
2 Periods Before Full-Scale Lockdown	-0.0012		-0.0319	
	(0.0163)		(0.0195)	
1 Period Before Full-Scale Lockdown	0.0300		0.0351	
	(0.0183)		(0.018)	
Full-Scale Lockdown	-0.4079		-0.4424	
	(0.0409)		(0.0512)	
2 Periods Before Partial Lockdown		0.0313		-0.0103
		(0.0356)		(0.0247)
1 Period Before Partial Lockdown		-0.0072		-0.0442
		(0.0264)		(0.0297)
Partial Lockdown		-0.0904		-0.0901
		(0.0277)		(0.0193)
Time FE	YES	YES	YES	YES
City pair FE	YES	YES	YES	YES
City pair trend	YES	YES	YES	YES
N	205278	205286	205278	205286

Note: The first two columns report the TWFE estimators. The last two columns report the estimated joiners' effect using de Chaisemartin and D'Haultfœuille (2020).

Note that "DID_M" estimates both the joiners' and leavers' treatment effect. The joiners' treatment effect compares the evolution of the mean outcome between $t-1$ and t in two sets of groups: the joiners (a group from untreated to treated) and those remaining untreated. The leavers' treatment effect compares the evolution of the mean outcome between $t-1$ and t between the leavers (a group from treated to untreated) and those remaining treated. Since we have few observations that have been treated in two consecutive periods, the control group for leavers, we choose to estimate the joiners' effect only.

To make the TWFE estimator be entirely comparable to that for the joiners' effect in "DID_M", we only keep the observations at T_0 for each lockdown period $[T_0, T_1]$. This drops 721 observations with lockdown in total.[30] Reassuringly, we find no negative weights in our TWFE regressions. Table A3 compares the TWFE estimators (column 1 and 2, which are very close

[30]Keeping the observations in the sample would lead to essentially the same results.

to those in the text) and those by "DID_M" (column 3 and 4). Both methods show no evidence for pretrends. The point estimates are also very similar.

A.3 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.[31] 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}).[32] 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

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

[32] See more dicussions about the gravity model in Carrère et al. (2020).

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:

Table A4: 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

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

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

Note that the within-city trade flow of city j is estimated by its total exports minus the sum of its between-city exports.[33] The estimated X_{ij} gives the expenditure share matrix used in the paper.

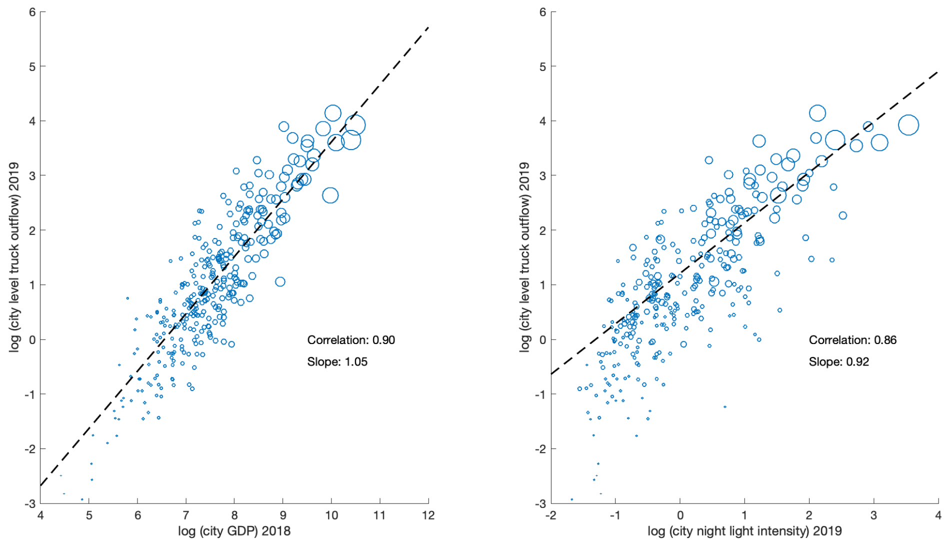
We then apply the same method to the 2012 and 2015 regional IO tables constructed by Ou et al. (2019) (CEADS2012) and Zheng et al. (2199) (CEADS2015).[34] Last, we also use the city-to-city trade flows constructed by value-added invoice tax data in 2018 (Luo, 2020) in estimation of economic cost of lockdown.

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

[34] CEADS2012 and CEADS2015 are from http://www.ceads.net/data/input-output-tables.

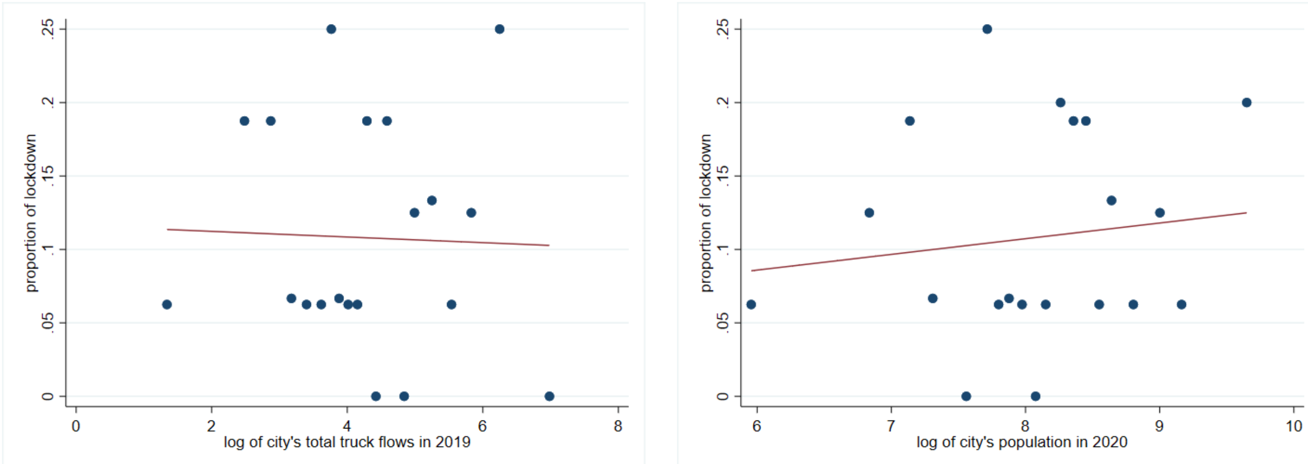
A.4 Additional Tables and Figures

Figure A1: Truck Outflow, GDP and Night Light



Note: The 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.

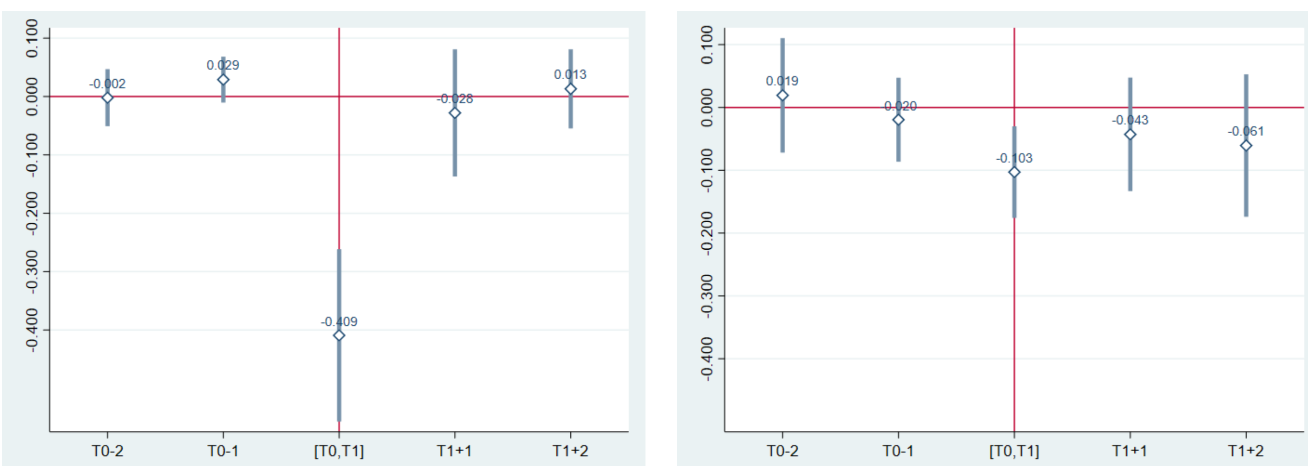
Figure A2: Lockdown and City's Size



(a) lockdown and city's truck flows (b) lockdown and city's population

Note: We sort cities into 20 groups of equal size by the total truck flows connected to the city in 2019 (left panel) or total population of the city in 2020 (right panel). The x-axis is the log truck flow (left panel) or log population (right panel). The y-axis is the proportion of the cities experienced lockdown in each group. The slope of the fitted line (solid line) is statistically insignificant in both panels.

Figure A3: Event Study with Two-way Clustering



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

Note: The figure reproduces Figure 2, with the standard errors clustered at both cities in the city pair (Cameron et al., 2011).

Table A5: Effects of Lockdown on Real Income, Robustness Check (unit: %)

		Benchmark	$\theta = 2$	$\theta = 6$	CEADS2012	CEADS2015	TAX
Shijiazhuang	Real income change of lockdown cities	-59.34%	-58.63%	-59.38%	-61.32%	-59.15%	-56.94%
	National real income change	-0.39%	-0.41%	-0.38%	-0.40%	-0.38%	-0.40%
	Spillover effects	10.52%	15.39%	8.47%	10.22%	8.02%	16.14%
Big 4 cities	Real income change of lockdown cities	-60.81%	-60.02%	-60.87%	-62.89%	-59.54%	-55.17%
	National real income change	-8.63%	-8.94%	-8.48%	-8.78%	-8.16%	-9.18%
	Spillover effects	11.27%	15.45%	9.55%	9.75%	8.13%	24.26%
All cities	National real income change	-52.86%	-52.88%	-52.63%	-50.33%	-51.83%	-47.00%

Note: The first column reports the benchmark counterfactual results. The second and third columns report the results in the model with $\theta = 2$ and $\theta = 6$, respectively. The last three columns maintain the benchmark value of θ but use different expenditure share matrix implied by the city-level IO tables in Appendix A.3. The effects of full-scale lockdown in all the robustness checks are obtained by conducting the counterfactual exercises in the models with re-estimated lockdown effects on the between- and within-city composite costs under different values of θ or expenditure share matrix.

A.5 Proof of Proposition 1

Let $\boldsymbol{e}$ be the vector of nominal expenditure ($e_n \equiv w_n \ell_n + \bar{d}_n$) and $\boldsymbol{\pi}$ be the vector of nominal income ($\pi_n \equiv w_n \ell_n$). We also define

$$T_{ni} \equiv S_{in} e_i / \pi_n$$

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

Then we have

$$\boldsymbol{\pi}' = \boldsymbol{e}'\boldsymbol{S} \tag{16}$$

$$\boldsymbol{e}' = \boldsymbol{\pi}'\boldsymbol{T} \tag{17}$$

Let $\boldsymbol{d}$ as the vector of city n's income-to-expenditure ratio ($d_n \equiv \pi_n / e_n$), which is equal to 1 with balanced trade. Let $\boldsymbol{D} \equiv Diag(\boldsymbol{d})$ be the diagonalization of the vector $\boldsymbol{d}$.

Define average outgoing cost from city i as

$$\mathrm{d} \ln Z_i^{out} = \sum_n T_{in} \, \mathrm{d} \ln z_{ni}$$

Also define average incoming cost to city i as

$$\mathrm{d} \ln Z_i^{in} = \sum_n S_{in} \, \mathrm{d} \ln z_{in}.$$

Taking total differentiation of equations (4), (6) and (7) and putting them together, we have

$$(\theta+1)\,\mathrm{d}\ln\pi_n = \theta\left(\sum_i T_{ni}\,\mathrm{d}\ln Z_i^{in} - \mathrm{d}\ln Z_n^{out}\right) + \theta\sum_{i,k} T_{ni}S_{ik}\,\mathrm{d}\ln\pi_k + \sum_i T_{ni}\,\mathrm{d}\ln e_i,$$

or in matrix

$$\mathrm{d}\ln\boldsymbol{\pi} = \left[(\theta+1)\mathbf{1} - \theta\boldsymbol{TS} - \boldsymbol{TD} + \mathbf{1}\boldsymbol{\pi}'\right]^{-1}\theta(\boldsymbol{T}\,\mathrm{d}\ln\boldsymbol{Z}^{in} - \mathrm{d}\ln\boldsymbol{Z}^{out}) \tag{18}$$

Again from equation (6) we have

$$\begin{aligned}\mathrm{d}\ln Q_{ni} &= \mathrm{d}\ln S_{ni} + \mathrm{d}\ln e_n - \mathrm{d}\ln\pi_i - \mathrm{d}\ln z_{ni}\\ &= -(\theta+1)\left(\mathrm{d}\ln z_{ni} + \mathrm{d}\ln\pi_i\right) + \theta\,\mathrm{d}\ln Z_n^{in} + \theta\sum_k S_{nk}\,\mathrm{d}\ln\pi_k + \mathrm{d}\ln e_n,\end{aligned}$$

and in matrix

$$\mathrm{d}\ln\boldsymbol{Q} = -(\theta+1)\left(\mathrm{d}\ln\boldsymbol{Z} + \mathbf{1}\,\mathrm{d}\ln\boldsymbol{\pi'}\right) + \theta\,\mathrm{d}\ln\boldsymbol{Z}^{in}\mathbf{1'} + (\theta\boldsymbol{S} + \boldsymbol{D})\,\mathrm{d}\ln\boldsymbol{\pi}\mathbf{1'} \tag{19}$$

Now we stack the matrixes $\mathrm{d}\ln\boldsymbol{Z}$ and $\mathrm{d}\ln\boldsymbol{Q}$ into vectors $\mathrm{d}\ln\boldsymbol{\mathcal{Z}}$ and $\mathrm{d}\ln\boldsymbol{\mathcal{Q}}$, respectively:

$$\mathrm{d}\ln\boldsymbol{\mathcal{Z}} \equiv \begin{bmatrix}\mathrm{d}\ln z_{11}\\ \vdots\\ \mathrm{d}\ln z_{1N}\\ \vdots\\ \mathrm{d}\ln z_{N1}\\ \vdots\\ \mathrm{d}\ln z_{NN}\end{bmatrix}_{N^2\times 1} \qquad \mathrm{d}\ln\boldsymbol{\mathcal{Q}} \equiv \begin{bmatrix}\mathrm{d}\ln Q_{11}\\ \vdots\\ \mathrm{d}\ln Q_{1N}\\ \vdots\\ \mathrm{d}\ln Q_{N1}\\ \vdots\\ \mathrm{d}\ln Q_{NN}\end{bmatrix}_{N^2\times 1}$$

Re-write equation (18), we have

$$\mathrm{d}\ln\boldsymbol{\pi} = \theta\left(\boldsymbol{VT}\tilde{\boldsymbol{S}} - \tilde{\boldsymbol{T}}\right)\mathrm{d}\ln\boldsymbol{\mathcal{Z}}, \tag{20}$$

where $\boldsymbol{V} = \left[(\theta+1)\boldsymbol{I} - \theta\boldsymbol{TS} - \boldsymbol{TD} + \mathbf{1}\boldsymbol{\pi}'\right]^{-1}$ and

$$\tilde{\boldsymbol{S}} = \begin{bmatrix}\boldsymbol{S}_1 & & \\ & \ddots & \\ & & \boldsymbol{S}_N\end{bmatrix}_{N\times N^2} \quad \text{with} \quad \boldsymbol{S}_n = \begin{bmatrix}S_{n1} & \cdots & S_{nN}\end{bmatrix}_{1\times N},$$

$$\tilde{\boldsymbol{T}} = \begin{bmatrix} \boldsymbol{T}_1 & \cdots & \boldsymbol{T}_N \end{bmatrix}_{N\times N^2} \quad \text{with} \quad \boldsymbol{T}_n = \begin{bmatrix} T_{1n} & & \\ & \ddots & \\ & & T_{Nn} \end{bmatrix}_{N\times N}.$$

Together with equations (19) and (20), we can get

$$\mathrm{d}\ln \boldsymbol{\mathcal{Q}} = \boldsymbol{G}\,\mathrm{d}\ln \boldsymbol{\mathcal{Z}} \tag{21}$$

where $\boldsymbol{G} = -(\theta+1)\boldsymbol{\mathcal{I}} + \left[-(\theta+1)\boldsymbol{\mathcal{I}}^{out} + \boldsymbol{\mathcal{I}}^{in}(\theta\boldsymbol{S}+\boldsymbol{D})\right]\theta\left(\boldsymbol{V}\boldsymbol{T}\tilde{\boldsymbol{S}} - \tilde{\boldsymbol{T}}\right) + \theta\boldsymbol{\mathcal{I}}^{in}\tilde{\boldsymbol{S}}$ is an $N^2\times N^2$ matrix; $\boldsymbol{\mathcal{I}}$ is an $N^2\times N^2$ identity matrix; $\boldsymbol{I}$ is an $N\times N$ identity matrix; $\mathbf{1}$ is an $N\times 1$ vector with all the entries equal to one; and

$$\boldsymbol{\mathcal{I}}^{out} = \begin{bmatrix} \boldsymbol{I} \\ \vdots \\ \boldsymbol{I} \end{bmatrix}_{N^2\times N} \qquad \boldsymbol{\mathcal{I}}^{in} = \begin{bmatrix} \mathbf{1} & & \\ & \ddots & \\ & & \mathbf{1} \end{bmatrix}_{N^2\times N}$$

This proves the first part of Proposition 1.

Last, total differentiation on Equation (5) gives us

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

which proves the second part of Proposition 1.

A.6 Closed-form Solution of Structural Approaches

To obtain analytical expressions for closed-form solution in structural approaches, we introduce the following notations:

$$\mathrm{d}\ln \boldsymbol{\mathcal{Q}}_t \equiv \begin{bmatrix} \mathrm{d}\ln Q_{11,t} \\ \vdots \\ \mathrm{d}\ln Q_{1N,t} \\ \vdots \\ \mathrm{d}\ln Q_{N1,t} \\ \vdots \\ \mathrm{d}\ln Q_{NN,t} \end{bmatrix}_{N^2\times 1}, \quad \boldsymbol{\mathcal{D}}_t^k \equiv \begin{bmatrix} D^k_{11,t} \\ \vdots \\ D^k_{1N,t} \\ \vdots \\ D^k_{N1,t} \\ \vdots \\ D^k_{NN,t} \end{bmatrix}_{N^2\times 1}, \quad \boldsymbol{\mathcal{W}}_t \equiv \begin{bmatrix} W_{11} \\ \vdots \\ W_{1N} \\ \vdots \\ W_{N1} \\ \vdots \\ W_{NN} \end{bmatrix}_{N^2\times 1}$$

for $k = h, l$ and $t = 1, 2, \cdots, T$. Also let

$$\boldsymbol{I}(n = i) \equiv \begin{bmatrix} 1 & & & & \\ & \ddots & & & \\ & & \boldsymbol{1}(n = i) & & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix}_{N^2 \times N^2}, \quad \boldsymbol{I}(n \neq i) \equiv \begin{bmatrix} 0 & & & & \\ & \ddots & & & \\ & & \boldsymbol{1}(n \neq i) & & \\ & & & \ddots & \\ & & & & 0 \end{bmatrix}_{N^2 \times N^2}$$

By Proposition 1, the simulated trade flow quantity changes can be written as

$$\mathrm{d} \ln \hat{\boldsymbol{\mathcal{Q}}}_t = \boldsymbol{G} \begin{bmatrix} \boldsymbol{I}(n \neq i)\boldsymbol{\mathcal{D}}_t & \boldsymbol{I}(n = i)\boldsymbol{\mathcal{D}}_t \end{bmatrix} \Psi, \tag{22}$$

where

$$\boldsymbol{\mathcal{D}}_t = \begin{bmatrix} \boldsymbol{\mathcal{D}}_t^h & \boldsymbol{\mathcal{D}}_t^l \end{bmatrix}, \quad \Psi = \begin{bmatrix} \beta^h \\ \beta^l \\ \gamma^h \\ \gamma^l \end{bmatrix} \tag{23}$$

Last, let

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

where T denotes the total number of periods in our sample.

The close-formed solution to the estimation of Ψ in (10) is given by

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