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Abstract

This paper examines the impact of Covid-19 lockdowns on exports in Chinese cities. We use city-level export data at a monthly frequency from January 2018 through April 2020. Differences-in-differences estimates suggest cities in lockdown experienced a *ceteris paribus* 34 percentage points reduction in the year-on-year growth rate of exports. The lockdown impacted the intensive and extensive margin, with higher exit and lower new entry into foreign markets. The drop in exports was smaller in *i*) coastal cities; *ii*) cities with a better developed ICT infrastructure, and *iii*) cities with a larger share of potential teleworkers. Products that relied more on imported (domestic) intermediates experienced a sharper (flatter) slowdown in export growth. The main findings are robust to a battery of checks, placebo tests and in 2SLS specifications where distance to Wuhan is used as an instrument. The rapid recovery in cities' exports after lockdowns were lifted suggest the policy was cost-effective in terms of its effects on trade.

Keywords: Covid-19; Lockdown; Export growth; Supply chain; China

JEL Codes: F14; C67; J61; O53

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1. Introduction

Balancing the trade-off between health and wealth has been a key concern for policy makers since the outbreak of Covid-19. Everywhere, policy makers grapple with the costs and benefits of alternative lockdown policies. They have limited time to react and lack complete knowledge on the nature and spread of the virus. What are optimal lockdown policies in such a situation? Modeling and estimating the effect of lockdowns on socio-economic outcomes helps inform this debate.

This paper provides one contribution by studying the impact on exports of lockdowns in Chinese cities. Lockdowns implemented by local policymakers were strict, but varied in terms of timing and duration until the virus was contained in their city. The epicenter of the coronavirus outbreak, the city of Wuhan, did not fully lift its lockdown until April 8 2020, or 76 days from its shutdown. The lockdown was effective in the sense that the number of cumulated cases in China remained roughly constant after March 11 2020. Whereas China accounted for two-third of globally confirmed cases at the time the World Health Organization characterized Covid-19 as a pandemic, its share was less than one percent by the end of June.

Yet, the strict lockdowns came at a price. This paper focuses on one socio-economic outcome, namely the impact it had on trade. The volume of China's exports fell by an unprecedented 41 percent in February 2020 compared to February 2019, see Figure 1. Yet, by July 2020 the export volume was back at levels last observed in December 2019. This rapid recovery contrasts to trends in export volumes for other major trading economies shown in the Figure, which were still below their peak trade

levels by August 2020.

Most businesses in China resumed operations around April 2020 and have continued since. Hence, it appears that supply disruptions have come to an end. This provides the unique opportunity to examine *ex post* the impact of lockdowns on exports.[1]

[Figure 1 is about here]

This paper uses city-level export data by destination at a monthly frequency from January 2018 through April 2020. We obtained this detailed dataset through contacting each of China's local customs offices. Lockdowns in China's cities varied in terms of their timing, and duration. This provides the opportunity to examine the impact of lockdowns on trade using a differences-in-differences model specification.

We find that cities in lockdown experienced a *ceteris paribus* 34 percentage points reduction in the year-on-year growth rate of exports. This translates into a decline of 3 million US dollars of export income compared to cities without a lockdown, which is a substantial loss in welfare. The quick rebound in exports after the virus had been contained and lockdowns were lifted suggests the policy was cost-effective in terms of its impact on trade.[2] Since the lockdowns in Chinese cities were very strict, the result may provide an upper boundary of economic trade costs.[3]

[1] If vaccination is successful in creating herd immunity to Covid-19, it is likely our analysis remains ex post.

[2] Concerns remain. In particular, whether trade will experience a sustained V-shaped recovery (pp. 63, The Economist, Sept. 12-18, 2020).

[3] As early as March 13, 2020, the New York Times compared policies containing Covid-19 in four

The lockdown impacted the intensive as well as the extensive margin of cities' exports. On the extensive margin, it led to higher exit from and lower new entries into foreign markets. Furthermore, substantial heterogeneity in the relation between exports and lockdowns is observed, which depends on the characteristics of cities, products, and sectors. Taking into account supply chains and its concomitant flow of intermediate inputs, we find that sectors relying more on imported (domestic) intermediates suffer a sharper (flatter) slowdown in export growth.

The key findings are robust to a battery of checks and placebo tests. For instance, we use alternative measures of the dependent variable and employ the Poisson-Pseudo-Maximum-Likelihood (PPML) estimator to confirm our results are not driven by zero trade flows. We also run a two-stage least squares (2SLS) estimation, where distance to Wuhan is used as an instrument. This is to address possible endogeneity concerns due to reverse causality, because cities that interact intensively with Wuhan were more likely to implement a lockdown to contain the spread of Covid-19.

Finally, we explore the mechanisms by which lockdowns result in a reduction in exports. Not surprisingly, lockdowns restricted the mobility of people. Our findings suggest this mobility of individuals is central to the decline in goods trade, which is in line with the theoretical framework proposed by Antràs et al. (2020).

Our study contributes to the literature on optimal lockdown policies and the theoretical

regions, namely China, Hong Kong SAR, Chinese Taipei, and Singapore. It argued that China's lockdown policy was most strict (see https://www.nytimes.com/2020/03/13/opinion/coronavirus-best-response.html). As the authors acknowledge, these regions are not completely comparable, not only in terms of population size, but also geographically. In any case, lockdown policies appear effective in these places; while economic costs may differ (see e.g., Aum et al., 2020).

modeling of pandemics and trade (Acemoglu et al., 2020; Alvarez et al., 2020; Antràs et al., 2020; Aum et al., 2020; Fajgelbaum et al., 2020; Jones et al., 2020). The empirical findings in this paper provide useful information to calibrate such models.

This paper also relates to the rapidly growing literature that studies the economic impact of the Covid-19 pandemic (Atkeson,2020; Bonadio et al., 2020; Chen et al., 2020; Eichenbaum et al., 2020; Fernandes and Tang, 2020). Two studies closely related to our analysis are Bonadio et al. (2020) and Fernandes and Tang (2020). Bonadio et al. (2020) argue that the renationalization of supply chains will not make a country more resilient to a contraction in labor supply caused by the pandemic. Our findings put that into question, which is likely related to China's large and increasingly diversified economy.

Fernandes and Tang (2020) examine the impact of SARS on the trade performance of Chinese firms and find that firms in regions with local transmission experienced a considerable drop in international trade. Yet, China's position in global supply chains at the outbreak of Covid-19 in 2019 was much more prominent compared with SARS in 2003. Also, the scope and duration of the Covid-19 pandemic is different. Although local governments implemented travel restrictions on their residents around the outbreak of SARS, they did not impose lockdowns like the one Wuhan experienced.

Further, our study is relevant to a vibrant branch of studies that investigate the consequences for the disruption of supply chains (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2020). Using the 2011 Tōhoku earthquake as a natural experiment, Boehm et al. (2019) document that Japanese multinational affiliates abroad,

who import intermediate inputs from Japan, experienced a drop in output following the earthquake. Carvalho et al. (2020) use firm-level input-output linkages to examine the propagation and amplification of the shock. They show that firms cannot find alternative intermediate input suppliers in the short run. We use inter-provincial inter-industry input-output linkages in China to shed light on the effects of supply disruptions on the exports of sectors.

Our paper also adds to the literature on the relationship between time lags and trade. The seminal work by Hummels and Schaur (2013) found that long transit delays were negatively associated with a country's probability to export, and this was especially the case for time-sensitive goods such as parts and components. Using different datasets and identification strategies, several other papers examined the role of time lags on bilateral trade (Djankov et al., 2006 and 2010; Freund and Rocha, 2011; Martinez-Zarzoso and Marquez-Ramos, 2008, Martincus et al., 2015). In addition, face-to-face meetings play an important role in building business relationships or buyer-seller linkages (Storper and Vanables, 2004; Benard et al., 2019), search and contracting (Startz, 2016), trade (Cristea, 2011), as well as foreign direct investment (Fageda, 2017; Campante and Yanagizawa-Drott, 2018).

The Chinese government implemented strict travel restrictions to contain the spread of Covid-19, such that most domestic and international business travel was suspended or canceled. We complement this strand of literature by exploring the lockdown as a natural experiment to examine the extent to which possible delays caused by the disruption of supply chains affected city-level exports. We document that

technology plays an important role in facilitating trade: cities with more teleworkers and a better Information Communication Technology (ICT) infrastructure are less affected by lockdowns (see also Papanikolaou and Schmidt, 2020).

The remainder of the paper is organized as follows. The next section traces the spread of Covid-19 in China and lockdowns in its cities. Section 3 presents data and summary statistics. Section 4 describes the econometric identification strategy, section 5 the main findings. Robustness checks are in section 6. Section 7 explores mechanisms behind the drop in exports following lockdowns. Finally, section 8 concludes.

2. The spread of Covid-19 and lockdowns in China

A. The spread of Covid-19 in China

To the best of our knowledge, the earliest date about Covid-19 can be traced to December 1 of 2019, when the first individual was diagnosed (Huang et al., 2020). On December 31, the Wuhan Municipal Health Commission informed the WHO about a cluster of 41 patients with pneumonia in Wuhan, and most patients had been to the Huanan Seafood Wholesale Market. Although health authorities claimed there was no evidence of human-to-human transmission, the government closed the seafood market on January 1, 2020. Also, the government announced the unknown pneumonia cases were not SARS or MERS. Meanwhile, they initiated a retrospective probe into the outbreak. It was not until January 20 that China's National Health Commission

confirmed that the Covid-19 could transmit from person to person. That day, president Xi Jinping issued important instructions on the prevention and control of the epidemic, emphasizing that people's lives and health are governments' top priority.

In response to the outbreak and spread of Covid-19, Wuhan went in lockdown on January 23, one day before China's New Year's Eve. Several days later, another 13 prefecture-level cities and 3 province-managing-cities went in lockdown. All of the intra-city and inter-city public transport were halted to restrict people's movements, and private vehicles were not allowed on highways. Shops closed and communities started to implement close-off management. Each household could only have one person to go out to purchase daily necessities. Using mobile phone geo-location data, Jia et al. (2020) documented that around 11.48 million people moved out of Wuhan between January 1 and January 24, of which 2.79 million went to other provinces. Thus, several other cities like Wenzhou, one of the main destinations of Hubei province's migration outflow, also implemented a (partial) lockdown on February 4 (Fang et al., 2020).

Different to SARS, Covid-19 can be transmitted if the infected has asymptomatic symptoms. Moreover, it was around China's Lunar New Year holidays (*Chunyun*). During *Chunyun* around 3 billion trips were expected (based on travel flows in 2019). By January 29, all of the 31 provinces had launched first-level public health emergency response, which meant that the State Council would take charge of the emergency coronavirus response and coordinate the local governments to fight against the virus. Given that local governments are all in political tournaments (Li and Zhou, 2005), local policymakers have strong incentives to follow the central government's epidemic

response.

Besides restrictions on travel and traffic control policies, the central government took several other measures to contain the spread of infections. On January 27, the State Council announced to extend the Spring Festival holidays to February 2, which was unprecedented, to strengthen the prevention and control of the new coronavirus. Meanwhile, the Ministry of Education also announced that all schools would extend their holidays, and the reopening time depended on the local progress of the prevention and control of the virus.

At the outbreak, there were over 290 million migrant workers in China, of which around 174 million worked outside their household registration (*hukou*) province. During the Spring Festival holidays, nearly all of these migrant workers would go back to rural areas for the family union, as well as college students and other people who were born in villages. Wuhan, the largest industrial center in central China, had a population of 11.21 million in 2019, of which around 5 million people were migrants that left the city during holidays. Additionally, as a major transport hub, millions of travelers would pass through or transfer from Wuhan to their hometowns.

Medical resources were scarce, such that initially people could not get tested in local hospitals. Thus, local rural governments set up temporary roadblocks and checkpoints at the entrance of each village to discourage people's movement. According to a report by the Ministry of Agriculture and Rural Affairs,[4] 88.3 percent of the 9,057 surveyed villages had set up roadblocks on rural roads to isolate themselves.

[4] See http://www.hzjjs.moa.gov.cn/xczl/202004/t20200403_6340842.htm for details.

As of February 24, only 0.81 percent of the surveyed villages had confirmed cases, while the proportion of villages with suspected cases was as low as 1.77 percent.

Resumption of work was another tough challenge for the prevention and control of the epidemic. To facilitate the resumption of work and production, local governments took several measures. Counties, cities, and districts were classified into three different risk-level areas according to the development of the epidemic. Firms located in the low-risk and medium-risk regions could resume business under the premise of a reasonable control of the epidemic, while those in the high-risk regions had to delay their resumption. Then, a color-based QR health code system, which relied on big data to track the user's movements, was used to check the user's health status. Checkpoints had been set up at the entrances and exits of railway stations and highways, as well as crowded locations like shopping malls. Passengers with a "green code" could travel as normal, while those with a yellow or red code would be limited to travel or quarantined. Finally, the local governments implemented economic measures, like cutting corporate taxes and lowering social insurance costs, to help firms, especially small and medium-sized firms, overcome difficulties brought about by Covid-19.

24 out of the 31 provinces announced that the firms could not reopen before February 10, while 6 other provinces announced that businesses could start the resumption of work and production on February 3. Hubei province, the epicenter of the coronavirus outbreak, announced that companies could resume business on February 14 at first. The Hubei government, however, extended its business shutdown to February 21 again, and to March 11 for a third time, 30 days later when compared to

the other provinces. In Wuhan, business was not allowed to resume until March 20, although firms serving daily needs, such as mask producers, utility firms, and pharmaceutical companies, had already restarted to supply soaring demands.

The resumption of work and production was one thing, the lockdown was another. For example, people working in Hubei province could go back to work under strict application procedures and quarantine requirements, but residents were not permitted to leave the province. A green QR health code was needed for workers to travel within the province. On March 25, the government removed travel restrictions in and out of the province. In the epicenter of the coronavirus outbreak, Wuhan, travel restrictions were lifted on April 8 after 76 days of lockdown. Wenzhou in Zhejiang province, one of the main recipients of passengers hailing from Wuhan, reopened entrances and exits of highways on February 20, 18 days after its partial lockdown.

B. The impact of lockdowns

Lockdowns were effective in preventing the spread of Covid-19. Figure 2 illustrates that most of the confirmed cases were spotted in Hubei province, while the number remained roughly constant after March 11, the first day that saw a single-digit increase in newly confirmed cases in Hubei province. As of June 2020, China's cumulative case number was 83,534, of which Hubei accounted for 81.57 percent or 68,135 cases (of which Wuhan 60.26 percent or 50,340 cases).

Although there are local rebounds of Covid-19 cases in cities, including in Beijing,

Dalian, Shulan, and Urumqi, local governments respond quickly and carry out policies like mass testing to track all possibly infected individuals. Importantly, these local government responses no longer include the imposition of lockdowns, as only a small proportion of firms and plants have to suspend operations. Thus, rebounds in local Covid-19 cases are quickly brought under control. The central government has implemented regular epidemic prevention and control measures since April 29, with the help of the health code system tracking each person's travel history.

[Figure 2 is about here]

When the World Health Organization (WHO) declared the coronavirus outbreak a pandemic on March 11, China had reported 80,908 cumulative confirmed cases, accounting for around 67 percent of the worldwide cases. However, the number of confirmed cases was soaring in the rest of the world, especially in Italy and Spain. These countries also started a partial or full nationwide lockdown to contain the spread of the virus. By the end of June 2020, the number of worldwide confirmed cases was 10,244,564, while that of China was 84,780, or 0.83 percent (see Figure 3).

[Figure 3 is about here]

The travel restrictions and traffic control policies had serious socio-economic consequences. First, China experienced a historical negative GDP growth in the first

quarter of 2020, falling by 6.8 percent year-on-year. In Hubei province, the epicenter of the coronavirus outbreak, there was a year-on-year decline in the growth rate of 39.2 percent in the first quarter. Second, according to Customs statistics, China's merchandise trade volume was RMB 6.57 trillion ($943 billion) in the first quarter of 2020, decreasing by 6.4 percent year-on-year. Moreover, total exports and imports fell 11.4 and 0.7 percent, respectively. Consequently, China's trade surplus fell by 80.6 percent to RMB 98.33 billion ($13.14 billion).

Hubei's export of goods from January through March 2020 was RMB 31.8 billion ($4.5 billion), decreasing by 39.5 percent year-on-year, see Figure 4. Taken together with imports, the decline of Hubei's trade in goods decreased by 22.5 percent compared with the first quarter of 2019. Although in other provinces such as Qinghai and Ningxia trade declined by 63.1 and 46.4 percent respectively, trade volumes of these provinces are much smaller than Hubei. The decline in trade volumes in other provinces was smaller compared to Hubei.

[Figure 4 is about here]

3. Data and summary statistics

We use four datasets. The first dataset is merchandise trade data from China's General Administration of Customs. We have two sets of trade data, one at the level of provinces and one for cities. The first customs data reports on a monthly basis the imports and exports by province and their trade partners at the HS 8-digit level for the period from January 2017 through June 2020. In addition, the data also records the trade mode, such

as whether it is regular or processing trade.

The second customs data, which we obtain through separately contacting each of China's local customs administration offices, includes monthly trade statistics by city and trade partner (but not by HS products).[5] Due to China's large area and population size, administrative divisions are complex and there are three levels of cities. That is, the trade data refers to each of China's prefecture and province-managing-city or a province-managing-county. For brevity we will refer to these as cities. This data make it possible for us to estimate the effect of lockdowns on city's exports.

The second dataset provides information on the number of daily Covid-19 cases by city, obtained from the China Stock Market & Accounting Research Database (CSMAR Database). The CSMAR database extracts the daily numbers of confirmed cases, recovered patients, and death cases from the national and local Center for Disease Control and Prevention (CDC). If a city does not report a new infected individual, it is assumed there is no new case. Since the trade data is available at a monthly frequency, we sum the daily number of newly confirmed cases by month. If we use the number of cumulative cases, month-end values are used.

The third dataset is the Baidu Mobility or Baidu Qianxi dataset. Baidu Inc., which is one of the largest internet companies in China, offers location-based services for its hundreds of millions of Chinese users. Based on various sources of information, such as the global positioning system (GPS) and IP addresses, Baidu visualize these data into

[5] Trade data for January and February 2020 are reported separately in this granular dataset (however, due to data constraint, prefectures of Yunnan province are not included; in fact, Yunnan accounted for only 0.53 percent of China's aggregate exports in the first quarter of 2020). In another dataset with trade statistics by province, these two months have been combined.

dynamic maps, as well as providing users with the original dataset. The latest available version is the Baidu Qianxi Rev. 3.0, which reports the Top 100 destination or source cities for migration flows of the reporting city from January 1 to April 30, 2020. We downloaded the dataset from the China Data Lab Dataverse, a free resource maintained by Hu et al. (2020). We use three indicators: the daily In-Migration Index (IMI), the daily Out-Migration Index (OMI), and the daily Within-City Migration Index (WCMI). The three indicators capture population mobility of a city, and will be utilized to examine the effects of lockdowns on population mobility.

The fourth dataset is weather data obtained from the China Meteorological Data Service Center (CMDC), which is affiliated to the National Meteorological Information Center of China. The dataset includes meteorological information such as average temperatures, relative humidity, precipitation, wind speed and direction, pressure, and sunshine duration for 613 weather stations in China. The role of the climate on the transmissibility of Covid-19 is hotly debated, and inconsistent conclusions are drawn in recent studies (Fang et al., 2020; Baker et al., 2020; Tobías and Molina, 2020). Also, several studies find that high temperatures have significantly negative impacts on export growth (Jones and Olken, 2010; Li et al., 2015). To capture the possible impact of climate variations on outcome variables and Covid-19 transmissions in cities, we will include weather data as control variables.

Following common practice, we create city-level weather measures by using the inverse distance weighting (IDW) method (Deschenes and Greenstone, 2007; Schlenker and Walker, 2015; Chen et al., 2020). We take the average of climate data

reported by the monitoring stations within 150 km of the city's centroid, weighting by the inverse distance between the station and the centroid.[6] Other city-level control variables are obtained from CEIC database and China City Statistical Yearbook. See Appendix Table A1 for summary statistics of the variables used in our main regressions.

Finally, following Fang et al. (2020), we define whether a city enforces a lockdown according to three conditions: (i) all public transportation and movement of private vehicles are banned; (ii) all residential buildings implement close-off management; (iii) citizens are forbidden to leave the city. We also consider cities that are under partial lockdown. For these cities, the majority of the public transportation has been temporarily shut down, checkpoints have been set up to control human mobility, and surveillance and tighter controls are in each neighborhood. The underlying reasons can be summarized as follows: firstly, these cities also carried out stringent measures to control people's movements; secondly, they were more likely to delay resumption of businesses. Hence, resulting in a slowdown of the recovery of the supply chain in these cities. In total, 16 cities in Hubei province implemented complete lockdown policies, while 7 other cities implemented partial lockdown policies. Following Fang et al. (2020), we prepared the list of lockdown and partial lockdown cities, and added their respective date of business resumption, see Appendix Table A2.[7]

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[6] We use a threshold on distance different from Chen et al. (2020), which draw a 100 km radius around the city's centroid. There are two reasons: (i) we use monthly weather data rather than daily data and the number of weather stations we obtained is 613, which is 207 fewer than what Chen et al. (2020) reported; (ii) the threshold of 100 km would exclude cities like Shijiazhuang, which is the capital city of Hebei province. Note that the distance used for Shihezi, which is located in the northern part of Xinjiang province, is 200 km, as the nearest monitoring station is about 180 km away from this city.

[7] Some cities implemented a partial lockdown when local new confirmed cases were reported, such as Beijing on June 16. We did not include these cities into our treatment group. There are two main reasons for doing so. First, only a small proportion of companies were targeted in the partial lockdown measures. Second, local governments took effective measures to quickly contain the spread of the virus and have

Figure 5 presents descriptive evidence on the effect of the lockdown on city's exports. The figure illustrates the average export values of treated and non-treated cities in deviation from their monthly average for the period January 2018 to June 2020. The exports of the treatment and control groups followed almost the same trend in the months before the exogenous shock. Then, treated cities witnessed a greater reduction in their exports compared to non-treated cities, and a stronger rebound when lockdowns were lifted. Our baseline sample period is until April 2020 as Wuhan lifted its lockdown on April 8, and the average export growth of the treated cities overpassed the control group again in April.

[Figure 5 is about here]

4. Identification Strategy

4.1 Estimation specification

The unprecedented lockdown of cities provides us an unusual natural experiment. We use a difference-in-differences (DID) design to estimate the impact of disruption of the supply chain on trade performance. Given that the lockdown policy only lasted for a few months and the lifting of the lockdown in Hubei province meant that business resumed operations, high-frequency data is necessary since the use of quarterly data would miss key dynamics of the event (Bricongne et al., 2012).

To address seasonality concerns, we take the log difference of the outcome variable over 12 months and focus on the changes in the city's export growth between the current

done so arguably successfully.

month and the same month in the previous year (see also, Amiti et al., 2019; Handley et al., 2020). Our empirical strategy can be summarized in the following equation:

$$(1) \qquad \Delta \ \log Y_{ict} = \beta Lockdown_i \times After_t + \gamma X_{it} + \sum_t \theta_t X_i \times \lambda_t + \eta_i + \delta_{ct} + \varepsilon_{ict}$$

where i, c, and t denote city, destination, and time, respectively. Our outcome variable $\Delta \ \log Y_{ict}$ is the 12-month log difference of city-destination export values. The variable lockdown_i is a dummy that equals 1 if city i imposed a lockdown policy to restrict people's movement. After_t is also a dummy variable, which takes 0 for all months before February 2020, and 1 from February until April 2020. The coefficient of interest, β, compares a city's trade performance before and after a lockdown to that of cities without a lockdown during the same period. X_{it} includes a set of control variables with time-varying city characteristics, such as average temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration.

As shown in Appendix Table A3, cities were lockdowns were implemented tend to be larger in population, and have a higher (lower) share of secondary (primary and tertiary) industry value added. We therefore control for the interaction between a city's pre-lockdown characteristics, i.e., average monthly export for 2019, and time dummies to allow for heterogenous flexible trends in outcomes among cities with different initial export sizes. This is represented by $\sum_t \theta_t X_i \times \ \lambda_t$ in equation (1). Moreover, we also include the interaction between total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, and time dummies to control for the presence of pre-lockdown differences between treated and untreated cities (Lu et

al., 2019).

η_i represents city fixed effects to control for time-invariant city characteristics. δ_{ct} represents the destination-time fixed effects that aim to control for time-varying factors like demand shocks and the stringency of lockdown measures across importer countries. ε_{ict} is the error term. As our independent variable of interest is at the city-level, we cluster standard errors at this level to control for potential serial correlation.

5 Results

This section presents empirical results for the impact on exports of lockdowns in Chinese cities. Section 5.1 examines the impact on exports of treated cities. Section 5.2 examines whether the impact is conditional on the share of potential teleworkers, the ICT infrastructure, the location of the city, and the share of processing trade. In section 5.3 we explore whether the impact is conditional on product and sector characteristics. Section 5.4 examines whether the impact is conditional on dependence of foreign intermediate inputs. Finally, section 5.5 examines the impact of lockdowns on the intensive and extensive margin of exporting.

5.1 Baseline Results

Table 1 presents estimates for the impact of the lockdown on the year-on-year growth rate of the city's exports. The first column only includes city fixed effects and destination-time fixed effects. The estimated coefficient on the interaction term $\text{Lockdown}_i \times \text{After}_t$, is negative and statistically significant, suggesting that cities in

lockdown experienced a sharper reduction in the export growth rate relative to cities in the control group.

[Table 1 is about here]

We include time-varying weather controls such as temperature, relative humidity and precipitation in Column (2), which are used to control for potential climate shocks. Only precipitation has a negative and statistically significant relation to the outcome variable, while other weather factors like temperature and humidity are not statistically significant.[8]

To control for heterogeneous trends in outcomes among cities, we further include the interaction between the log value of the city's average monthly exports during the pre-policy period and time dummies in Column (3). The coefficient of -0.341 on the interaction term $\text{Lockdown}_i \times \text{After}_t$ suggests that on average cities in lockdown expierenced a 34% percentage point lower export growth rate compared to cities without a lockdown. The effect is also economically substantial. The sample mean exports between a city-destination pair is 8.80 million dollars. Hence, the average additional decline in exports of cities in lockdown is 3 (= 8.80×0.341) million dollars.

5.2 Heterogeneous treatment effects

This sub-section investigates possible heterogeneous treatment effects of cities in

[8] These results are not shown for the sake of brevity, but available upon request.

lockdown. We split treated cities into two groups according to four metrics: the fraction of teleworkable employment, mobile phone penetration, whether the city is along the coast or not, and the processing trade share. Specifically, we categorize cities into two groups, according to whether the city is above or below the sample median on these four measures. Table 2 presents the results, which are discussed in turn.

[Table 2 is about here]

5.2.1 Heterogeneous effects in the share of potential teleworkers

To contain the spread of the virus, firms are required to implement strict policies and practices such as social distancing in the workplace. Workers have to wear masks if admitted to be physically present on site, and students are not allowed to leave campus without permission. Working at home is an alternative, but not all tasks can be performed at home. According to Dingel and Neiman (2020), 37 percent of jobs in the USA can be performed at home, varying significantly across sectors.

Bonadio et al. (2020) documented that the average fraction of work can be done at home is 33.9 percent for manufacturing, while the average share is 54.3 percent for services. China, the world's largest manufacturing factory, would therefore face a tough trade-off between resuming businesses and prevention and control of the virus. Using a sample from China's 2010 Population Census (the latest census data) with 4,667,340 observations, we estimated the share of jobs in manufacturing industries that can be performed at home in China (see the online data appendix).

The pandemic forced employees to work from home. Hence, cities with a higher share of potential teleworkers are expected to be more resilient to a lockdown. Consistent with this argument, the estimated coefficients presented in Columns (1) and (2) show that the impact of lockdowns on the year-on-year export growth rate is smaller for cities with a higher share of potential teleworers (i.e., -0.274 for cities with higher teleworkable employment *vs.* -0.436 for other cities). This heterogeneity in treatment effects is statistically significant across the two subgroups.

5.2.2 Heterogeneous effects depending on the ICT infrastructure

Information and Communication Technologies (ICT) play a critical role for limiting coordination costs in fragmented production networks (Abramovsky and Griffith, 2006; Baldwin, 2011; Blyde and Molina, 2015). Video calls and online meetings make it possible to coordinate production without having face-to-face contact. Moreover, a well-developed ICT infrastructure may make it easier to find alternative suppliers if firms are faced with supply disruptions.

We thus conjecture that cities in lockdown with a better developed ICT infrastructure are more resilient and witness a lower decline in exports. Specifically, we use mobile phone subscriptions per 100 inhabitants to proxy the city's ICT infrastructure. The coefficient of lockdown in Column (3), i.e. -0.256 is about half that of Column (4), i.e. -0.460, suggesting that cities with better ICT infrastructure are more resilient to lockdowns. The equality test for the coefficients shows this heterogeneity is also statistically significant.

5.2.3 Heterogeneous effects for the location of the city

Many local governments carried out travel restriction measures such as partially shutting down highway entrances or canceling trains to prevent the outbreak of coronavirus, especially for cities adjacent to Hubei province. Moreover, roadblocks were set up to control people's movements, which especially happened in rural areas where medical resources were short in supply. Maritime transport is still a dominant way to export goods, and inland cities as a result would suffer an increase in the time lost to bring goods to ports.

Hence, inland cities might export less compared to coastal cities when facing a lockdown, which could be even more pronounced for cities exporting time-sensitive goods (Hummels, 2001; Hummels and Schaur, 2013; Djankov et al., 2006, 2010). Consistent with this logic, the estimated coefficients presented in Columns (5) and (6) show that merchandise export growth among coastal cities in lockdown decreased by less (i.e., -0.279) compared to their inland counterparts in lockdown (i.e., -0.396). The p-value of 0.042 indicates that heterogeneous treatment effects are statistically significant for these two sub-samples.

5.2.4 Heterogeneous effects depending on the share of processing trade

Processing trade played an important role in China's merchandise exports during the 2000s. However, the proportion of processing trade in China's total exports has fallen steadily and is 29.4 percent by 2019. Processing trade might fall more sharply due to a contraction on both the supply- and the foreign demand-side during the global

pandemic. Hence, cities with a higher processing trade share could be hit harder. In our baseline regressions, we include destination-time fixed effects to absorb such demand-side shocks.

However, processing trade is also likely more labor-intensive, resulting in extra production costs for the prevention and control of the spread of the virus. If this is the case, we would expect that the effects of lockdown are larger for cities with an above-median proportion of processing trade. Columns (7) and (8) of Table 2 present the estimates of lockdown on cities' exports over these two groups. The coefficient on the interaction term is slightly larger for cities with a lower processing trade share. Nonetheless, the test for equality of coefficients reports a p-value of 0.302, suggesting that there is no significant heterogeneity between these two groups.

5.3 Heterogeneous effects by product and sector characteristics

The trade data for cities does not allow us to examine effects conditional on product characteristics and neither to disentangle quantity and prices. Instead, we turn to provincial export data at the HS 8-digit level and calculate unit product prices by dividing export values by quantities. Even though the dataset is comprehensive, there is one constraint (due to the new practice of China Customs) namely that the provincial trade data for January and February 2020 are combined. To be consistent with the organization of data, we combine the export data of January and February for 2018 and also for these months in 2019 and then as before measure the log change of the outcome variables over 12-months.

In Appendix Table A4 we regress the log change in the outcome variable on the triple interaction between our main interaction term and four different measures of product and sector characteristics used in the literature: (i) time sensitivity at HS 4-digit product level (Hummels and Schaur, 2013); (ii) measures of industry upstreamness constructed from China's 2017 Input-Output table (Antràs et al., 2012); (iii) an indicator for differentiated goods (Rauch, 1999); (iv) inventory to sales ratio's constructed from China's industrial production survey.

The main findings are as follows. First, we find that time-sensitive goods experienced a sharper reduction in export growth in terms of values, quantities, and prices, confirming that time can be an important trade barrier. Second, differentiated goods that typically have longer supply chains and tend to be more dependent on relationship-specific investments also witnessed a larger reduction in export growth, both in values and quantities. The insignificant coefficient estimate for unit values suggests the lockdown did not impact prices received by domestic exporters.

Third, downstream products experienced a relatively larger reduction in export growth compared with upstream products, which could relate to downstream products being more sensitive to supply shocks as downstream plants are more likely running short of intermediate inputs during the post-lockdown period. Finally, the coefficients for the interaction terms of the inventory to sales ratios are positive but not statistically significant for values and quantities, although the estimate for unit values is negative. Taken together, the results suggest heterogeneity in the impact on exports of lockdowns conditional on product and sector characteristics.

5.4 Disruption to supply chains: accounting for input-output relations

This section aims to examine the effects of supply disruptions at the sector level, taking into account international supply chain relations.

To contain the spread of Covid-19, local governments restricted people's movements across cities and provinces. However, to balance the tradeoff between the spread of the virus and economic costs, local governments announced that firms with a relatively complete supply chain within the province would enjoy priority in resuming business. Furthermore, local customs offices implemented travel restrictions on inbound passengers, together with strict sanitary inspection and Covid-19 tests on imported goods. Thus, we conjecture that sectors depending more (less) on imported (domestic) intermediate inputs would be more (less) affected by supply disruptions due to the lockdown.

We aggregate province-destination-product (HS-8 digit level) data to the province-destination-sector level using the concordance provided by China's National Bureau of Statistics.[9] This enables using input-output linkages to examine the extent to which supply disruptions affect the export of sectors. We use three related indicators of dependence on imported intermediate inputs.[10] We estimate a triple difference-in-differences specification that compares export growth by sector with varying

[9] We are indebted to Mr. Jie Chen, Director of the Department of Input-Output Accounting at the National Bureau of Statistics, for providing the concordance table between HS codes and input-output sectors.

[10] They are, respectively, the direct import coefficient (defined as import per unit of output), the total import coefficient (defined as direct import coefficient multiplied by the Leontief inverse), and the domestic value added content in exports (see e.g., Hummels et al., 2001; Chen et al., 2018). The data are from China's 2017 Input-Output table, which is the latest benchmark table available, with imported and domestically produced intermediate inputs distinguished.

dependence on imported intermediate inputs (first difference) before and after 2020 (second difference) and across provinces with and without a lockdown (third difference). The regression is summarized in the following equation:

(2) $\Delta \log Y_{pcst} = \beta(Lockdown_p \times After_t \times Import\ dependency_s) + \lambda_{ps} + \eta_{pt} + \delta_{cst} + \epsilon_{pcst}$

The outcome variable denotes the change in log exports of province *p*, for sector *s*, to country *c* at month *t*. The independent variable of interest is the interaction term between, $Import\ dependency_s$, defined as the fraction of required imported intermediate inputs for sector *s* to produce one unit of output, $Lockdown_p$, a dummy variable for Hubei province, and $After_t$, a dummy variable taking the value of one for the year of 2020 (noting that for the trade statistics by province, January and February have been combined). In equation (2), λ_{ps}, η_{pt}, and δ_{cst} are province-sector fixed effects, province-time fixed effects, and destination-sector-time fixed effects to control for time-invariant province-sector characteristics and time-varying unobserved shocks across provinces and destination-sectors, respectively. We cluster standard errors at the province-sector level to account for potential serial correlation.

[Table 3 is about here]

Table 3 presents the results from estimating equation (2). The coefficient of interest on the triple interaction term is negative and statistically significant, suggesting that sectors

that rely more on imported intermediates experienced a stronger decline in exports when local governments enforced a lockdown (see column 1). The negative coefficient of 1.7 suggests that going from the 25th to the 75th percentile (from 0.02 to 0.10, respectively) in imported input dependency translates into an additional decrease of 13.6 (=1.7*(0.10-0.02)*100) percentage point export growth rate.

Column (2) uses a more sophisticated measure of import dependence, namely the direct import coefficient multiplied by the Leontief inverse of the matrix of domestic intermediate inputs. This aims to capture the total effect of imports embodied in domestic inputs. The results are similar. Comparing the results in columns (1) and (2), the direct effect appears larger compared to the total effect. A possible explanation for this is that the indirect impact takes time before it propagates from sector to sector, yet the analysis examines short-run effects only.

Finally, the coefficient on the triple interaction term in Column (3) is positive and statistically significant, suggesting that sectors with a relatively higher domestic value added share (i.e. sectors that are relatively less exposed to foreign intermediate inputs) are associated with a comparative lower reduction in the export growth rate.

5.5 Adjustments in the extensive margin

This last sub-section examines the effect of the lockdown on the city's probability to export to foreign markets. We consider all possible export destinations from January 2018 through April 2020. We fill the trade matrix with ones whenever the export value is positive and zeros otherwise. Hence, $Export_{ict}$, denotes whether city i exports to a

specific foreign market *c* in month *t*.

Second, we create three dummies: (i) $Entry_{ict}$, a dummy variable which indicates whether the city entered a new foreign market compared to the same month in the previous year; (ii) $Exit_{ict}$, a dummy variable which indicates whether the city exits a foreign market compared to the same month in the previous year;[11] and (iii) $Surviving_{ict}$, a dummy variable indicating the city continues exporting to the specific foreign market during the same month of two consecutive years. The estimated specifications are summarized in Equations (3)-(6):

$$(3)\quad Export_{ict} = \beta Lockdown_i \times After_t + \gamma X_{it} + \sum_t \theta_t X_i \times \lambda_t + \eta_i + \delta_{ct} + \varepsilon_{ict}$$

$$(4)\quad \begin{aligned} Entry_{ict} &= 1\left[Export_{ict} = 1 \cap Export_{ict-12} = 0\right] \\ &= \beta Lockdown_i \times After_t + \gamma X_{it} + \sum_t \theta_t X_i \times \lambda_t + \eta_i + \delta_{ct} + \varepsilon_{ict} \end{aligned}$$

$$(5)\quad \begin{aligned} Exit_{ict} &= 1\left[Export_{ict} = 0 \cap Export_{ict-12} = 1\right] \\ &= \beta Lockdown_i \times After_t + \gamma X_{it} + \sum_t \theta_t X_i \times \lambda_t + \eta_i + \delta_{ct} + \varepsilon_{ict} \end{aligned}$$

$$(6)\quad \begin{aligned} Surviving_{ict} &= 1[Export_{ict} = 1 \cap Export_{ict-12} = 1] \\ &= \beta Lockdown_i \times After_t + \gamma X_{it} + \sum_t \theta_t X_i \times \lambda_t + \eta_i + \delta_{ct} + \varepsilon_{ict} \end{aligned}$$

The empirical results are presented in Table 4. Intuitively, the coefficient of interest, β, is expected to be negative, negative, positive, and negative for Equations (3), (4), (5),

[11] Note that the analysis in this sub-section is at the city-level and the time interval is a month. If the exit dummy is 1, it implies all firms registered in the city did not export to a specific destination, which could be a rare event. In fact, with firm-level, data at a monthly frequency one may observe spurious entry and exit. Yet at the city-level, by construction, this is less likely.

and (6), respectively. In Column (1), the coefficient on the interaction term $Lockdown_i \times After_t$ is negative and statistically significant, suggesting the lockdown reduces the probability of exporting. This effect is split into entry and exit effects in Columns (2) and (3). As expected, the lockdown is associated with a reduction in the probability to enter a new foreign market. On average, the treated city witness a 2.5 percentage point lower probability to enter a new market, yet the coefficient is not statistically significant.

[Table 4 is about here]

The probability to exit, shown in column (3), is positive and significant. The estimate suggests treated cities experienced a 4.8 percentage point higher probability to exit a foreign market relative to cities in the control group. Finally, the result in Column (4) suggests treated cities have a lower probability to continue exporting to a foreign market. Summing up, we find a significant negative effect of lockdown on the city's extensive margin of exporting.

6. Robustness check

This section examines several potential issues that could affect our baseline specification. They are i) pre-existing trends test, ii) placebo tests, iii) more robustness check by altering core variables, and iv) addressing endogeneity issues. The findings presented in this section suggest our baseline results are robust.

6.1 Pre-existing Trends

One key assumption in the DID identification strategy is the parallel trends assumption: Without a lockdown policy, the export of treated cities would have evolved in the same way as that of cities in the control group. To examine whether there is a common pre-existing trend across treated and untreated cities, we replace the $After_t$ dummy in the interaction term $Lockdown_i \times After_t$ with monthly dummies that equal one except for the reference month, January 2020. This specification enables us to treat the coefficient estimates relative to a base month before lockdowns were enforced.

In particular, we bin event times ≤-6 together (i.e., for the period 6 months and earlier ahead of the lockdown policy, we let them equal to those exactly 6 months prior to the lockdown was implemented) and then re-estimate Equation (1). The coefficients of interest are those on the interaction before the lockdown. If trends are similar, the coefficient is small in magnitude and statistically insignificant. Figure 6 plots the interaction coefficient along with the 95 percent confidence intervals. Before the lockdown, the coefficients are close to 0 and statistically insignificant, suggesting trends were similar in treated and untreated cities. It is comforting that the average negative effects of the lockdown are only significant during the first three months after lockdowns were introduced. Furthermore, there is a sign of recovery in the third month, April 2020.

[Figure 6 is about here]

6.2 Placebo Tests

Another concern is that our main findings are driven by chance. This sub-section

presents three placebo tests. First, cities adjacent to Hubei province might be more likely to implement a lockdown. If so, we would expect these cities experience lower export growth compared to other cities. We assign 13 cities contiguous to Hubei province to the treatment group and rerun the main regression. We exclude the cities with a "true" lockdown in Column (1) of Table 5 and include them in Column (2) for comparison. The coefficients for the interaction term are trivial in magnitude and statistically insignificant, suggesting there is no significant difference between neighboring and other cities.

Secondly, an alternative falsification test is to focus on the 26 cities that reported zero confirmed cases by the end of June 2020. For these cities, the travel restrictions targeted to contain the spread of the virus are likely less stringent, and companies located in these cities could resume businesses quicker and earlier compared to other cities. If so, we expect the coefficient of the interaction term for these cities' dummies and the period dummy not to differ from zero; otherwise, there could be confounding factors driving our main findings. The results in columns (3) and (4) show the coefficients of interest are not significantly different from zero. This suggests the main findings are likely not driven by other confounding factors.

[Table 5 is about here]

Third, we randomly allocate to the treatment group 23 out of the 353 cities in our main regressions, assuming these cities imposed a lockdown in February 2020. Then we run Equation (1) with these randomly chosen cities and save the coefficient estimates on

the interaction term $Lockdown_i \times After_t$. We repeat this procedure 1,000 times and plot these coefficients.

Figure 7 presents the distribution of the coefficients. The actual coefficient drawn from Column (2) of Table 1 lies well to the left of the distribution. In particular, the actual coefficient on the interaction term $Lockdown_i \times After_t$ is -0.34, around 4 standard deviations (0.083) larger than the mean (-0.001) of the distribution. This provides further reassuring evidence that it is the lockdown rather than other confounders that drive our main results.

[Figure 7 is about here]

6.3 Robustness checks

This sub-section, provides further robustness checks of our main results. First, we consider alternative measures to proxy the stringency of the lockdown. Column (1) of Table 6 shows results if we consider the number of monthly newly confirmed cases. The virus is transmitted from person to person. Hence, once there is an infected case, residents living in the same building or even the whole community face restrictions in their movement. Thus new cases imply a strengthening in control and prevention measures, which are likely to slow down supply chain recovery. The coefficient of the interaction term is negative and significant, suggesting that newly confirmed cases are negatively associated with the city's export growth. Alternatively, column (2) uses the total cumulative case load, and the results are similar.

Second, we consider cities with a full lockdown, while relegating cities with a

partial lockdown to the control group. The coefficient for the interaction term shown in column (3) is statistically significant as before, and more importantly, it is larger in magnitude. Third, we exclude observations for Yunnan province, which only reports aggregate export data for the first two months of 2020. About one percent of the observations for the whole sample are dropped, and the estimation results are given in Column (4).

[Table 6 is about here]

We use the 12-month log differences of export values for our main regressions, but one might be concerned that zero trade flows could drive the findings. To address this concern, we use alternative measures of our dependent variable, as well as alternative estimation methods. Appendix Table A5 reports the results for additional robustness checks.

First, to alleviate concerns our results are driven by zero exports that are omitted due to the log change specification, we use the inverse of the hyperbolic sine transformation, $\log[x + (x^2 + 1)^{0.5}]$, and re-estimate equation (1). The number of observations increases by about 55 percent. The coefficient for the interaction term in column (1) of Appendix Table A5 is statistically significant and similar in magnitude to the baseline results.

Second, following Bricongne et al. (2012), we replace the dependent variable with

mid-point growth rates.[12] To do so, we calculate the mid-point growth rates for each city-destination pair by month. In Column (2), the coefficient for the interaction term is again similar to the baseline results in magnitude and statistically significant.

Third, we carry out another robustness check by using the Poisson-pseudo-maximum-likelihood (PPML) estimator, which allows inclusion of zero trade flows (Silva and Tenreyro, 2006). It is worth noting that the estimator precludes us to take log difference of the outcome variables of interest, as the difference may lead to negative dependent variables. Thus, we use city-quarter fixed effects instead to address seasonality concern in our outcome variables. The coefficient on the interaction term is not directly comparable with our earlier results, still the results shown in Colum (3) confirm the baseline findings.

6.4 Endogeneity

Because the Chinese government did not implement a lockdown during the 2003 SARS epidemic, it is plausible to consider the lockdown in Wuhan and other cities as an exogenous shock. However, one might still be concerned that there was a reverse causality, i.e., cities that interact intensively with Wuhan were more likely to implement a lockdown policy to contain the spread of Covid-19.[13] To formally address this concern, we instrument the lockdown policy using the city's distance from Wuhan, and run a two-stage least squares (2SLS) regression.

[12] For a typical city i exporting value of x to region c at month t, the mid-point growth rate is defined as follows: $g_{ict}=(x_{ict}-x_{ic,t-12})/[\frac{1}{2}(x_{ict}+x_{ic,t-12})]$.

[13] We regress an indicator if the city implemented a lockdown on the log value of the city's monthly average export value in 2019. The estimated coefficient is 0.0078 (s.e. 0.0058) suggesting that local trade has little predictive power on whether a lockdown was enforced.

The first and second-state regressions take the following form:

(7) $$Lockdown_i \times After_t = \alpha_0 + \alpha_1 \log Distance_i \times After_t + \alpha_2 X_{it} + \sum_t \theta_t X_i \times \lambda_t + \eta_i + \delta_{ct} + \varepsilon_{ict}$$

(8) $$\Delta \log Y_{ict} = \beta \widehat{Lockdown}_i \times After_t + \gamma X_{it} + \sum_t \theta_t X_i \times \lambda_t + \eta_i + \delta_{ct} + \varepsilon_{ict}$$

The city's distance from Wuhan is our instrumental variable, which is time-invariant. To facilitate the interpretation of the quantitative implications of the estimates, we use the standardized value of log distance between the source city and Wuhan.[14] Other control variables and fixed effects are defined as before (see equation 1).

The parameter of interest is the second-stage parameter β, which captures the causal effect of the lockdown on the city's export growth. An instrumental variable analysis needs to meet three conditions: (i) the source city's distance from Wuhan is correlated with its lockdown policy (relevance); (ii) the distance is exogenous; and (iii) the distance exclusively affects the source city's export growth through its first-stage impact on whether a lockdown is enforced (exclusion condition).

According to Jia et al. (2020), there were 11,478,484 people, who were potential infectors, migrating from or transiting through Wuhan during the period from 1 January to 24 January 2020. In particular, 8,685,007 of the total moved to other prefectures within Hubei, while the remaining 2,793,477 persons moved to prefectures in other provinces. It is clear that most potential infectors traveled within a short distance from Wuhan, and thus this fact provides an opportunity to use the city's distance from Wuhan to instrument the probability of the lockdown.

[14] Following Head and Mayer (2002) we calculate the distance to Wuhan as: $d_{ii}=0.67(\text{area}/\pi)^{1/2}$.

[Table 7 is about here]

Table 7 presents results from 2SLS regressions. Panel A provides the second-stage estimates of lockdown on the city's export growth, while Panel B shows the first-stage results to examine the validity of the IV. Consistent to the baseline OLS estimates, the coefficients for the interaction term is negative and statistically significant. A lockdown is associated with a 51.5 percentage point lower export growth rate. This result suggests the OLS estimate (a 34.1 percentage points reduction in the growth rate) is possibly biased upwards. Most importantly, the results are reassuring in the sense that they suggest a causal relationship between the lockdown and a slowdown in the city's export growth.

7. Mechanisms

The lockdown in Wuhan and other cities impeded people's mobility and disrupted supply chains. This section offers suggestive evidence on the disruption. First, we examine the role of the lockdown in restricting people's movements. Following Fang et al. (2020) and Chen et al. (2020), we use the Baidu Qianxi dataset, which provides us three migration intensity indicators. These three indicators are the daily in-migration Index (IMI), the daily out-migration index (OMI), and the daily within-city migration index (WCMI), respectively. Because the dataset has daily observation, it enables us to define the treatment and control group in a more flexible way. Our regression

specification is as follows:

$$(9) \quad logY_{it} = \alpha + \beta Lockdown_{it} + \gamma X_{it} + \lambda_i + \delta_t + \varepsilon_{it}$$

where Y_{it} represents the three daily migration intensity indicators. $Lockdown_{it}$ is a dummy variable, which takes the value 1 if the city imposed a lockdown on that date and 0 otherwise. X_{it} denotes the weather controls similar to Equation (1). λ_i and δ_t represent city and time fixed effects, while ε_{it} is the error term. The coefficient of interest, β, estimates the difference in the outcome between the treated and control cities.

We include city fixed effects to control for time-invariant city characteristics like geographical conditions that may affect our outcomes. Also, we include date fixed effects to account for nationwide shocks that are common to all cities, such as the Spring Festival holidays. To control for heterogeneity and possible serial correlation, standard errors are two-way clustered by city and time.

Table 8 presents estimates for the relation between lockdown and mobility. The coefficient of interest, β, is negatively and statistically significant in all of the three columns. The coefficients imply that cities in lockdown experienced a 52.4 percent reduction in the in-migration index, a 47.8 percent decrease in the out-migration index, and a 24 percent decrease in the within-city migration index compared to cities without formal lockdown policies. These measures concern population movements for various purposes, of which business travel is only one of the possible purposes. Nevertheless, it suggests the underlying mechanism is plausibly at work here.

We also conduct an event study to check the dynamic effects of lockdown on

people's movements. To do so, we replace the lockdown dummy with a set of dummies indicating the treatment status before and after the lockdown. In particular, we put seven days into a bin to avoid the noise caused by fluctuations of daily measures. The benchmark week is one week before the introduction of lockdown.

We plot the coefficients on the dummies in Appendix Figure 1. It illustrates that the effect of a lockdown may last as long as seven weeks for the out-migration index (Panel B) and the within-city migration index (Panel C), and even more than eight weeks for the in-migration index (Panel A). Although the coefficient on lockdown status for four weeks or longer is negative and statistically significant in Panel A, its magnitude is smaller than those for post-lockdown weeks. Moreover, pre-existing trends in treated and untreated cities are presumably similar, as the coefficients in Panel B and Panel C for lockdown status are not statistically significantly different from zero before the introduction of the lockdown.

To the best of our knowledge, statistics offices do not collect inter-city trade data, so there is no official data to measure the monthly flow of goods among cities. Instead, we turn to use the less-than-truckload shipping data provided by G7, a leading technology firm of the Internet of Things (IoT) in China. The data includes the total number of waybill –a waybill is a list of goods being carried on a vehicle– inflows and outflows across provinces grouped into ten primary categories.[15] We only have access

[15] The number of waybills itself, however, cannot tell the quantity and value of the goods transported. In this sense, the results can only provide suggestive evidence that lockdown policies impeded the movement of goods. Specifically, the ten categories include daily necessities: *agricultural goods, food and beverage, daily use items; industrial goods: chemicals, minerals and metals, manufacturing goods and machinery equipment, and building materials; and other goods: furniture and home furnishing, home appliance and electronics, clothes and textiles*.

to the province-level waybills data from 2019 January to 2020 April, and thus we restrict the treated province to Hubei province, whose prefectures and province-managing cities (except for Shennongjia Forestry District) all imposed a lockdown by the end of January 2020. Furthermore, we restrict the sample period to the first four months for 2019 and 2020 to account for the seasonal changes. In particular, we implement this investigation by running the following regression:

$$Y_{pkt} = \alpha + \beta_1 Lockdown_p \times After_t + \beta_2 Lockdown_p \times After_t \times Daily_k + \beta_2 Lockdown_p \times After_t \times Industrial_c + \gamma X_{pt} + \lambda_{pk} + \delta_{kt} + \varepsilon_{pkt} \quad (10)$$

where Y_{pt} denotes the province p's total number of waybill inflows or waybill outflows of category k at month t. We employ a PPML estimator to conduct this examination, as our dependent variable is a count. Lockdown is a dummy variable, which takes the value of 1 for Hubei province and 0 otherwise. $After_t$ takes 1 for February 2020 onwards, and 0 otherwise. We also include a triple-interaction term to examine whether there is a heterogeneous effect between daily necessities, industrial goods and other goods. X_{it} denotes the weather controls similar to Equation (1), and we include the province-category fixed effects to control for time-invariant provincial characteristics and category-time fixed effects to control for shocks to goods supply or demand. The standard errors are clustered at by province and category.

[Table 8 is about here]

The results are presented in columns (4) and (5) of Table 8. The coefficient for the

interaction term is negative and statistically significant, suggesting the lockdown impeded the movement of goods. Given that Hubei province relied on inflows from other provinces to satisfy demands for daily necessities during the lockdown, the government gave priority to the transport of theses goods. This is reflected in the coefficient on the triple interaction term for daily necessities, which is positive and statistically significant (see column 4). Interestingly, as shown in column (5), there is no significant heterogeneous effect between daily necessities and other goods exported by Hubei province. Finally, we observe no heterogeneous effect between industrial and other goods.

8. Concluding remarks

On March 11, 2020, the WHO characterized the outbreak of Covid-19 as a pandemic. Clearly, the pandemic has a major ongoing impact on health and mortality. It also has a major impact on economic performance (Baldwin and di Mauro, 2020). Policy responses to prevent the virus from spreading created a supply shock that reduced trade and economic growth.

This study uses real-time trade data at the city-level for China. We find that cities implementing a lockdown experienced a *ceteris paribus* 34 percentage point lower export growth rate compared to cities that did not. This effect translates to a 3 million US dollar additional decline in trade for cities in lockdown, implying a substantial welfare loss. The effect appears largely due to social-distancing policies, which were used to contain the spread of the virus via restricting people's mobility (echoing the

mechanism emphasized in Antràs, et al., 2020).

Most businesses in China resumed operations around April 2020 and have continued since. Hence, it appears that supply disruptions have come to an end. Moreover, the rapid recovery in cities' exports suggest the lockdown policy was cost-effective in terms of its impact on trade.[16]

Several other economies, such as Japan and South Korea, also successfully contained the spread of Covid-19 whereas others did not. Future research may therefore seek to investigate the impact of lockdowns on firm responses and trade performance across economies, both in the short- and long-run. More generally, examining the various socio-economic outcomes due to lockdown policies will be helpful for understanding the impact it has and guide future policymaking during pandemics.[17]

[16] From a behavioral perspective, experimental studies show that Chinese participants tend to cooperate in a public goods game under top-down governance (Vollan et al., 2017); which may differ from agents in other economies. In this regard, the cooperative nature of different agents should be taken into account when designing lockdown policies (see e.g. Akbarpour et al., 2020).

[17] For example, He et al. (2020) evaluate the short-term impact of the Covid-19 lockdown on urban air pollution in China. They find that lockdowns led to improvements in air quality, although PM 2.5 concentrations were still above WHO standards.

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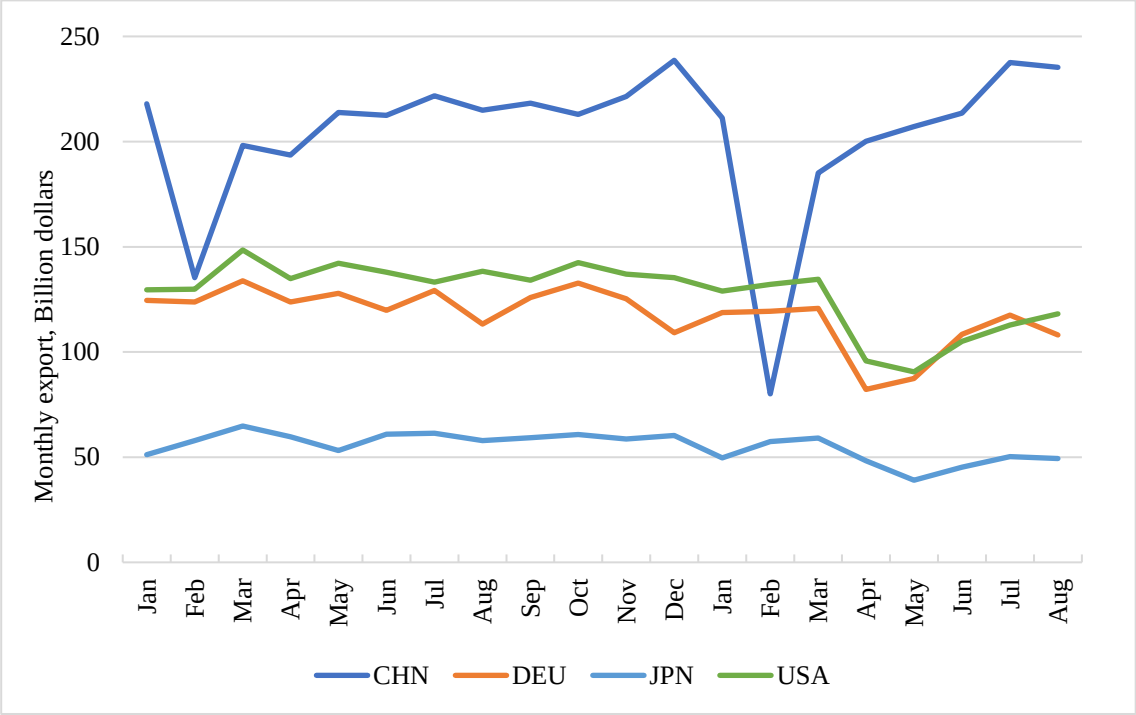


Figure 1 Monthly merchandise exports for selected countries, 2019-2020

Note: As China only reports aggregate export data for January and February in 2020, we sum up city-level monthly exports to obtain the value at country-level. Monthly export data for other countries are from WTO trade statistics.

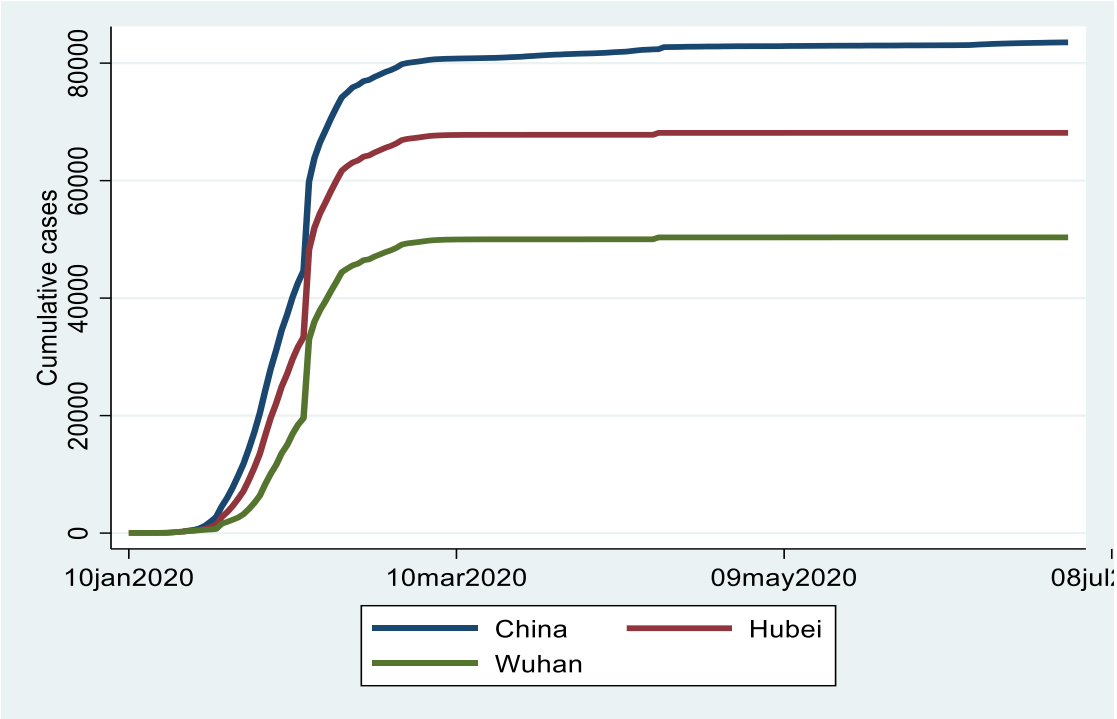


Figure 2 The distribution of China's cumulative COVID-19 cases

Data source: Authors' calculations using the CSMAR database

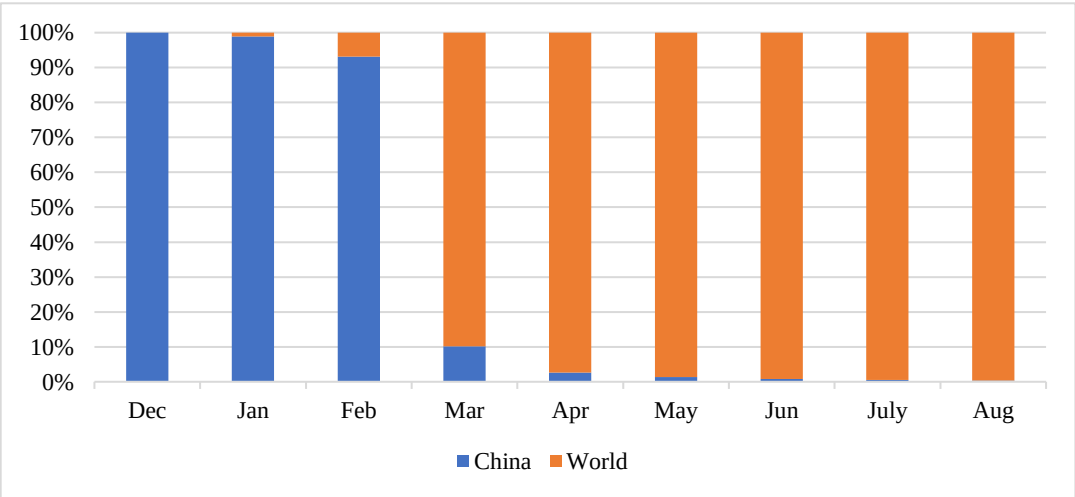


Figure 3 China's COVID-19 cases over the total cases worldwide

Data source: Authors' calculations using the CSMAR database

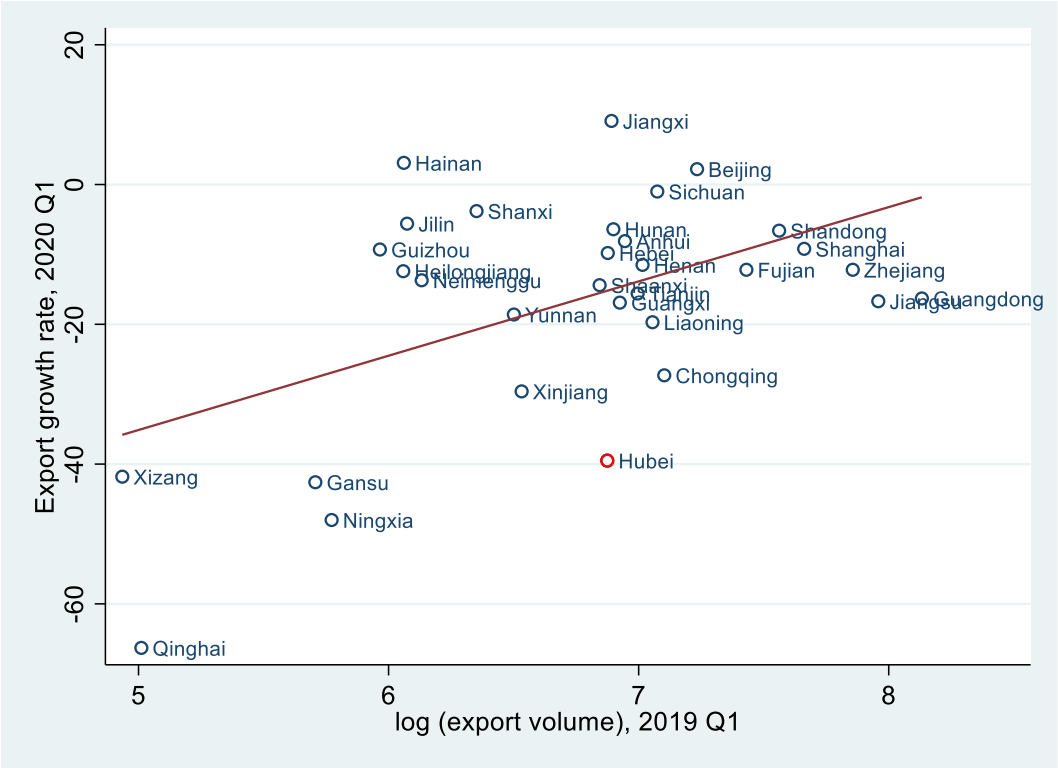


Figure 4 Year-on year export growth rate in 31 provinces for 2020 Q1

Source: Authors' calculations from the Customs data

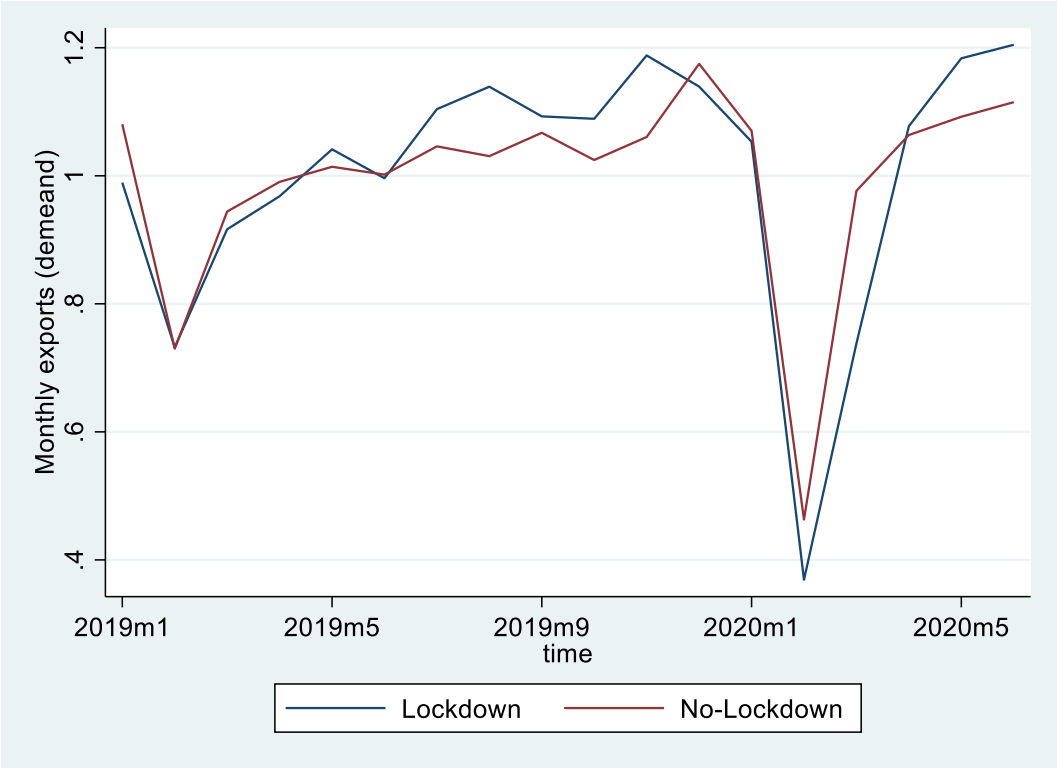


Figure 5 Deviations from the average export values by treatment status

Note: Demeaned export values of cities that went in lockdown and cities that did not. Values are demeaned by dividing the city's exports by their monthly average export value over the period from January 2018 to June 2020.

Data source: Authors' calculations from the Customs data

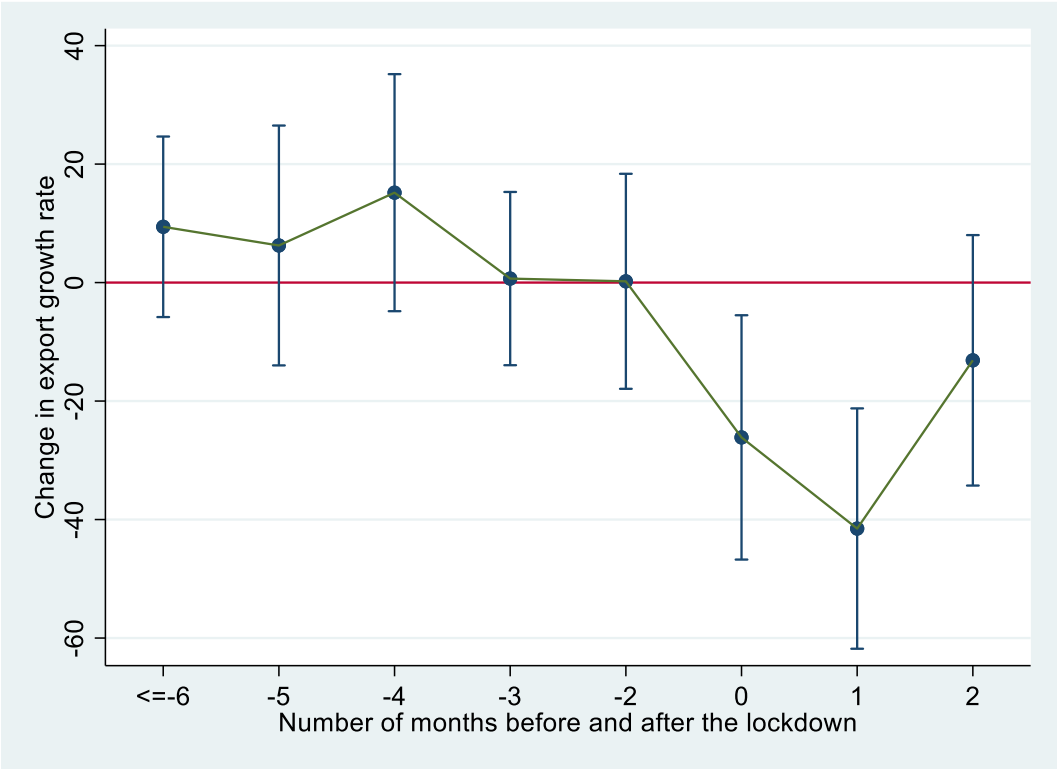


Figure 6 Event study of the lockdown policy

Data source: Authors' calculations from the Customs data

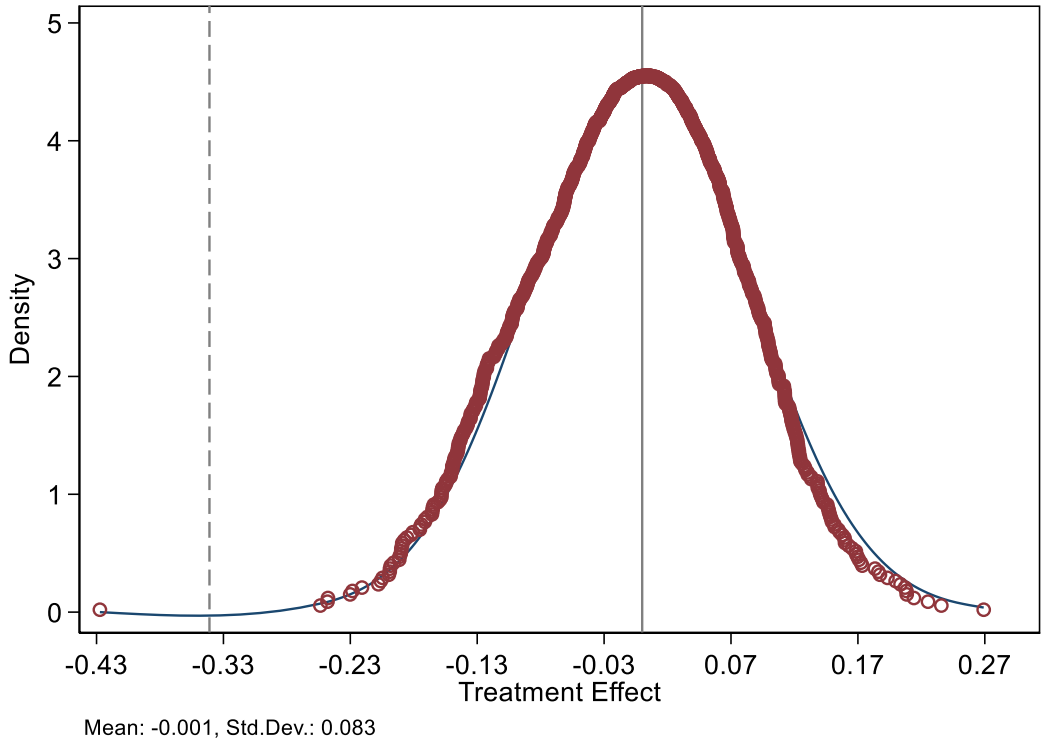


Figure 7 Placebo test with randomly chosen treated cities

Data source: Authors' calculations from the Customs data

Table 1 Baseline Results

VARIABLES	(1) Δ Exports	(2) Δ Exports	(3) Δ Exports
Lockdown × After	-0.353***	-0.349***	-0.340***
	(0.074)	(0.073)	(0.078)
Observations	359,356	359,332	359,332
R-squared	0.064	0.065	0.067
City FE	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes
Weather Controls		Yes	Yes
Covariates × Time dummies			Yes

Notes: Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the city's total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. The standard errors in parentheses are clustered at the city level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 2 Heterogeneous treatment effects

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Teleworkable employment		ICT infrastructure		Geographic location		Processing trade share	
	High	Low	High	Low	Coastal	Inland	High	Low
Lockdown × After	-0.274***	-0.436***	-0.256***	-0.460***	-0.279***	-0.396***	-0.279***	-0.315***
	(0.104)	(0.120)	(0.093)	(0.130)	(0.095)	(0.100)	(0.097)	(0.110)
Test for Equal Coeff.	p-value=0.033		p-value=0.021		p-value=0.042		p-value=0.302	
Observations	200,864	151,305	214,162	136,571	103,032	256,194	205,630	140,414
R-squared	0.084	0.077	0.083	0.073	0.117	0.073	0.081	0.094
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates × Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the city's total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. The standard errors in parentheses are clustered at the city level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 3 Results for supply disruptions at the sector level

VARIABLES	(1) Δ Exports	(2) Δ Exports	(3) Δ Exports
Lockdown × After × imported_input_ dependency (direct)	-1.700**		
	(0.807)		
Lockdown × After ×imported_input_ dependency (total)		-1.535**	
		(0.744)	
Lockdown × After × DVAR			0.248***
			(0.086)
Observations	1,344,658	1,344,658	1,344,658
R-squared	0.167	0.167	0.167
Province-Time FE	Yes	Yes	Yes
Province-Sector FE	Yes	Yes	Yes
Country-Sector-Time FE	Yes	Yes	Yes

Notes: The standard errors in parentheses are clustered at the province-sector level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 4 Results for extensive margin adjustment

VARIABLES	(1) Export	(2) Entry	(3) Exit	(4) Surviving
Lockdown × After	-0.055***	-0.025	0.048**	-0.029**
	(0.021)	(0.015)	(0.020)	(0.014)
Observations	555,233	555,233	555,233	555,233
R-squared	0.258	0.141	0.113	0.413
Weather Controls	Yes	Yes	Yes	Yes
Covariates × Time dummies	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes

Notes: Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the city's total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. The standard errors in parentheses are clustered at the city level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 5 Placebo Tests

VARIABLES	(1) Neighbor cities	(2) Neighbor cities	(3) Cities with zero cases	(4) Cities with zero cases
Neighbor × After	-0.035	-0.002		
	(0.093)	(0.093)		
Lockdown × After			-0.171	-0.141
			(0.118)	(0.126)
Observations	326,362	359,332	326,362	359,332
R-squared	0.065	0.066	0.065	0.066
Weather Controls	Yes	Yes	Yes	Yes
Covariates × Time dummies	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes

Notes: The odd-numbered columns exclude the cities with a "true" lockdown, while the even-numbered columns include the placebo and 'in true lockdown' cities. Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the city's total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. The standard errors in parentheses are clustered at the city level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 6 Robustness check

VARIABLES	(1) New cases	(2) Total cases	(3) Complete lockdown	(4) Exclude Yunnan
log New cases	-0.040**			
	(0.016)			
logTotal cases		-0.043**		
		(0.017)		
Lockdown × After			-0.417***	-0.413***
			(0.129)	(0.130)
Observations	359,332	359,332	359,332	355,688
R-squared	0.066	0.066	0.067	0.067
Weather Controls	Yes	Yes	Yes	Yes
Covariates × Time dummies	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes	Yes

Notes: Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the city's total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. The standard errors in parentheses are clustered at the city level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 7 2SLS Results

VARIABLES	(1) Δ Exports	(2) Δ Exports	(3) Δ Exports
Panel A: Second Stage			
Lockdown × After	-0.738***	-0.700***	-0.512**
	(0.248)	(0.244)	(0.205)
Panel B: First Stage			
logdistance ×After	-0.131***	-0.130***	-0.145***
	(0.025)	(0.025)	(0.025)
F-statistic instrument	24.15	23.86	28.90
Observations	359,332	359,332	359,332
City FE	Yes	Yes	Yes
Destination-Time FE	Yes	Yes	Yes
Weather Controls		Yes	Yes
Covariates × Time dummies			Yes

Notes: Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the city's total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. The standard errors in parentheses are clustered at the city level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 8 Results for mechanisms

VARIABLES	(1) IMI	(2) OMI	(3) WCMI	(4) Goods_IM	(5) Goods_EX
Lockdown	-0.524***	-0.478***	-0.240***		
	(0.124)	(0.0941)	(0.0663)		
Lockdown × After				-0.714***	-0.913***
				(0.050)	(0.082)
Lockdown × After × Daily				0.271***	0.164
				(0.076)	(0.117)
Lockdown × After × Industrial				-0.023	-0.174
				(0.063)	(0.141)
Constant	-6.696***	-6.672***	-0.0439	-18.710***	-7.312
	(2.107)	(2.182)	(1.320)	(4.387)	(8.511)
Observations	42,469	42,469	42,469	2,328	2,329
R-squared	0.939	0.918	0.789	0.978	0.976
Weather controls	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes		
Date FE	Yes	Yes	Yes		
Province-category FE				Yes	Yes
Category-time FE				Yes	Yes

Notes: Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. The standard errors in parentheses are two-way clustered at the city and daily level for Column (1)-(3), and robust standard errors are clustered at the province-category level in Column (4)-(5). ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Online Appendix

Data Construction

Employment share of potential teleworkers

First, we map the 3-digit China's SOC codes into 2-digit ISCO 88 codes, and we calculate the total employment by city and occupation using individual observations from China's 2010 population census. Second, following Dingel and Neiman (2020), if one 6-digit SOC code maps into two or more 2-digit ISCO codes, we allocate the SOC's US employment weight across the ISCO codes in proportion to ISCO employment shares in China. Third, we use the teleworkable share by occupation from Dingel and Neiman (2020), and then use the employment weight to calculate our city's measure of the employment share of potential teleworkers.

ICT infrastructure

We use mobile phone subscriptions per 100 inhabitants for 2018 to measure the city's ICT infrastructure level, obtained from the CEIC database, China City Statistical Yearbook, and China Statistical Yearbook (county-level). If 2018 is not available, we use the latest available year instead.

Geographic location

This is a dummy variable, which takes 1 for coastal cities, and zero otherwise. We obtained the city's geographic information from the map and web searching.

Processing trade share

We aggregate the firm's trade data at HS 8-digit level by trade type and city, and calculate the city's share of processing trade for 2016. This disaggregated transaction-level trade data is obtained from China's General Administration of Customs, and 2016 is the latest year available.

Sensitivity to delivery time

This measure is widely used to proxy the extent to which goods are sensitive to delivery time. We obtain this measure from Hummels and Schaur (2013), and we thank them for kindly sharing the data. We winsorized this measure at the 1st and 99th percentiles to drop extreme values.

Differentiated goods

Rauch (1999) classifies differentiated and homogeneous products depending whether it is sold on an organized exchange. We use the broad classification and the concordance provided by UN Comtrade to map the HS 2017 at 6-digit level to SITC Rev.2.

Industry upstreamness

Following Antràs et al. (2012), we construct this measure based on China's 2017 Input-Output table (the latest benchmark table), which includes 149 sectors. We use the concordance table provided by NBS to map the HS 8-digit product into the IO sectors. We take the logarithm of this measure.

Inventory to sale ratio

This measure aims to capture the extent to which the sector is resilient to supply disruptions. We extract the sales and inventory data from the China industry statistical yearbook for 2018, and then map the CIC 4-digit industry into IO sectors to calculate this ratio.

Dependency on imported intermediate inputs

This measure captures the extent to which the sector is dependent on foreign supplies. Three indicators are computed, i.e. the direct import coefficient, the total import coefficient, and domestic value added in trade. Using China's latest benchmark IO table for year 2017 with imported inputs and domestic inputs separated, we define the direct import coefficient as import per unit of total output. The total import coefficients are obtained by post-multiplying the Leontief inverse with the direct import coefficient

matrix. Further, we estimate the domestic content in exports by applying the formula proposed in Hummels et al. (2001) and Chen et al. (2018). Finally, these indicators are mapping to HS 8-digit products using the concordance provided by the National Bureau of Statistics.

Appendix Table A1 Date of Lockdown and Business Resumption

City	Province	Date of Lockdown	Date of Business Resumption
Panel A. Complete Lockdown			
Wuhan	Hubei	2020/01/23	2020/03/20
Huanggang	Hubei	2020/01/23	2020/03/10
Ezhou	Hubei	2020/01/23	2020/03/10
Xiaogan	Hubei	2020/01/24	2020/03/10
Jingzhou	Hubei	2020/01/24	2020/03/10
Suizhou	Hubei	2020/01/24	2020/03/10
Huangshi	Hubei	2020/01/24	2020/03/10
Yichang	Hubei	2020/01/24	2020/03/10
Jingmen	Hubei	2020/01/24	2020/03/10
Xianning	Hubei	2020/01/24	2020/03/10
Shiyan	Hubei	2020/01/24	2020/03/10
Xiantao	Hubei	2020/01/24	2020/03/10
Tianmen	Hubei	2020/01/24	2020/03/10
Enshi	Hubei	2020/01/24	2020/03/10
Qianjiang	Hubei	2020/01/24	2020/03/10
Shennongjia	Hubei	2020/01/24	2020/03/10
Xiangyang	Hubei	2020/01/28	2020/03/10
Panel B. Partial Lockdown			
Harbin	Heilongjiang	2020/02/04	From February 10, firms can resume work and production in areas where the epidemic is not severe and risk-controllable. While firms located in areas where the epidemic is severe and risk-control are difficult have resumed work and production in late February.
Wenzhou	Zhejiang	2020/02/02	February 18 or later for “whitelist” firms[18]; February 23 or later for other firms.
Hangzhou	Zhejiang	2020/02/04	From February 10, "whitelist" firms (e.g., those that are necessary for epidemic prevention and control, necessities for production and households) are allowed to declare and resume work in an orderly manner. From February 15, employees mainly from other non-epidemic areas and companies with relatively complete local

[18] http://www.gov.cn/xinwen/2020-02/12/content_5477911.htm

			supply chains are allowed to declare resumption of work. From February 20, the rest may resume work after reporting and review[19].
Ningbo	Zhejiang	2020/02/04	From February 10 onwards, key exporters, listed firms, key manufacturing firms, and other qualified firms, which have sufficient producing materials, well-prepared epidemic prevention measures, and a large proportion of local employees, have the priority to resume their businesses in an orderly manner.
Zhengzhou Zhumadian	Henan	2020/02/04	February 10 for firms with employees mainly from within the city, and supply chains located locally; February 17 for firms with limited employees from epidemic regions and with inputs mainly from local supply. The rest can resume work from February 24.
Fuzhou	Fujian	2020/02/04	February 10 for firms that are essential to the epidemic prevention and control, people's daily needs. Firms in Cangshan District cannot resume business before February 15. And firm can only resume work after reporting and review.

Data source: Fang et al.(2020) and authors' compilation based on information released by local governments.

Note: The local governments require firms that are necessary for epidemic prevention and control like mask producers, for production and households like utilities and food supply to resume their businesses as soon as possible.

[19] http://qt.hangzhou.gov.cn/art/2020/2/9/art_1657687_41893302.html

Appendix Table A2 Summary Statistics

VARIABLES	N	Mean	S.D.	Min	Max
Δ log exports (year-on-year growth rate)	359,332	-0.01	1.60	-15.05	17.24
Exports (10 thousand dollars)	359,332	879.62	7,877.85	0.0001	942,019
Lockdown	359,332	0.09	0.29	0	1
After	359,332	0.18	0.38	0	1
Total cumulative cases (persons)	359,332	84.79	1,729.61	0	50,333
New confirmed cases (persons)	359,332	24.55	834.70	0	45,342
Temperature (℃)	359,332	15.08	9.42	-24.21	34.81
Precipitation (mm)	359,332	85.17	94.87	0	942.29
Wind speed (m/s)	359,332	2.20	0.60	0.64	5.60
Atmospheric pressure (hPa)	359,332	990.23	40.73	605.20	1,028.91
Relative humidity (%)	359,332	70.20	13.29	13.54	95.36
Sunshine duration (hours)	359,332	158.15	66.34	2.40	370.90
log average monthly exports, 2019	359,332	10.53	1.82	0.54	14.52
log total population, 2018	359,332	8.44	0.64	4.70	10.44
log hospital bed per 1000 persons, 2018	359,332	1.57	0.39	0.54	2.57
Industry value-added (% of GDP), 2018	359,332	0.43	0.08	0.12	0.73

Notes: The 359,332 observations refer to observations for 347 cities during 2019 January and 2020 April. Singleton observations are dropped, as our main regressions are estimated using the Stata *reghdfe* package developed by Correia (2014).

Sources: see main text.

Appendix Table A3 Summary statistics: city characteristics comparison pre-lockdown

Variables	Lockdown	Non-lockdown	Difference	Standard error
Average monthly export(log)	9.367	8.598	0.769	0.53
Total population (log)	8.345	7.931	0.414**	0.199
Hospital bed per 1000 population (log)	1.546	1.498	0.049	0.079
Industry value added (% of GDP)	0.451	0.41	0.041*	0.023

Appendix Table A4 Heterogeneous Treatment Effects, Product or Sector Characteristics

VARIABLES	(1) Δ Value	(2) Δ Quantity	(3) Δ Price	(4) Δ Value	(5) Δ Quantity	(6) Δ Price	(1) Δ Value	(2) Δ Quantity	(3) Δ Price	(4) Δ Value	(5) Δ Quantity	(6) Δ Price
Lockdown × After × time sensitivity	-0.894***	-0.452***	-0.442***									
	(0.160)	(0.099)	(0.091)									
Lockdown × After × differentiated				-0.205***	-0.176***	-0.029						
				(0.037)	(0.038)	(0.024)						
Lockdown × After × logupstreamness							0.416***	0.408***	0.008			
							(0.041)	(0.039)	(0.029)			
Lockdown × After × inventory sales										0.592	0.601	-0.009
										(0.416)	(0.461)	(0.278)
Observations	6,645,173	6,645,173	6,645,173	6,180,841	6,180,841	6,180,841	6,649,833	6,649,833	6,649,833	6,180,785	6,180,785	6,180,785
R-squared	0.271	0.264	0.245	0.281	0.274	0.253	0.266	0.260	0.241	0.268	0.261	0.242
Province-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-HS-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

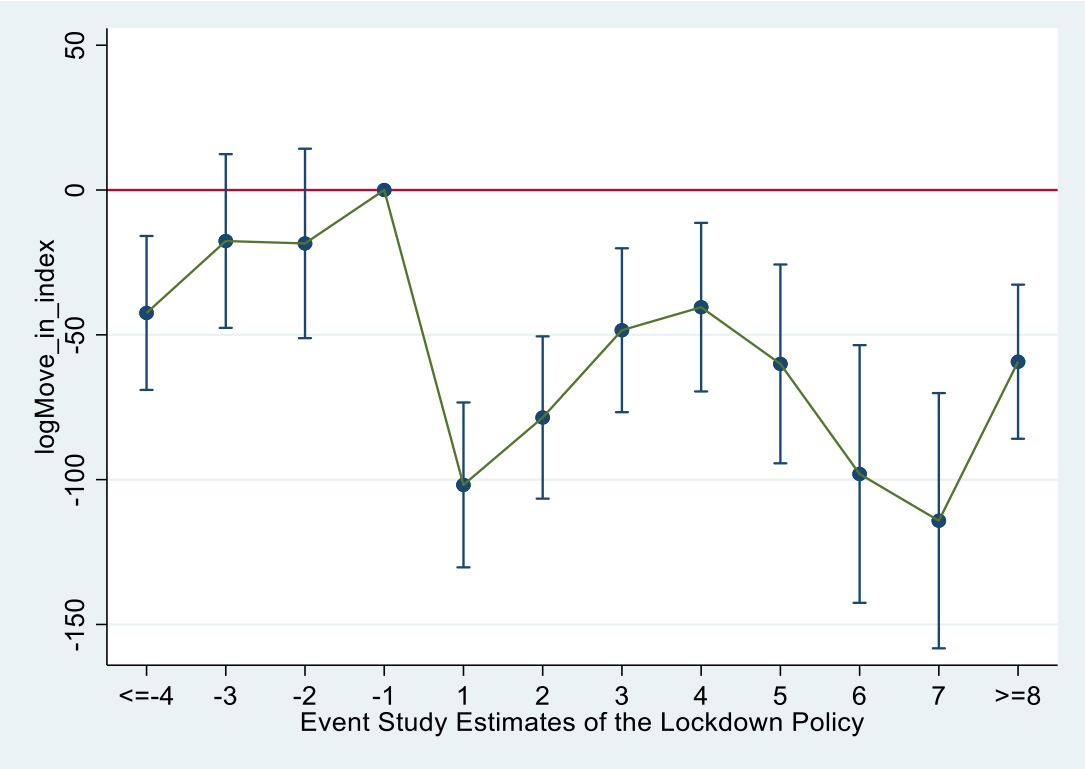
Notes: Column (1) includes province-HS4 fixed effects; Column (2) includes province-HS6 fixed effects; Column (3) and (4) include province-IO sector fixed effects. The standard errors in parentheses are two-way clustered at the province and HS-8 digit level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Appendix Table A5 Additional Robustness checks: Zero Trade Flows

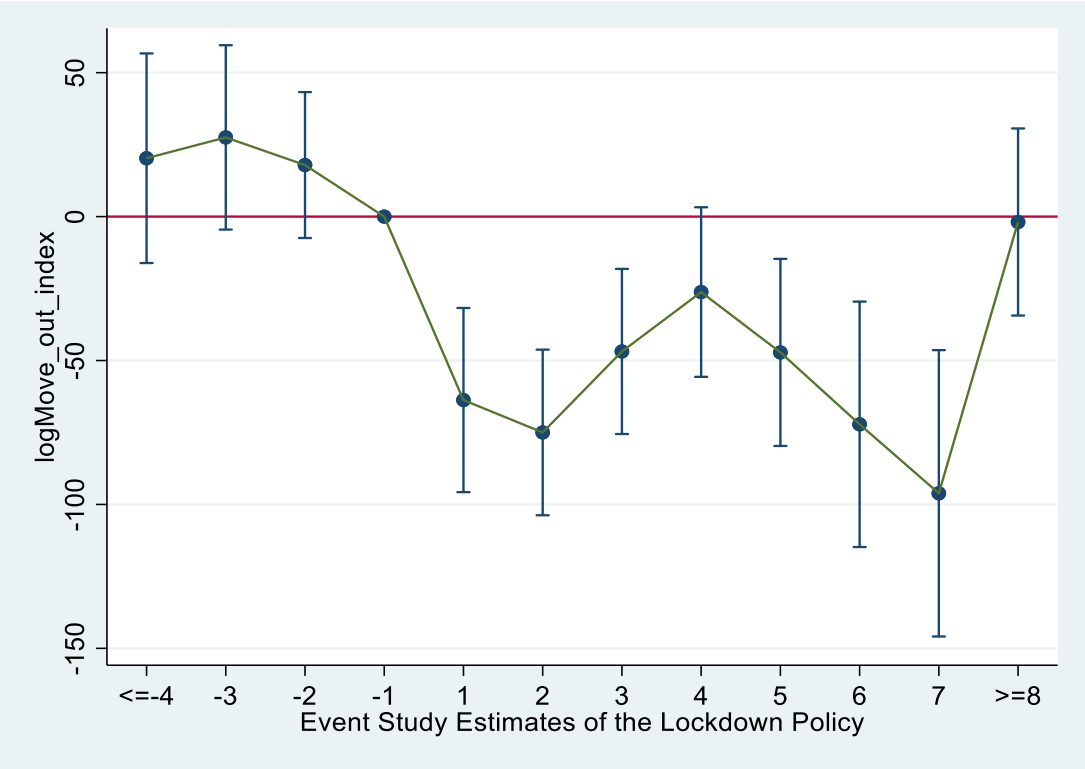
VARIABLES	(1) Δ logexport_inverse	(2) Mid-point growth	(3) Export
Lockdown × After	-0.315***	-0.331***	-0.125**
	(0.072)	(0.075)	(0.048)
Observations	555,233	500,754	555,170
R-squared	0.057	0.075	
Weather Controls	Yes	Yes	Yes
$X_i \times \lambda_t$	Yes	Yes	Yes
City FE	Yes	Yes	
Destination-Time FE	Yes	Yes	Yes
City-Quarter FE			Yes

Notes: Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the city's total population, hospital beds per 1,000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. A constant term is included in Column (3). Robust standard errors in parentheses are clustered at the source city level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

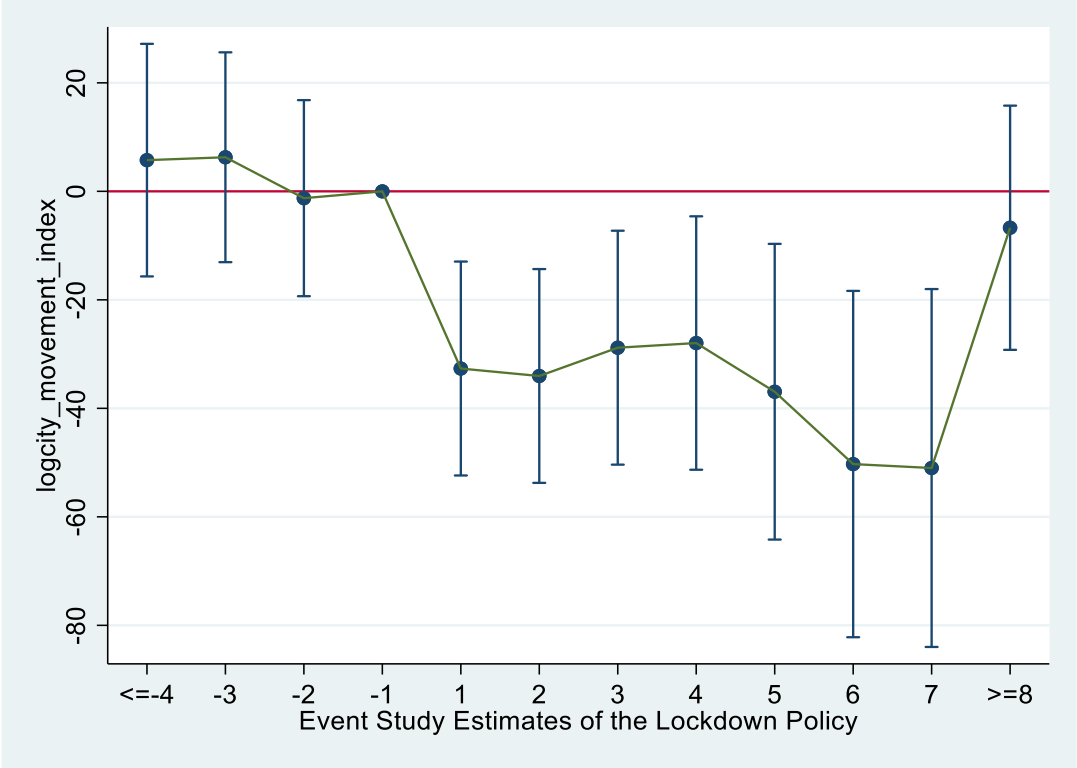
Panel A: In-migration Index



Panel B: Out-migration Index



Panel C: within-city migration index



Appendix Figure A1 Event study for the effect of lockdown on human mobility