International trade and Covid-19: City-level evidence from China's lockdown policy

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Abstract
This paper examines the impact of Covid-19 lockdowns on exports by 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 better-developed ICT infrastructure; and (iii) cities with a larger share of potential teleworkers. Time-sensitive and differentiated goods experienced a more pronounced decline in export growth. Global supply chain characteristics matter, with more upstream products and industries that had accumulated larger inventories experiencing a smaller decline in export growth. Also, products that relied more on imported (domestic) intermediates experienced a sharper (flatter) slowdown in export growth. The rapid recovery in cities' exports after lockdowns were lifted suggests the policy was cost-effective in terms of its effects on trade.

KEYWORDS
China, cities, Covid-19, exports, global supply chains, lockdown

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Balancing the trade-off between health and wealth has been a key concern for policy makers since the outbreak of Covid-19. Everywhere, policymakers 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 measures in such a situation? Modeling and estimating the effect of lockdowns on socioeconomic 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 it curbed the number of cumulated cases in China after March 11, 2020. Whereas China accounted for two-thirds of globally confirmed cases at the time the World Health Organization characterized Covid-19 as a pandemic, its share was less than 1% by the end of June 2020.

Yet, the strict lockdowns came at a price. This paper focuses on one socioeconomic outcome, namely the impact it had on trade. The volume of China’s exports fell by an unprecedented 41% 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 with trends in export volumes for other major trading economies shown in Figure 1, 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 strict lockdowns of cities have come to an end. This provides the unique opportunity to examine ex post the impact of lockdowns on exports.1

This paper uses city-level export by destination data at a monthly frequency from January 2018 through April 2020. We obtained this detailed data set by contacting each of China’s local customs offices. To contain the spread of the new coronavirus, some cities implemented a lockdown policy, while others did not. This provides the opportunity to examine the impact of lockdowns on trade using a differences-in-differences design.

We find that cities in lockdown experienced a ceteris paribus 34 percentage points reduction in the year-on-year growth rate of exports. As the sample mean of city-destination exports is 8.8 million US dollars, this number 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

The lockdown impacted the intensive as well as the extensive margin of cities’ exports. On the extensive margin, it led to higher exits from and lower new entries into foreign markets. Furthermore, substantial heterogeneity in the relationship between exports and lockdowns is observed, which depends on the characteristics of cities, products, and sectors. We find that coastal cities, cities with more advanced ICT infrastructure, or a larger share of potential teleworkers tend to be more resilient to supply disruptions from lockdown measures, whereas no significant effect for the share of processing trade is observed. Time-sensitive goods and differentiated goods witnessed a more pronounced drop in export growth, while products and industries locate more upstream or having accumulated larger inventories experienced a smaller decline in export growth. Furthermore, from the perspective

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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 (p. 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 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., 2021).
of global supply chains and their concomitant flow of intermediate inputs, we find that sectors relying more on imported (domestic) intermediates experience a sharper (flatter) slowdown in export growth.

The baseline finding that cities in lockdown experienced a significant reduction in the year-on-year growth rate of exports relative to cities without a lockdown is 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. Another concern is that cities implementing a lockdown are not comparable to cities without a lockdown. To address this concern, we use propensity score matching (PSM) procedures. In particular, we use the nearest-neighbor matching approach to match each treated city with four untreated cities. Thereafter, we rerun our main specification and find the results still hold. To address possible endogeneity concerns due to reverse causality—because cities that are larger in terms of exports or economic size could be more likely to implement a lockdown to contain the spread of Covid-19—we confirm the baseline findings by running two-stage least squares (2SLS) regressions, where the distance to Wuhan is used as an instrument.

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 Antrás et al. (2020).

Our study contributes to the literature on optimal lockdown measures and the theoretical modeling of pandemics and trade (Acemoglu et al., 2020; Alvarez et al., 2020; Antrás et al., 2020; Aum et al., 2021; 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; H. Chen et al., 2021; Eichenbaum et al., 2020; Fernandes & Tang, 2020). Two studies closely related to ours 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 are different. Although local governments implemented travel restrictions on their residents around the outbreak of SARS, they did not impose lockdowns as the one Wuhan experienced.

Further, our study is relevant to a vibrant branch of studies that investigate the consequences of supply chain disruptions (Barrot & Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). 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 substantial drop in output following the earthquake. Carvalho et al. (2021) 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 industry input–output linkages in China to shed light on the effect of supply disruptions on exports.

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, 2010; Freund & Rocha, 2011; Martinus et al., 2015; Martinez-Zarzoso & Márquez-Ramos, 2008). In addition, face-to-face meetings play an important role in building business relationships or buyer-seller linkages (Bernard et al., 2019; Storper & Venables, 2004), search and contracting (Startz, 2016), trade (Cristea, 2011), as well as foreign direct investment (Campante & Yanagizawa-Drott, 2018; Fageda, 2017).

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 better information and communications technology (ICT) infrastructure are less affected by lockdowns (see also Papanikolaou & Schmidt, 2020).

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

2 | THE SPREAD OF COVID-19 AND LOCKDOWNS IN CHINA

Section 2.1 provides a brief review on the use of lockdowns by local policy makers to prevent the virus from spreading in China. Section 2.2 explores the evolution of confirmed Covid-19 cases in cities that did and did not have a lockdown.

2.1 | The spread of Covid-19 in China

On December 31, the Wuhan Municipal Health Commission informed the World Health Organization 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. It was not until January 20 that China’s National Health Commission confirmed that 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 people’s lives and health as the governments' top priority.
In response to the outbreak and spread of Covid-19, Wuhan went in lockdown on January 23, 1 day before China’s New Year’s Eve. 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 (H. Fang, Wang, et al., 2020). Several days later, another 13 prefecture-level cities and three province-managing-counties went in lockdown. All intra- and inter-city public transport was halted to restrict people’s movement, and private vehicles were not allowed on highways. Shops closed and communities started to implement close-off management.

Different from SARS, Covid-19 can be transmitted even when the infected have 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 (H. Li & Zhou, 2005), local policymakers have strong incentives to follow the central government’s epidemic response.

The resumption of work after the Lunar New Year holidays was a 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 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.

Twenty-four out of the 31 provinces announced that firms could not reopen before February 10, while six 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, and producers of masks, utility firms, and pharmaceutical companies had already restarted to supply soaring demands. 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.

2.2 | The impact of lockdowns

Lockdowns appear to have been effective in preventing the spread of Covid-19. Figure 2 compares the accumulated cases between cities that implemented a lockdown and those that did not. Clearly most confirmed cases were spotted in cities in lockdown. As of June 2020, China’s cumulative case number was 83,534, of which Hubei accounted for 81.57% or 68,135 cases (of which Wuhan 60.26% or 50,340 cases).

The lockdown aims to contain the spread of the virus and reduce new cases within the city. Yet, due to the travel restrictions, it also prevents potentially infected people from moving to other cities. Therefore, the lockdown has “positive” spillover effects on cities that did not go in lockdown. This makes it harder to isolate the effect of lockdowns on the spread of Covid-19. However, Figure 2 suggests that accumulated cases stopped increasing more abruptly in cities that implemented a lockdown than in cities that did not implement a lockdown.

There were local rebounds of Covid-19 cases in nonlockdown cities, including in Beijing, Dalian, Shulan, and Urumqi. Learning from the experience of Wuhan, local governments responded quickly and carried out policies like...
mass testing to track all possibly infected individuals. Importantly, these local governments implemented precise and differentiated strategies rather than complete lockdowns. The policies helped to bring rebounds in local Covid-19 cases under control.

The travel restrictions and traffic control policies had serious socioeconomic consequences. First, China experienced historical negative GDP growth in the first quarter of 2020, falling by about 6.8% year-on-year. In Hubei province, the epicenter of the coronavirus outbreak, there was a year-on-year decline in its provincial GDP growth rate of around 39.2% 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% year-on-year. Moreover, total exports and imports fell 11.4% and 0.7%, respectively. Consequently, China’s trade surplus fell by 80.6% 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% year-on-year, see Figure 3. Taken together with imports, Hubei’s trade in goods decreased by 22.5% compared with the first quarter of 2019.

3 | DATA AND DESCRIPTIVE STATISTICS

We use four data sets. The first data set is merchandise trade data from China’s General Administration of Customs. We have two sets of merchandise trade, namely one at the level of provinces and one for cities. The first customs data reports monthly trade data by province and their trade partners at the HS 8-digit level for the period from January 2017 through June 2020. Also, it records the trade mode, such as whether it is normal 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).\(^4\) The primary trade data are at the prefecture level. Hubei and Hainan province provide trade data for

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\(^4\)Trade data for January and February 2020 are reported separately in this granular data set. Due to data constraints, prefectures of Yunnan province are not included. Yunnan accounted for only 0.53% of China’s aggregate exports in the first quarter of 2020. In the customs data set with trade statistics by province, January and February 2020 are not reported separately but combined.
province-managing-counties (PMCs). The detailed trade data enables us to estimate the effect of lockdowns on the city’s exports. For brevity, we will refer to prefectures and PMCs as cities.

The second data set provides information on the number of daily Covid-19 cases by city, obtained from the China Stock Market and Accounting Research (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 newly 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 data set is the Baidu Mobility or Baidu Qianxi data set. 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 visualizes these data into dynamic maps, as well as providing users with the original data set. 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 May 3, 2020. We downloaded the data set 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 the population mobility of a city and will be utilized to examine the effects of lockdowns on population mobility.

The fourth data set is weather data obtained from the China Meteorological Data Service Center (CMDC), which is affiliated to the National Meteorological Information Center of China. The data set includes meteorological information such as average temperature, precipitation, relative humidity, wind speed pressure, and sunshine duration for 613 weather stations in China. The role of climate in the transmissibility of Covid-19 is hotly debated, and inconsistent conclusions have been drawn in recent studies (Baker et al., 2020; L. Q. Fang, Zhang, et al., 2020; Tobias & Molina, 2020). Also, several studies find that high temperatures have significantly negative impacts on export growth (Jones & Olken, 2010; C. 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 (S. Chen et al., 2020; Deschênes & Greenstone, 2007; Schlenker & Walker, 2016). 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. Other city-level control variables are obtained from the CEIC database, China City Statistical Yearbook, and city-level statistical communique on national economic and social development. See Online Appendix Table D1 for summary statistics of the variables used in our main regressions.

Finally, following H. Fang, Wang, 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: first, these cities also carried out stringent measures to control people’s movements compared to other cities; second, they also delayed the resumption of businesses, resulting in a slowdown in the recovery of the supply chain in these cities. In total, all of the 16 cities in Hubei province implemented complete lockdown policies, while seven other cities implemented partial lockdown policies. Following H. Fang, Wang, et al. (2020), we prepared the list of lockdown and partial lockdown cities, and added their respective date of business resumption, see Online Appendix Table D2.

Figure 4 presents descriptive evidence on the effect of the lockdown on the city’s exports. The figure illustrates the log average exports of treated and nontreated cities in deviation from their monthly average for the period January 2018 through 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 nontreated 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.

4 | IDENTIFICATION STRATEGY

The unprecedented lockdown of cities provides us with an unusual natural experiment. We use a difference-in-differences (DID) design to estimate the impact of lockdowns 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 businesses resumed operation, 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 changes in the city’s export growth between the current 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:

\[
\Delta \log Y_{ict} = \eta_i + \delta_{ct} + \beta \text{Lockdown}_i \times \text{After}_t + \gamma X_{it} + \sum \theta_{iz} Z_i \times \lambda_i + \epsilon_{ict},
\]

(1)

We use a threshold on distance different from S. 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 S. 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. Also, Shennongjia Forest District implemented a complete lockdown. This forest district hardly reports trade. It has only 14 recorded transactions between 2017 and 2020 of which one in 2019 and zero in 2020. It is not included in the analysis.

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 done so arguably successfully.
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 to restrict people’s movement. $\lambda$, 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, $\beta$, 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.

We control for the interaction between a city’s prelockdown characteristics $Z_i$ and time dummies $\lambda$, that is, $\sum \theta_i Z_i \times \lambda_t$. This aims to control for potential prelockdown differences between treated and control cities (Lu et al., 2019). The covariates $Z_i$ that we include are the log average monthly exports, log total population, log hospital beds per 1000 persons, and the industry value added share of the city’s GDP.

$\eta_i$ represents city fixed effects to account for unobservable time-invariant city characteristics that may affect the city’s export growth. $\delta_{ct}$ represents the destination-time fixed effects that aim to control for time-varying factors like demand shocks and the stringency of lockdown measures across importing countries. $\epsilon_{ict}$ 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 | MAIN 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 explores whether the impact is conditional on the coastal location of the city, ICT infrastructure, the share of potential teleworkers, and the share of processing trade. Section 5.3 examines whether the impact is conditional on product and sector characteristics. Section 5.4 examines
if the impact is conditional on the dependence of foreign intermediate inputs. Finally, Section 5.5 examines the impact of lockdowns on the intensive and extensive margin of exports.

### 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 Lockdown × After is negative and statistically significant, suggesting that cities in lockdown experienced a sharper reduction in the export growth rate relative to cities without a lockdown.

We include time-varying weather controls such as temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration 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. The DID estimates could be biased due to pre-existing differences in characteristics between cities with and without a lockdown (such differences are further discussed in Section 6). To alleviate this concern, we include the interaction terms between the prelockdown city characteristics and time dummies, which controls for pre-policy differences (as in Lu et al., 2019). Results with these additional controls in Column (3) are qualitatively the same and comparable in magnitude.

The coefficient of −0.341 on the interaction term Lockdown × After suggests that on average cities in lockdown experienced a 34 percentage point lower export growth rate compared to cities without a lockdown. The effect is also economically substantial. The sample mean of exports between a city-destination pair is 8.80 million dollars. Hence, the average additional decline in exports of cities in lockdown is (8.80 × 0.341=) 3 million dollars.

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**Note:** The dependent variable is the 12-month log difference of city-destination export values. Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the log average monthly export, log city's population, log hospital beds per 1000 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.

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**TABLE 1** Baseline results

|          | (1)     | (2)     | (3)     |
|----------|---------|---------|---------|
| Lockdown × After | −0.353*** | −0.349*** | −0.340*** |
|           | (0.074) | (0.073) | (0.078) |
| Observations | 359,356 | 359,332 | 359,332 |
| $R^2$     | 0.064   | 0.065   | 0.067   |
| City FE   | Yes     | Yes     | Yes     |
| Destination-time FE | Yes     | Yes     | Yes     |
| Weather controls | Yes     | Yes     | Yes     |
| Covariates × Time dummies | Yes     |         | Yes     |

Note: The dependent variable is the 12-month log difference of city-destination export values. Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the log average monthly export, log city's population, log hospital beds per 1000 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.

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*These results are not shown for the sake of brevity, but available upon request.*
5.2 | Heterogeneous treatment effects

This sub-section investigates possible heterogeneous treatment effects of cities in lockdown. We split treated cities into two groups according to four metrics: whether the city is located along the coast or not, the ICT infrastructure, the fraction of potential teleworkers, 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 measures. Table 2 presents the results, which are discussed in turn.

5.2.1 | Heterogeneous effects for the location of the city

Many local governments enforced travel restrictions, such as partially shutting down highway entrances or canceling trains to prevent the outbreak of the coronavirus, especially in 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 in short 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 (Djankov et al., 2006, 2010; Hummels & Schaur, 2013). Consistent with this logic, the estimated coefficients presented in Columns (1) and (2) 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 subsamples.

5.2.2 | Heterogeneous effects depending on the ICT infrastructure

Information and communications technology (ICT) play a critical role in limiting coordination costs in fragmented production networks (Abramovsky & Griffith, 2006; Baldwin, 2011; Blyde & 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 less pronounced decline in exports. We use mobile phone subscriptions per 100 inhabitants to proxy the city’s ICT infrastructure. The coefficient of lockdown in Column (3), that is, $-0.256$ is about half that of Column (4), that is $-0.460$, 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 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

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9The geographical location is treated as a dummy variable, with the dummy for coastal cities equal to one. The correlation coefficients between the variables used to split cities in two groups are lower than 0.25, except for a correlation coefficient of 0.47 between the share of potential teleworkers and ICT infrastructure. The low correlation coefficients suggest different cities are considered depending on the variable used to split the sample.
### Table 2  Heterogeneous treatment effects: City characteristics

| Variables          | Geographic location | ICT infrastructure | Teleworkable employment | Processing trade share |
|--------------------|---------------------|--------------------|-------------------------|------------------------|
|                    | Coastal (1) | Inland (2) | High (3) | Low (4) | High (5) | Low (6) | High (7) | Low (8) |
| Lockdown × After   | -0.279***   | -0.396***   | -0.256*** | -0.460*** | -0.274*** | -0.436*** | -0.279*** | -0.315*** |
|                    | (0.095)     | (0.100)     | (0.093)  | (0.130)  | (0.104)  | (0.120)  | (0.097)  | (0.110)  |
| Test for equal coeff. | $p$ value = 0.042 | $p$ value = 0.021 | $p$ value = 0.033 | $p$ value = 0.302 |
| Observations       | 103,032     | 256,194     | 214,162  | 136,571  | 200,864  | 151,305  | 205,630  | 140,414  |
| $R^2$              | 0.117       | 0.073       | 0.083    | 0.073    | 0.084    | 0.077    | 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      |

Note: The dependent variable is the 12-month log difference of city-destination export values. Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the log average monthly export, log city's population, log hospital beds per 1000 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.
performed at home. According to Dingel and Neiman (2020), 37% of jobs in the United States can be performed at home, varying significantly across sectors.

Bonadio et al. (2020) document the average fraction of work that can be done at home is 33.9% for manufacturing, while the average share is 54.3% for services. China, the world’s largest manufacturer, 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 4.67 million observations, we estimate the share of jobs in manufacturing industries that can be performed at home in China (see the Online Data Appendix A).

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 (5) and (6) show that the impact of lockdowns on the year-on-year export growth rate is smaller for cities with a higher share of potential teleworkers (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.

5.2.4 | 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% 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, and we thus focus on the supply-side response to the lockdown policy here.

Processing trade is likely more labor-intensive, resulting in extra production costs for the prevention and control of the spread of the virus. If so, we expect that the effects of the lockdown are larger for cities with an above-median proportion of processing trade. Columns (7) and (8) of Table 2 present estimates of the 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 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 data set is comprehensive, there is one constraint namely that the provincial trade data we obtained are combined for January and February 2020. 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 Table 3, 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 the HS 4-digit product level (Hummels & 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. The first three columns examine whether time sensitive goods would suffer more from lockdowns, which cause substantial delays in goods transportation. Not surprisingly, the coefficients on the triple interaction are negative and statistically significant, confirming that time can be an important trade barrier.
TABLE 3  Heterogeneous treatment effects: Product or sector characteristics

|                          | (1)   | (2)   | (3)   | (4)   | (5)   | (6)   | (7)   | (8)   | (9)   | (10)  | (11)  | (12)  |
|--------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| Lockdown × After × Time  |       |       |       |       |       |       |       |       |       |       |       |       |
| sensitivity              | −0.894*** | −0.452*** | −0.442*** | (0.160) | (0.099) | (0.091) |       |       |       |       |       |       |
|                          |       |       |       |       |       |       |       |       |       |       |       |       |
| Lockdown × After ×       |       |       |       |       |       |       |       |       |       |       |       |       |
| Differentiated goods     | −0.205*** | −0.176*** | −0.029 | (0.037) | (0.038) | (0.024) |       |       |       |       |       |       |
|                          |       |       |       |       |       |       |       |       |       |       |       |       |
| Lockdown × After × Log   |       |       |       |       |       |       |       |       |       |       |       |       |
| upstreamness             | 0.416*** | 0.408*** | 0.008 | (0.041) | (0.039) | (0.029) |       |       |       |       |       |       |
|                          |       |       |       |       |       |       |       |       |       |       |       |       |
| Lockdown × After ×       |       |       |       |       |       |       |       |       |       |       |       |       |
| Inventory to             |       |       |       |       |       |       |       |       |       |       |       |       |
| sales ratio              | 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 | 6,649,833 | 6,649,833 | 6,649,833 | 6,180,785 | 6,180,785 | 6,180,785 | 6,649,833 |
|                          |       |       |       |       |       |       |       |       |       |       |       |       |
| $R^2$                    | 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 (HS/IO)  | Yes  Yes  Yes  Yes  Yes  Yes  Yes  Yes  Yes  Yes  Yes  Yes  |

Note: The dependent variables are the 12-month differences in log sector’s export value, quantity, and unit price by province and destination country for every three columns. Column (1)–(3) includes province-HS4 fixed effects; Column (4)–(6) includes province-HS6 fixed effects; Column (7)–(12) 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.
We also investigate the impact of lockdowns on export growth when differentiated goods are present. A priori the effect is ambiguous. On the one hand, differentiated goods are less substitutable than their homogenous counterparts thus they could be more resilient to supply shocks (i.e., the demand elasticity is relatively low). On the other hand, differentiated goods typically have longer supply chains and tend to be more dependent on relationship-specific investments, increasing their vulnerability to supply shocks. The estimates presented in Columns (4)–(6) show the reduction in export growth is larger when differentiated goods are pervasive, both in values and quantities, which suggests that the latter effect dominates. Nonetheless, the insignificant coefficient estimate for unit values suggests the lockdown did not impact export prices.

Columns (7)–(9) show that 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, Columns (10)–(12) examine the role of inventories in mitigating and/or worsening the impact of the lockdown on export growth. Intuitively, industries holding more inventories are expected to experience a smaller decline in export growth compared to those holding fewer inventories. The coefficients on the triple interaction terms are positive for values and quantities, which is consistent with this expectation. Yet, the differential effect is not statistically significant. Taken together, the results suggest heterogeneity in the impact on exports of lockdowns conditional on product and sector characteristics.

5.4 Disruption to global supply chains

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. Meanwhile, 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. This enables using input-output linkages to examine the extent to which supply disruptions affect the export of different sectors. We use three related indicators of dependence on imported intermediate inputs. We estimate a triple difference-in-differences specification that compares export growth by sector with varying 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:

$$\Delta \log Y_{pcst} = \beta_{Lockdown} \times After_t \times Import \ dependence_s + \lambda_{ps} + \eta_{pt} + \delta_{cst} + \epsilon_{pcst}. \quad (2)$$

We are indebted to Mr. Jie Chen, former 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.

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., Q. Chen et al., 2018; Hummels et al., 2001; Johnson and Noguera, 2012). 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.
The outcome variable denotes the 12-month change in log exports of province $p$, for sector $s$, to destination country $c$ at month $t$. The independent variable of interest is the interaction term between, $\text{Import dependencys}_p$, defined as the fraction of required imported intermediate inputs for sector $s$ to produce one unit of output, $\text{Lockdown}_p$, a dummy variable for Hubei province, and $\text{After}_t$, 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), $\lambda_{pss}$, $\eta_{pt}$, and $\delta_{cst}$ are province-sector fixed effects, province-time fixed effects, and destination-sector-time fixed effects to account for unobserved time-invariant province-sector characteristics and time-varying shocks across provinces and destination-sectors, respectively. We cluster standard errors at the province-sector level to account for potential serial correlation.

Table 4 presents the results from estimating Equation (2). As presented in Column (1), 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. 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 $13.6 (=1.7 \times (0.10 - 0.02) \times 100)$ in the 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 high 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.

### Table 4 Disruptions conditional on global supply chain participation: Sectoral evidence

|                         | (1)          | (2)          | (3)          |
|-------------------------|--------------|--------------|--------------|
| Lockdown $\times$ After $\times$ Imported input dependency (direct) | $-1.700^{**}$ |              |              |
|                         | (0.807)      |              |              |
| Lockdown $\times$ After $\times$ Imported input dependency (total) |              | $-1.535^{**}$ |              |
|                         |              | (0.744)      |              |
| Lockdown $\times$ After $\times$ Log DVAR                            |              | 0.248***     |              |
|                         |              | (0.086)      |              |
| Observations            | 1,344,658    | 1,344,658    | 1,344,658    |
| $R^2$                   | 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          |

Note: The dependent variable is the 12-month difference in log sectoral exports by province and destination country. The standard errors in parentheses are clustered at the province-sector level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.
5.5 | Adjustments in the intensive and 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, filling the trade matrix with ones whenever the export values are positive and zeros otherwise. Hence, \( \text{Export}_{ict} \) denotes whether city \( i \) exports to a specific foreign market \( c \) in month \( t \). Second, we create three other dummies: (i) \( \text{Entry}_{ict} \), a dummy variable which indicates whether the city entered a new foreign market compared to the same month in the previous year; (ii) \( \text{Exit}_{ict} \), a dummy variable which indicates whether the city exits a foreign market compared to the same month in the previous year; and (iii) \( \text{Surviving}_{ict} \), a dummy variable indicating whether the city exports to the specific foreign market during the same month of two consecutive years. The estimated specifications are summarized in Equations (3)–(6):

\[
\text{Export}_{ict} = \eta_i + \delta_{ct} + \beta \text{Lockdown}_i \times \text{After}_i + \gamma X_{it} + \sum_t \theta_t Z_t \times \lambda_i + \epsilon_{ict},
\]

\[
\text{Entry}_{ict} = 1[\text{Export}_{ict} = 1 \cap \text{Export}_{ict-12} = 0] = \eta_i + \delta_{ct} + \beta \text{Lockdown}_i \times \text{After}_i + \gamma X_{it} + \sum_t \theta_t Z_t \times \lambda_i + \epsilon_{ict},
\]

\[
\text{Exit}_{ict} = 1[\text{Export}_{ict} = 0 \cap \text{Export}_{ict-12} = 1] = \eta_i + \delta_{ct} + \beta \text{Lockdown}_i \times \text{After}_i + \gamma X_{it} + \sum_t \theta_t Z_t \times \lambda_i + \epsilon_{ict},
\]

\[
\text{Surviving}_{ict} = 1[\text{Export}_{ict} = 1 \cap \text{Export}_{ict-12} = 1] = \eta_i + \delta_{ct} + \beta \text{Lockdown}_i \times \text{After}_i + \gamma X_{it} + \sum_t \theta_t Z_t \times \lambda_i + \epsilon_{ict}.
\]

The empirical results are presented in Table 5. Intuitively, the coefficient of interest, \( \beta \), is expected to be negative, negative, positive, and negative for Equations (3)–(6), respectively. In Column (1), the coefficient on the interaction term \( \text{Lockdown} \times \text{After} \) 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 has a 2.5 percentage point lower probability to enter a new market, yet the coefficient is not statistically significant. 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 without a lockdown. 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 exports.

6 | ROBUSTNESS ANALYSIS

This section examines issues that could affect our baseline specification, namely: pre-existing trends (Section 6.1), propensity score matching (Section 6.2), and additional robustness checks (Section 6.3). The findings suggest our baseline results are robust.

6.1 | Pre-existing trends

One key assumption in the DID identification strategy is the assumption of parallel trends: without a lockdown policy, the export of treated cities would have evolved in the same way as that of untreated cities. To examine

\[\text{Note that the analysis in this subsection is at the city-level and the time interval is a month. If the exit dummy is 1, it implies all firms registered in the city did not export to a specific destination, which could be a rare event. In fact, with firm-level data at a monthly frequency one may observe spurious entry and exit. Yet at the city-level, by construction, this is less likely.}\]
whether there is a common pre-existing trend across treated and untreated cities, we replace the After dummy in the interaction term Lockdown × After 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 less than or equal to −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 before 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 5 plots the interaction coefficient along with the 95% confidence intervals. Before the lockdown, the coefficients are small in magnitude 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.

### 6.2 Propensity score matching

A potential concern is that pre-existing differences in certain city characteristics between lockdown and non-lockdown cities may bias the DID estimates. To alleviate this concern, we include prelockdown city characteristics interacted with time dummies to control for prepolicy differences in our baseline regressions (see Lu et al., 2019, for a similar treatment). Our results, with or without these additional controls, are qualitatively the same and comparable in magnitude (cf. Table 1). The parallel trend test also appears satisfied. Nonetheless, to formally address this concern, we implement a propensity score matching procedure here.13

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13As our dependent variable of interest is measured at the city-country-month level, rather than city-month level, we implement the propensity score matching with care. In particular, we first match the treated cities with comparable control cities using the observable city characteristics, which are measured before the lockdown policy, that is, the year of 2019. Second, we merge back the matched city-pairs to our main regression sample and re-estimate specification (1). In results not reported here (available upon request), we also collapse our data to the city-month level to obtain the city’s aggregate export by month, and find the main results still hold. We appreciate the suggestion by the editor and the anonymous referees to implement a propensity score matching procedure.
We utilize the nearest-neighbor matching approach to construct control cities for treated cities. In particular, we match a treated city with four control cities. If multiple potential matches have the same propensity score, we randomly choose one. We prefer to use prelockdown city characteristics that may simultaneously affect the treatment and the outcome variable to implement the matching procedure (Caliendo & Kopeinig, 2008). Before doing the matching, we observe differences between cities that faced a lockdown and those that did not, namely in temperature, population size, economic development, and industry structure. Yet, cities with and without a lockdown appear comparable in other dimensions, such as precipitation, export size, and distance to a port (see Online Appendix Table D4).

We fit a logit regression to estimate propensity scores obtaining city-pairs of treated and control cities to implement the DID estimation. Thus, we identify the effect of lockdowns using variation within the matched city-pairs (Kahn et al., 2021). To test the quality of matching, we use a two-sample t test to check whether the covariates are balanced after matching. The results in Table 6 suggest that matching balanced the distribution of covariates in the two groups. Finally, we re-examine the pretreatment parallel trends assumption as in Section 6.1. The coefficients on the pre-lockdown event dummies are not statistically different from zero, suggesting that pretreatment trends are similar between treated and control cities.

Table 7 gives the DID estimates using the matched sample. The coefficient for the interaction term is similar to the baseline results in magnitude and statistical significance. In Columns (1) and (2), matched cities appear only once. In Column (3) we allow cities to appear more than once—for example, if a control city is matched with two cities that implemented a lockdown—resulting in a larger number of observations. We add city-pair fixed effects,

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**FIGURE 5** Event study of the lockdown policy. This figure plots the event study estimates and corresponding 95% confidence intervals. The dependent variable is the 12-month log difference of city-destination export values. The omitted month before the lockdown policy is the benchmark. Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the log average monthly export, log city's population, log hospital beds per 1000 persons, and the share of industry value added in the city's GDP, interacted with time dummies. Source: Authors' calculations from China’s Customs data.

14 One treated city, Wuhan, which is surrounded by other lockdown cities, could not be matched to control cities due to its unique weather conditions. Alternatively, we matched Wuhan with control cities without considering weather variables and re-run the regressions, the results still hold.

15 For that we use Stata’s *joinby* command.
thus the analysis exploits within-pair variation to identify treatment effects. Findings in Column (3) indicate the main result still holds.

So far, we considered the lockdown in several cities as an exogenous shock. This is plausible, as the Chinese government did not implement a lockdown during the 2003 SARS epidemic. However, one might still be concerned about reverse causality, that is, cities that are larger in terms of exports or economic size could be more likely to implement a lockdown to contain the spread of Covid-19. To alleviate the concern, we employ a 2SLS estimator, where we use the city's distance to Wuhan as an instrumental variable. Online Appendix B reports the implementation of the IV estimator. The IV results suggest lockdowns are associated with a 51.2 percentage points lower export growth rate. This suggests the OLS estimate is possibly biased upwards (towards a less negative effect). More importantly, the results suggest a causal relationship between the lockdown and a slowdown in the city's export growth.

**TABLE 6** Balancing test for propensity score matching

| Variables                | Mean Treated | Mean Matched | t test t statistic | p value |
|--------------------------|--------------|--------------|-------------------|---------|
| Temperature              | 16.876       | 17.048       | -0.17             | 0.867   |
| precipitation            | 81.813       | 87.731       | -0.49             | 0.629   |
| Log export               | 11.670       | 12.152       | -0.57             | 0.571   |
| Log population           | 8.286        | 8.508        | -0.88             | 0.381   |
| Log GDP per capita       | 9.224        | 9.261        | -0.23             | 0.817   |
| Industry value-added share| 0.422        | 0.407        | 0.48              | 0.635   |
| Log distance from a port | 5.825        | 5.528        | 0.76              | 0.449   |

Note: The nearest neighbor matching approach is used to match the treated cities with four control cities, and the t test results indicate that there are no significant differences in covariate means after the matching.

**TABLE 7** Results for propensity score matching

|                  | (1)         | (2)         | (3)         |
|------------------|-------------|-------------|-------------|
| Lockdown × After | -0.313***   | -0.332***   | -0.341***   |
|                  | (0.083)     | (0.078)     | (0.080)     |
| Observations     | 127,794     | 127,794     | 253,013     |
| $R^2$            | 0.104       | 0.107       | 0.135       |
| City FE          | Yes         | Yes         | Yes         |
| Destination-time FE | Yes         | Yes         | Yes         |
| Weather controls | Yes         | Yes         | Yes         |
| Covariates × Time dummies | Yes         | Yes         |
| City-pair FE    | Yes         |             |             |

Note: The dependent variable is the 12-month log difference of city-destination export values. Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the log average monthly export, log city's population, log hospital beds per 1000 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.
Additional robustness checks

This section provides further robustness checks of the main results. One potential concern is that the findings are driven by chance. Online Appendix C presents three placebo tests. In one placebo test, we randomly allocated 23 out of the 348 cities to the treatment group, assuming these cities imposed a lockdown in February 2020. We run Equation (1) with these randomly chosen cities, repeating the procedure 1000 times, and plot the coefficients on the interaction term $\text{Lockdown} \times \text{After}$ (see Appendix Figure C1). The actual coefficient on the interaction term $\text{Lockdown} \times \text{After}$ is around 4 SDs (0.083) larger than the mean ($-0.001$) of the estimated distribution. This suggests it is the lockdown rather than other confounders that drive our main results.

Next, we consider alternative measures to proxy for the stringency of the lockdown. Column (1) of Table 8 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 recovery in trade. 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.

In another robustness analysis, we consider cities with a full lockdown, while relegating cities with a partial lockdown to the control group. The coefficient for the interaction term in Column (3) is statistically significant as before, and more importantly, it is larger in magnitude. We also consider sensitivity of the results to excluding observations for Yunnan province, which only reports aggregate export data for the first 2 months of 2020. About one percent of the observations for the whole sample is dropped. The results are similar, see Column (4).

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. To facilitate these examinations, we treat a

| TABLE 8  Robustness check |
|---------------------------|
| Variables                | (1) New cases | (2) Total cases | (3) Only complete lockdown | (4) Yunnan excluded |
| Lockdown stringency      | $-0.040^{**}$ | $-0.043^{**}$ | \(0.016\)                  | \(0.017\)          |
| Lockdown $\times$ After  | \(-0.340^{***}\) | \(-0.335^{***}\) | \(0.078\)                  | \(0.078\)          |
| Observations             | 359,332       | 359,332       | 359,332                    | 355,688            |
| $R^2$                    | 0.066         | 0.066         | 0.067                      | 0.067              |
| Weather controls         | Yes           | Yes           | Yes                        | Yes                |
| Covariates $\times$ Time dummies | Yes | Yes | Yes | Yes |
| City FE                  | Yes           | Yes           | Yes                        | Yes                |
| Destination-time FE      | Yes           | Yes           | Yes                        | Yes                |

Note: The dependent variable is the 12-month log difference of city-destination export values. Weather controls include temperature, precipitation, wind speed, atmospheric pressure, relative humidity, and sunshine duration. Covariates include the log average monthly export, log city's population, log hospital beds per 1000 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.

6.3 Additional robustness checks
destination country reporting a positive export over our sample period as a potential foreign market, filling the trade matrix with zeros whenever the export value is missing.

First, to alleviate concerns our results are driven by zero exports that are omitted due to taking the log of exports, we use the inverse of the hyperbolic sine transformation, $\log\left(x + (x^2 + 1)^{0.5}\right)$, for the 12-month difference and re-estimate Equation (1). The number of observations increases by about 55%. The coefficient for the interaction term in column (1) of Online Appendix Table D3 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. To do so, we calculate the mid-point growth rates for each city-destination pair by month. In Column (2), the magnitude of the coefficient for the interaction term is again similar to the baseline and statistically significant.

Finally, we carry out another robustness check by using the PPML estimator, which allows the inclusion of zero trade flows (Silva & Tenreyro, 2006). It is worth noting that the estimator precludes us to take the log difference of the outcome variable of interest, as the difference may lead to negative values for the dependent variable. We use city-quarter fixed effects instead to address seasonality concerns in our outcome variable. The coefficient on the interaction term is not directly comparable with our earlier results, still the results shown in Column (3) of Online Appendix Table D3 confirm the baseline finding.

7 | MECHANISMS

In line with the mechanism modeled in Antrás et al. (2020), the lockdown in Wuhan and other cities impeded people’s mobility and thus disrupted supply chains. This section offers suggestive evidence on the disruption. We examine the role of the lockdown in restricting people’s movements. Following H. Fang, Wang, et al. (2020) and H. Chen et al. (2021), we use the Baidu Qianxi data set, which provides us three migration intensity indicators. These three indicators are the daily IMI, the daily OMI, and the daily WCMI, respectively. Because the data set has daily observations, it enables us to define the treatment and control group in a more flexible way. Our regression specification is as follows:

$$\log Y_{it} = \alpha + \beta Lockdown_{it} + \gamma X_{it} + \lambda_i + \delta_t + \epsilon_{it}$$

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). $\lambda_i$ and $\delta_t$ represent city and time fixed effects, while $\epsilon_{it}$ is the error term. The coefficient of interest, $\beta$, estimates the difference in outcomes between treated and control cities during the same period. We include city fixed effects to control for unobserved 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 9 presents estimates for the relationship between lockdowns and human mobility. The coefficient of interest, $\beta$, is negatively and statistically significant in all of the three columns. The coefficients imply that cities in lockdown experienced a 52.4% reduction in the in-migration index, a 47.8% decrease in the out-migration index, and a 24% 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.

16For a typical city $i$ exporting value of $x$ to destination country $c$ at month $t$, the mid-point growth rate is defined as follows:

$$\gamma_{ict} = \frac{(K_{ict} - K_{ict-12})}{\frac{1}{2}(K_{ict} + K_{ict-12})}.$$
We also conduct an event study to check the dynamic effects of lockdowns on people’s movements. To do so, we replace the lockdown dummy with a set of event dummies indicating the number of weeks 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 1 week before the introduction of lockdown. We plot the coefficients on the event dummies in Online Appendix Figure D1. It illustrates that the effect of a lockdown may last as long as 7 weeks for the out-migration index (Panel B) and the within-city migration index (Panel C), and even more than 8 weeks for the in-migration index (Panel A). It’s plausible that 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. Besides, although the coefficient on lockdown status for 4 weeks or before is negative and statistically significant in Panel A, its magnitude is smaller than those for post-lockdown weeks.

### TABLE 9 Results for mechanisms

|               | Column (1) | Column (2) | Column (3) |
|---------------|------------|------------|------------|
| Lockdown      | -0.524***  | -0.478***  | -0.240***  |
|               | (0.124)    | (0.0941)   | (0.0663)   |
| Observations  | 42,469     | 42,469     | 42,469     |
| $R^2$         | 0.939      | 0.918      | 0.789      |
| Weather controls | Yes       | Yes       | Yes       |
| City FE       | Yes        | Yes        | Yes        |
| Date FE       | Yes        | Yes        | Yes        |

Note: The dependent variables are the log In-migration index, the log Out-migration index, and the log Within-city migration index in Columns (1)–(3), respectively. 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.

***, **, and * indicate significance at the 1%, 5%, and 10% level.

8 | CONCLUDING REMARKS

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

This study uses monthly city-level trade data to examine the impact of China’s lockdown policies on the city’s trade performance. In our baseline analysis, 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). To alleviate concerns that the DID estimates are biased due to differences in characteristics between cities with and without a lockdown, we employ a propensity score matching procedure and re-estimate our main specification. The findings are similar to our baseline results. In addition, estimates using the city’s distance to Wuhan as an instrument for the likelihood of a lockdown also indicate that our results are robust.
Our findings show substantial heterogeneity in the relationship between export growth and lockdowns. Coastal cities, cities with better ICT infrastructure, and cities with a larger share of potential teleworkers tend to be more resilient to supply disruptions caused by lockdown measures, whereas no significant effect for the share of processing trade is observed. We also find that time-sensitive goods and differentiated goods experienced a more pronounced drop in export growth, while products and industries locate more upstream and/or with larger inventories had a smaller drop in export growth. Furthermore, considering global supply chains and their concomitant flow of intermediate inputs, we find that sectors relying more on imported (domestic) intermediates suffer a sharper (flatter) slowdown in export growth.

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 suggests the lockdown measures were cost-effective in terms of their impact on trade.17

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 socioeconomic outcomes due to lockdown policies will be helpful for understanding the impact it has and guide future policymaking during pandemics.18

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DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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17From 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).
18For 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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