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How did China's zero Covid policy affect its exports?

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Abstract
This paper examines the impact of China's "Zero-Covid" policy on subnational cross-region export performance during 2019–2021. Using monthly export data at the product-destination level for China's 31 provinces and municipality cities, we find that new infections in a region have a significantly negative effect on the region's export growth, particularly for non-processing exports and industries with low dependence on remote working and products that are more substitutable and used mostly in the downstream of supply chains. However, restrictions on people inflows have no significant effect. The severity of the pandemic in export destinations is negatively correlated with China's export growth, suggesting an important demand-side reason for China's export downturn during the pandemic.

KEYWORDS
Covid-19, global supply chains, human mobility, post-pandemic recovery, trade collapse

JEL CLASSIFICATION
F13, F14, F16, J61

1 | INTRODUCTION

Since the initial outbreak of the Covid-19 pandemic in 2020, there has been widespread speculation about how it will shape the global economy in the short and long term. China implemented the "Zero Covid" policy from January 2020 to the end of November 2022, imposing significant restrictions on human mobility. These measures have had a significant impact on China's economy, the second largest in the world, as well as on many other economies due to their trade and financial ties with China.

This paper aims to provide a systematic empirical analysis of the impact of the Covid-19 pandemic and related policies in China on the country's export performance, using disaggregated data. By examining the effects of new Covid infections, local government policy responses, and global demand fluctuations on China's exports, this study aims to offer policy implications that can be applied to future public health crises. The empirical evidence presented in this paper will shed light on the complex relationship between the pandemic and China's export performance and contribute to a better understanding of the pandemic's economic consequences.

This study uses monthly export data for China's 31 provinces and municipality cities at the product-destination level to investigate the effects of local infections and inferred local government restrictions on human mobility on regional export performance, while controlling for destination market demand shocks. The results show that an increase in the number of new infections in a region, which serves as a proxy for the local government's restrictions on human mobility, has a significantly negative impact on regional export growth. Specifically, a 10% increase in the (lagged) number of infections compared to same month the previous year in a region is associated with a 0.9% decline in the region's export growth over the same period. These results remain robust to the control of unobserved product cycles and regional comparative advantages in China.

This effect is more pronounced in industries that depend less on remote working and in the downstream of the supply chains, and for products that are more substitutable, with longer-lasting effects for non-processing exports. Conversely, local government restrictions on human inflows from other regions have an insignificant effect. As expected, the severity of the pandemic in the export destination is negatively correlated with China's export growth. In particular, a 10% year-on-year increase in the number of newly confirmed infections in the destination is associated with a 0.04% decline in a Chinese region's exports on average (i.e., average across regions, products, and destinations). These results suggest an important demand-side factor behind China's export downturn during the Covid pandemic.

This paper relates to several strands of literature. First, it relates to the extensive literature on economic recession triggered by trade fluctuation (Baldwin, 2009; Bems et al., 2013; Chor & Manova, 2012; Levchenko et al., 2010). Second, the mobility restriction indices used in this paper are closely related to the studies on remote work and migration patterns (Brinatti et al., 2021; Espitia et al., 2022; Ramani & Bloom, 2021), transmission of infections (Fang, Wang, & Yang, 2020) and optimal lockdown policies (Acemoglu et al., 2020; Fajgelbaum et al., 2020; Moser & Yared, 2020) of the current Covid-19 pandemic. This paper also adds to the heated discussion about the impact of pandemic on global economic performance, including its implications for economic uncertainty (Jiang et al., 2021), productivity (Bloom et al., 2020), labor market (Antràs, 2020; Chernoff & Warman, 2020; Fang, Ge, et al., 2020) and gender inequality (Alon et al., 2020; Fairlie et al., 2021).

Third, this paper contributes to the rapidly growing literature on the impact of the current Covid-19 pandemic on international trade. In particular, Antràs et al. (2023) study the effects of the pandemic shock and its resulting reduction in cross-border business travel on international trade, and hence the overall welfare changes. Chen et al. (2022) evaluate the economic cost of China's lockdown policies using data on truck flows across cities. Finally, this paper discusses the heterogeneous effect of Covid-related shocks for different product types and stages of production along the global supply chains, and it is thus related to the studies on the macroeconomic shocks on supply chain resilience (Acemoglu & Tahbaz-Salehi, 2020; Bonadio et al., 2020; di Giovanni et al., 2022; Grossman et al., 2021).

The goal of this paper is straightforward—to examine how the changes in the severity of the Covid-19 infections and the government's corresponding travel restrictions within and between regions under China's so-called "Zero Covid" policy affect regional and thus national export performance, as well as potential heterogeneous effects across products and industries. These facts are important for understanding the way the pandemic and its related policy shape China's exports and thus global trade. The results may help us forecast the development of global trade when China's draconian pandemic restrictive policies are finally retreated.

2 | CHINESE LOCAL GOVERNMENTS' COVID-RELATED RESTRICTIONS ON HUMAN MOBILITY

The Covid-19 outbreak first emerged in Wuhan, located in the geographical center of China, in late 2019. The initial outbreak was concentrated in Hubei province in the first quarter of 2020, but the number of new infections decreased sharply after Wuhan's government implemented draconian lockdown measures that restricted human mobility within and between cities. By the end of the first quarter, the number of new infections had dropped to close to a single digit (see Figure 1). However, the pandemic spread to other regions in China, leading to sporadic outbreaks of infections.

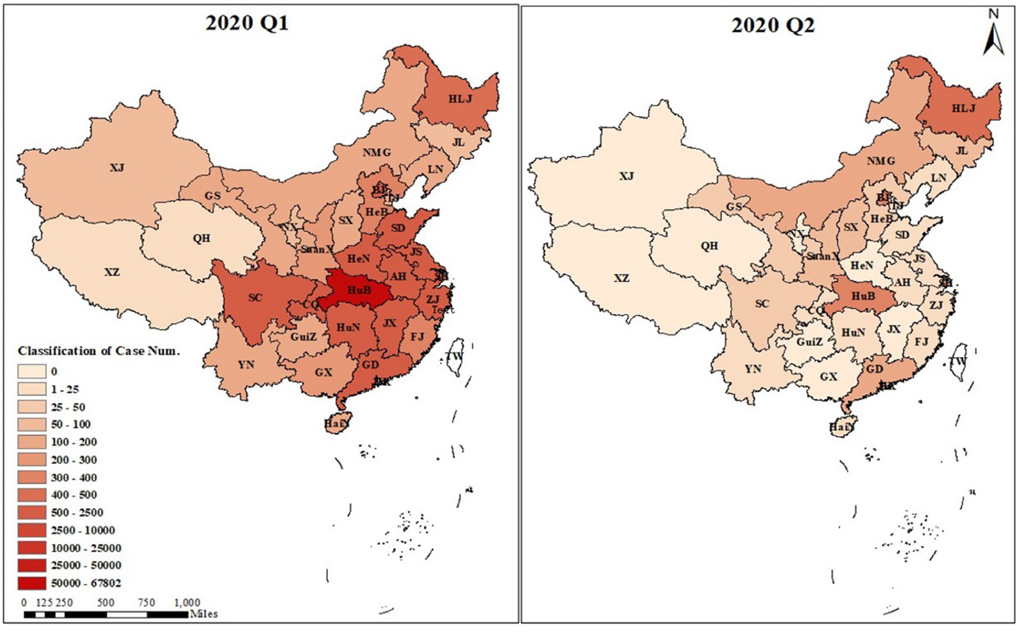


FIGURE 1 Number of new infections at the province level during the initial period. This figure illustrates the numbers of newly confirmed infection cases by China's 31 provinces and municipality cities in the first and second quarters of 2020, when the initial outbreak began. The shades of red in the legend represent the number of new infections. The darker the color, the more newly confirmed infection cases there are. The two quarters share the same legend, so the numbers can be compared across quarters. Limited to availability, data of Hong Kong, Macao and Taiwan are not included. [Colour figure can be viewed at wileyonlinelibrary.com]

To contain the outbreak, cities with high risks of transmission adopted lockdown policies. Wuhan's lockdown policy lasted for almost 3 months from January 23, 2020 to April 8, 2020, and affected human mobility in various ways. For example, during the lockdown period, total outflow, inflow, and intra-city mobility in Wuhan all decreased (see Figure 2). Although restrictions on outflow were tight during the entire lockdown period, restrictions on people inflow (see Figure 3)

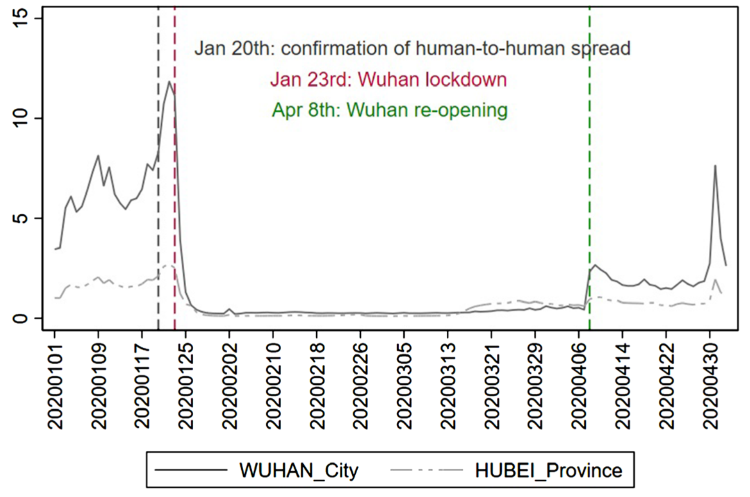


FIGURE 2 Total Outflow Index of Wuhan City and Hubei Province in early 2020. This figure demonstrates the change of human mobility from the total outflow direction for Wuhan City and Hubei Province during early 2020, when the Covid-pandemic outbreak began and the lockdown policy was carried out. [Colour figure can be viewed at wileyonlinelibrary.com]

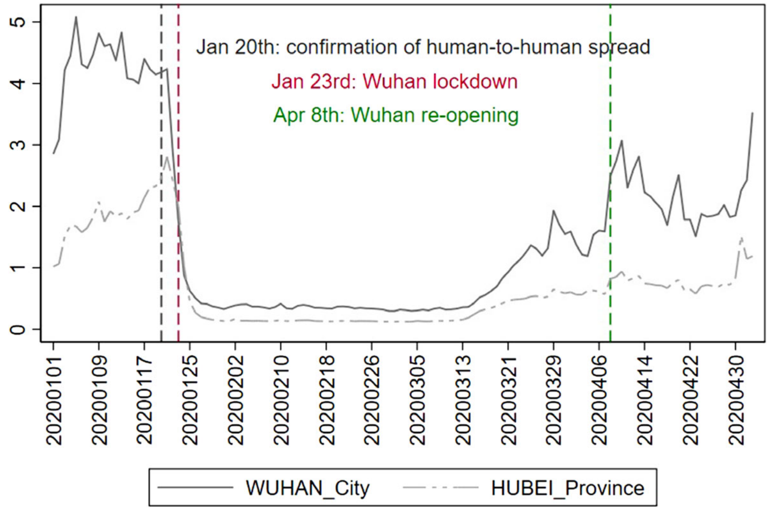


FIGURE 3 Total Inflow Index of Wuhan City and Hubei Province in early 2020. This figure demonstrates the change of human mobility from the total inflow direction for Wuhan City and Hubei Province during early 2020, when the Covid-pandemic outbreak began and the lockdown policy was carried out. [Colour figure can be viewed at wileyonlinelibrary.com]

and within-city mobility (see Figure 4) began to ease gradually in mid-March 2020. Other provincial and city governments implemented similar policies at different times, providing cross-region and cross-time variations for the regression analysis.

The Covid-19 pandemic is expected to have a lasting impact on human mobility, both within and between cities. Using the normalized human inflow of 1 for January 1, 2020, Wuhan's human inflow index has not fully recovered to pre-pandemic levels, except for sharp rebounds during

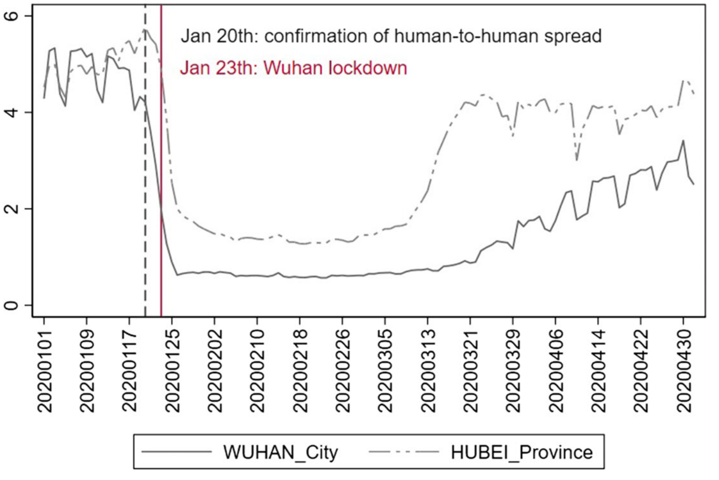


FIGURE 4 Within-city Intensity Index of Wuhan City and Hubei Province in Early 2020. This figure demonstrates the change of within-city mobility intensity index of Wuhan City and Hubei Province during early 2020, when the Covid-pandemic outbreak began and the lockdown policy was carried out. [Colour figure can be viewed at wileyonlinelibrary.com]

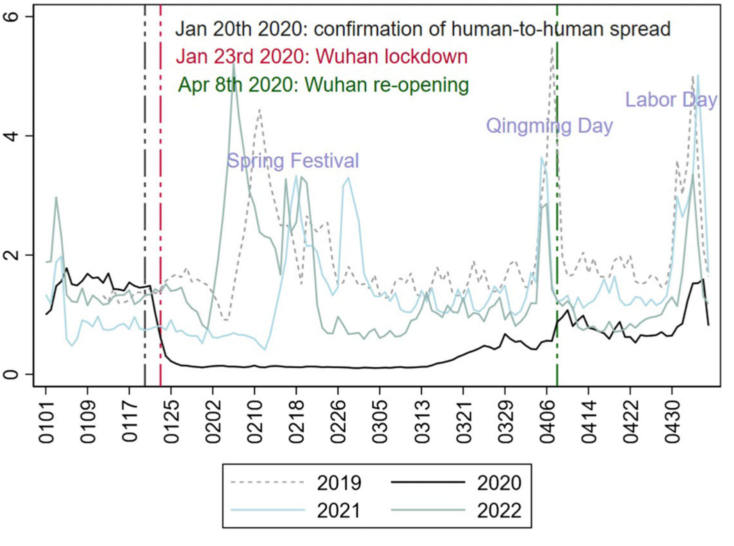


FIGURE 5 Normalized Inflow Index of Wuhan City of the first 4 months across 2019–2022. This figure shows the trend of normalized inflow index of Wuhan City of the first 4 months across 2019–2022. The lines in different colors correspond to different years, respectively. By normalizing the index to 1 on Jan 1st, 2020, the normalized inflow index is comparable across years. [Colour figure can be viewed at wileyonlinelibrary.com]

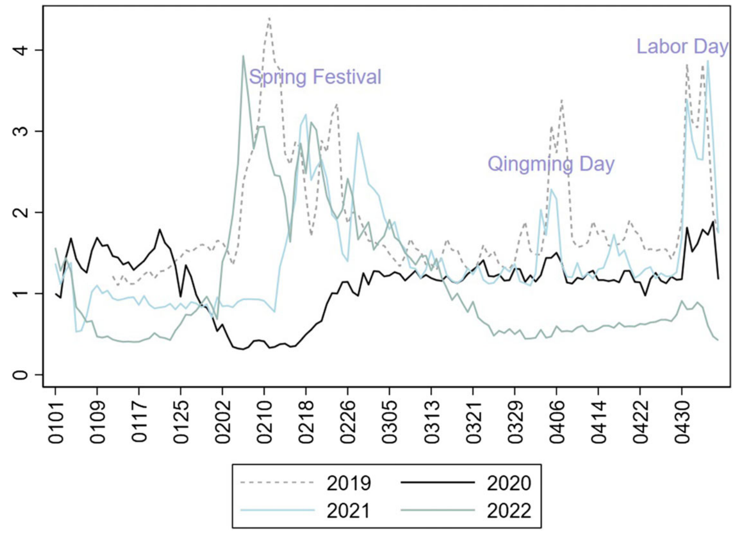


FIGURE 6 Normalized Outflow Index of Henan Province of the first 4 months across 2019–2022. This figure shows the trend of normalized outflow index of Henan Province of the first 4 months across 2019–2022. The lines in different colors correspond to different years respectively. By normalizing the index to 1 on Jan 1st, 2020, the normalized outflow index is comparable across years. [Colour figure can be viewed at wileyonlinelibrary.com]

holiday travel periods, as shown in Figure 5. Similarly, Henan Province's normalized outflow index, China's largest province in terms of labor supply, has not yet returned to pre-Covid levels, as illustrated in Figure 6. Although Covid-related restrictions on human mobility may not be the only factor impacting movement patterns, policies that limit inter-regional interactions could play an important role.

3 | DATA AND IDENTIFICATION

3.1 | Trade data

We source our data on exports from the China Customs official website (http://stats.customs.gov.cn/) and collected information from 2018 to 2021. The dataset includes monthly export values (in US dollars) at the product level (HS 8-digit) for 31 provinces (four of which are municipality cities) and every export destination (over 200 economies) in various trade regimes (e.g., ordinary trade regime, processing trade regime, etc.). To account for infrequent trade and reduce noise, we aggregated the data to the monthly province-HS4-destination level. We then calculated the (log) difference in export value between each month and the same month in the previous year. Using the year-on-year difference variable as the dependent variable allows us to control for the pre-trend of the pandemic period that began in January 2020.

3.2 | Covid-19 infection data

We obtain information on Covid-19 infection cases in China's export partners from the World Health Organization (WHO) website (https://covid19.who.int/data). The number of Covid-19 infection cases in China's 31 provinces and municipality cities was released by China's National Health Commission and provincial official governments, and collected continuously multiple times a day by the web-crawling server of DXY, a prominent online platform and digital service provider in the healthcare industry in China. To ensure data accuracy, we cross-checked the two data sources and consulted news reports for the day.

In general, the extent of lockdown measures imposed was proportional to the number of confirmed infection cases. Our regression analysis at the aggregated year-month-province level shows a significant negative correlation between an increase in the number of new infections of a province and its total export value, but no correlation with the number of export product categories (see Table A2). However, as the severity of the pandemic in most foreign countries has been worse than that in China since the second quarter of 2020, it is important to control for the pandemic's severity in destination economies in our regression analysis.[1]

3.3 | Human mobility data

The data on China's human mobility from 2019 to 2022 is sourced from the Baidu Qianxi web platform (https://qianxi.baidu.com/), which records the real-time location of every smartphone through its Maps Location Based Service (LBS). Baidu Huiyan big data service further analyzes the information to construct various indices, including within-city human mobility intensity, total inflow and outflow indices for each city, and inter-city inflow and outflow indices. The reliability of this dataset is confirmed by research in Science (Kraemer et al., 2020).

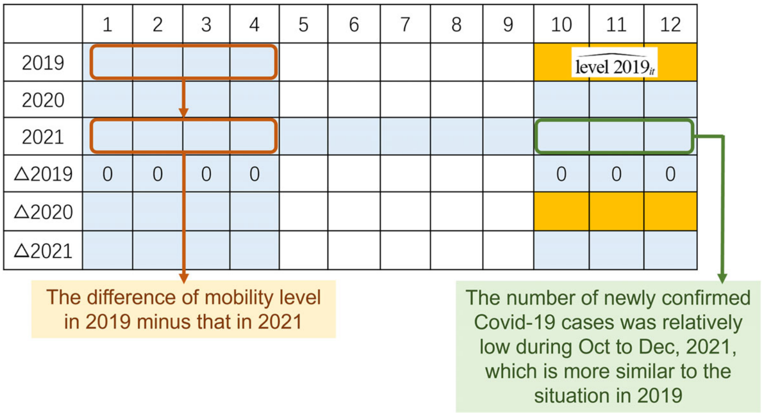
The human mobility index from Baidu Qianxi is defined as an exponential function of the ratio of the number of traveling people to the population, which measures the extent of travel activities within and across cities. Although we cannot obtain the exact number of people flowing into or out of the city, the index is comparable across cities and time (Fang, Wang, & Yang, 2020). We construct comparable travel-restriction indicators within and between provinces triggered by the "Zero Covid" policy, based on the year-on-year decline in the normalized inflow and outflow indices. To construct a balanced panel and due to data availability, we use the inflow index from January to April and October to December in the years 2019 to 2021 (see Figure 7). We fill in the missing mobility index from October to December in 2019 by adding the average subtraction of the mobility level in 2021 from that in 2019 to the mobility index level in the same month in 2021, given that the number of new infections in the fourth quarter of 2021 was relatively low, close to the pre-Covid situation in 2019. We construct Covid-related travel restrictions by setting the value in all months of 2019 to be 0, considering that the lockdown policy started in January 2020.

We construct the inflow restriction variable according to Equation (1):

$$\mathrm{Norm\_Inflow}_{it} = \frac{\mathrm{Inflow}_{it}}{\mathrm{Inflow}_{i,Jan1st2020}}$$

$$\mathrm{Inflow\_Restriction}_{it} = \ln\left(\mathrm{Norm\_Inflow}_{i,t-1}\right) - \ln(\mathrm{Norm\_Inflow}_{it}) \tag{1}$$

To construct province-level inflow restrictions, we first generate a daily inflow index for each city by normalizing the raw inflow index to 1 on January 1st, 2020, following the methodology of Chen et al. (2022). Next, we take the log of the normalized index, compute the 1-year difference, and multiply it by −1 to reflect the degree of inflow restriction, with higher numbers indicating more restrictive travel policies. We then calculate the province-level inflow restriction by taking a



$$\widehat{\text{level 2019}}_{it} = \text{level 2021}_{it} + \left(\overline{\text{level 2019 Jan to Apr}} - \overline{\text{level 2021 Jan to Apr}}\right),\ t = 10,11,12$$

FIGURE 7 Explanation of the data availability of mobility index. This figure shows the data availability of mobility indices. We have inflow mobility index from the months of January to April and October to December in the years 2019–2021. However, the data for the fourth quarter of 2019 is not released. We fill in the missing mobility index (of October to December in 2019) by adding the average substruction of mobility level in 2021 from that in 2019, to the level of mobility index in the same month in 2021, given that the number of new infections in the fourth quarter of 2021 was relatively low, which is close to the pre-Covid situation in 2019. [Colour figure can be viewed at wileyonlinelibrary.com]

weighted average of city-level inflow restriction, with weights equal to the share of a city's population in the province it belongs to. We obtain city-level population size data from the China City Statistical Yearbook 2019, which reports data for 2018. Monthly inflow restriction is computed by taking the simple average of daily inflow restriction.

Figure 8 shows the degree of province-level inflow restriction from 2020 to 2022. As illustrated in the figure, restrictions on people inflows were first strengthened in 2020 and then eased in 2021, with the exception of Heilongjiang. However, in 2022, inflow restrictions in most provinces were tightened again, although the level of restriction was less severe than that in 2020, except for Shanghai.

3.4 | Empirical strategy

1. Regressions at the Year-Month-Province-HS4 Level

We first estimate the impact of Covid-related policies on China's export growth at the year-month-province-product (HS 4-digit) level. In our empirical specifications, China's "Zero Covid" policy is proxied by two variables: local Covid-19 new infections and restrictions on people inflow, which are discussed in Section 3.3.

China has adhered to the "Zero Covid" policy since the outbreak of the pandemic in January 2020 until the end of November 2022. The extent of the within-region travel restrictions, in the extreme version a complete lockdown, was often strongly correlated with the severity of a Covid outbreak under China's "Zero Covid" agenda. As Figure A1 in the appendix illustrates, the correlation between the within-city human mobility index and the (log) number of new infections

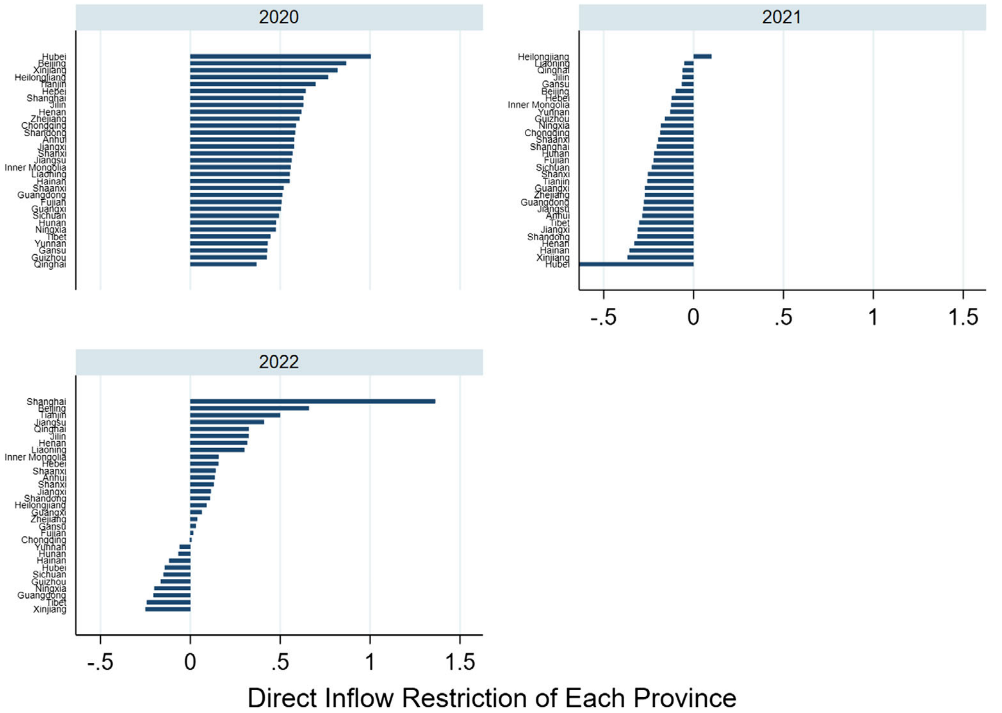


FIGURE 8 Inflow restriction degree of 31 provinces across 2020–2022. This figure shows the constructed inflow restriction degree of 31 provinces in China across 2020–2022. First, we generate each city's daily inflow index by normalizing the raw inflow on Jan 1st, 2020 to 1, which refers to Chen et al. (2022). We then take negative 1-year difference of the normalized inflow index (in logarithmic form). Finally, province-level inflow restriction degree is constructed by taking weighted average of city-level inflow restriction degree, with weights being the proportion of city population size accounted in that of the province. Monthly inflow restriction is generated by taking the simple average of the daily inflow restriction. The constructed inflow restriction degree is comparable across years. Limited to availability, data of Hong Kong, Macao and Taiwan are not included. [Colour figure can be viewed at wileyonlinelibrary.com]

is −0.42. It is deemed to be difficult to separately identity the independent effect of Covid-related policy, the degree of the illness, or people's self-imposed travel restrictions. Therefore, we use the number of newly confirmed Covid-19 cases as a proxy for within-region travel restriction, which possibly includes the effect of illness on temporary local labor supply and estimate the following specification:

$$\begin{aligned}\Delta \ln(1+\text{Value})_{ipt} = {} & \beta_0 + \beta_1 \ln(1+\text{Infections})_{i,t-1} \times \text{Post}_{t-1} + \beta_2 \ln(1+\text{Infections})_{i,t-2} \times \text{Post}_{t-2} \\ & + \beta_3 \ln(1+\text{Value})_{ip,t-12} + \mathbf{FE} + \varepsilon_{ipt} \\ \text{Post}_t = {} & \begin{cases} 1, & \text{if year} \geq 2020 \\ 0, & \text{otherwise} \end{cases}\end{aligned} \tag{2}$$

The dependent variable in Equation (2) is the change in province i's monthly (t) log export value of product p, from the same month in the previous year ($ln(1+\text{Value})_{ipt} - ln(1+\text{Value})_{ip,t-12}$), with t equal to any of the 36 months over the 2019–2021 period. The main regressors of interest, denoted by $ln(1+\text{Infections})_{i,t-1}$ and $ln(1+\text{Infections})_{i,t-2}$, represent the log of province i's new infections in month $t-1$ and $t-2$, respectively, and are interacted with Post_t, a dummy variable taking the value of 1 for all months in 2020 and 2021, and zero otherwise. The pre-treatment period corresponds to year-to-year changes for each month in 2019, while the treatment period corresponds to those after 2020 for the provinces with infections. Different combinations of fixed effects, denoted by **FE**, are included to control for unobserved aggregate determinants (e.g., the seasonal fluctuation in product cycles) of provincial and sectoral export growth that could be related to the pandemic. The province's one-year lagged (log) export value, $ln(1+\text{Value})_{ip,t-12}$, is also included. The error term is denoted by ε_{ipt} and standard errors are clustered at the province level. The coefficients β_1 and β_2 capture the differential effect of the number of Covid-19 infections on China's export growth, while controlling for pre-Covid trends.

Quarantine measures for high-risk groups and social distancing are two effective strategies to control the spread of Covid-19. In a region, the extent to which human mobility is reduced is indicative of the strength of local travel restrictions. The direct effect of either the Covid-related policy, the outbreak itself, or people's self-imposed travel restriction cannot be separately identified. However, we can still estimate a variant of Equation (2) to examine the effect of local governments' restrictions on people inflows, by replacing the independent variable of new infections with the Covid-related restrictions in inbound travelers, as follows:

$$\begin{aligned} \Delta \ln(1+\text{Value})_{ipt} &= \beta_0 + \beta_1 \text{Inflow}_{i,t-1} \times \text{Post}_{t-1} + \beta_2 \text{Inflow}_{i,t-2} \times \text{Post}_{t-2} \\ &\quad + \beta_3 \ln(1+\text{Value})_{ip,t-12} + \mathbf{FE} + \varepsilon_{ipt} \\ \text{Post}_t &= \begin{cases} 1, & \text{if year} \geq 2020 \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{3}$$

In Equation (3), $\text{Inflow}_{i,t-1}$ stands for the Covid-related inflow restriction of province or municipality city i. It is interacted with Post_t, a dummy variable indicating whether the month was after or being 2020 (which takes the value of 1 when being or after year 2020, and zero otherwise). Limited to data availability, we use inflow index from the months of January to April and October to December in the years 2019 to 2021 (see Figure 7). We set the Covid-related inflow restriction to be 0 in 2019. The coefficients β_1 to β_2 identify the differential effect of the Covid-related travel restrictions on China' export growth, controlling for the pre-Covid trends. The meanings of other variables are consistent with that in Equation (2).

2. Regressions at the Year-Month-Province-HS4-Destination Level

To account for the severity of the pandemic in the export destination, we introduce a more granular level of analysis by including the dimension of the export destination economy in the following specification:

$$\begin{aligned} \Delta \ln(1+\text{Value})_{ipdt} &= \beta_0 + \beta_1 \text{Covid}_{i,t-1} \times \text{Post}_{t-1} + \beta_2 \text{Covid}_{i,t-2} \times \text{Post}_{t-2} \\ &\quad + \beta_3 \ln(1+\text{Infection}_{dt}) + \beta_4 \ln(1+\text{Value})_{ipd,t-12} + \mathbf{FE} + \varepsilon_{ipdt} \\ \text{Post}_t &= \begin{cases} 1, & \text{if year} \geq 2020 \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{4}$$

In Equation (4), the dependent variable is the change of province i's monthly (t) log export value of product p to destination d, from the same month in the previous year (ln(1 +

Value)$_{ipdt}$ − ln(1 + Value)$_{ipd,t-12}$) over the 2019–2021 period. The independent variable $\text{Covid}_{i,t-1}$ and $\text{Covid}_{i,t-2}$ are equal to $ln(1 + \text{Infections})_{i,t-1}$ and $ln(1 + \text{Infections})_{i,t-2}$ as in Equation (2), or the Covid-related local inflow restriction as in Equation (3).

$ln\,(1 + \text{Infection}_{dt})$ is the log of monthly (t) new infections in export destination economy d, while the province's 1-year lagged (log) export value $ln(1 + \text{Value})_{ipd,t-12}$ is also included. ***FE*** represent different combinations of fixed effects, to take aggregate shocks into account. ε_{ipdt} is an error term. Standard errors are clustered at the province level.

3. Heterogeneity test with product or industrial characteristics

To study which products were more vulnerable to the Covid-related policies, we estimate the following specification with interaction terms of product or industrial characteristics:

$$\begin{aligned}\Delta \ln(1 + \text{Value})_{ipdt} = {} & \beta_0 + \beta_1 \text{Covid}_{i,t-1} \times \text{Post}_{t-1} + \beta_2 \left(\text{Covid}_{i,t-1} \times \text{Post}_{t-1} \times Z_p\right) \\ & + \beta_3 \text{Covid}_{i,t-2} \times \text{Post}_{t-2} + \beta_4 \left(\text{Covid}_{i,t-2} \times \text{Post}_{t-2} \times Z_p\right) \\ & + \beta_5 \ln(1 + \text{Infection}_{dt}) + \beta_6 \ln(1 + \text{Value})_{ipd,t-12} + \mathbf{FE} + \varepsilon_{ipdt} \\ \text{Post}_t = {} & \begin{cases} 1, & \text{if year} \geq 2020 \\ 0, & \text{otherwise} \end{cases}\end{aligned} \tag{5}$$

In Equation (5), Z_p is a vector of product or industrial characteristics to explain the export decline. These characteristics are measured based on the data before 2018, prior to the initial period of Covid-19, to avoid changes induced by the pandemic that would bias the estimates. The coefficients β_2 and β_4 capture the differential changes induced by Covid-related policies according to those characteristics. The meanings of other variables are consistent with that in Equation (4). Table A1 in the Appendix A provides the summary statistics of the variables of interest used in the regressions.

4 | RESULTS

4.1 | Baseline results

Table 1 reports the estimates of Equations (2) and (3). In column (1), we find that controlling for province-year (to tackle unobserved province-specific supply side factors), product-year (to control for global product cycles), and year-month (to control for seasonal effects like the Lunar New Year effects) fixed effects, we find that the increase in the number of newly confirmed (cases normalized by city population) is negatively correlated with a region's export growth, relative to the pre-Covid period. Specifically, a 10% increase in the (lagged) number of infections compared to same month the previous year in a region is associated with a 0.9% decline in the region's export growth over the same period. In column (2), when the year-on-year changes in the number of new infections lagged by 1 and 2 months are both included, we find that the 1-month lagged infection shock that has a quantitatively larger effect (−0.9% decline for each 10% increase in the number of cases year on year) is associated with a more-than-double effect compared to the 2-month lagged infection shock (−0.4%). In columns (3) and (4), when we replace the product-year and year-month fixed effects by the product-year-month (to control for a more higher frequency global

TABLE 1 The impact of "Zero Covid" policy on China's export, at province-HS4 level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δln(1 + Value)							
Normalized new infections (in lag 1 month)	−0.0915***	−0.0900***	−0.0915***	−0.0903***				
	(0.008)	(0.008)	(0.008)	(0.008)				
Normalized new infections (in lag 2 months)		−0.0437***		−0.0438***				
		(0.006)		(0.006)				
Inflow restriction (in lag 1 month)					−0.1377	−0.1189	−0.1447	−0.1289
					(0.102)	(0.090)	(0.106)	(0.094)
Inflow restriction (in lag 2 months)						−0.0448		−0.0555
						(0.056)		(0.060)
Observations	642,311	604,785	640,749	603,223	325,457	260,639	324,645	259,943
R-squared	0.251	0.257	0.305	0.311	0.277	0.297	0.331	0.35
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HS4-Year FE	Yes	Yes	—	—	Yes	Yes	—	—
Year-Month FE	Yes	Yes	—	—	Yes	Yes	—	—
Year-Month-HS4 FE	—	—	Yes	Yes	—	—	Yes	Yes

Note: Observations are by year-month-province-product (HS 4-digit) level. Data of Panel A (Infection Shock) are for each of the 12 months from 2019 to 2021 (columns 1–4). Data of Panel B (Mobility Restriction Shock) are for the months of January to April and October to December from the years 2019 to 2021 (columns 5–8). The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The infection shock and mobility restriction shock as the independent variables in 2019 are set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

and domestic product cycles) fixed effects, we find quantitatively similar effects of the infection shocks.

However, the impact of local governments' inflow restrictions on exports are not significant (columns 5–8). Since the impact of mobility restriction on economic performance may take time, we repeat the analysis at the quarterly rather than monthly level. As shown in Table A3 in the Appendix A, results in columns (3) and (4) show a significantly negative correlation between a region's local inflow restriction and its export growth, when quarterly data are used.

4.2 | Robustness checks

Trade is a bilateral economic activity, which is influenced by the economic and social conditions of both the exporting and importing economies. Therefore, we exploit the rich customs data by adding the destination dimension to our data set, as discussed in Equation (4), controlling for the number of newly confirmed infections in destination economies. Results in Table 2 indicate that after controlling for the severity of new infections or other destination-year level aggregate shocks, the negative impact of new infections on China's regional export growth remains significant (columns (1) to (4)). Moreover, we find a significantly negative correlation between the severity of the pandemic in export destinations and China's export growth (columns (1), (2) and (6)). Specifically, a 10% year-on-year increase in the number of newly confirmed infections in the destination is associated with a 0.04% decline in a Chinese region's exports on average (i.e., average across regions, products, and destinations). This result suggests an important demand-side reason for China's export downturn during the pandemic.

The impact of local governments' inflow restrictions on export growth remains insignificant based on monthly sample (columns 5–8), but as shown in Table A3 in the Appendix A, they exert a significantly negative effect when quarterly data are used, implying that the inflow restriction policy may take time for the full effects to be observed.

4.3 | Considering the different waves of the Covid variants in China

One may be concerned about the comparability of new infections or mobility restriction as proxies for regional Covid-related travel policy, as initial Covid policies may be more restrictive (e.g., the lockdown of Wuhan in the early part of 2020 and that of Shanghai in 2022). Therefore, we take the waves of main variants into consideration, since stricter lockdowns were implemented during early stage of the outbreak, when people had limited understanding of or effective medical treatments to respond to a new SARS-CoV-2 variant. The trending and perishing time of each variant of Covid-19 in mainland China is sourced from the GISAID Initiative database, based on Elbe and Buckland-Merrett (2017).

Controlling for the different combinations of fixed effects and regions' (provinces and municipality cities) lagged total exports to the same dimension, column (1) to (4) in Table 3 indicate that, at the early stage of the pandemic (Initial Period, Jan 2020 to Nov 2020), the negative impact of new infections on export growth lasted at least for 2 months, but the degree of obstruction decreases over time. During the Alpha & Beta variant waves (Dec 2020 to Jun 2021), the negative impact of new infections on export growth had a lag time of approximately 1 month, but during which the degree of obstruction was even greater than that in the initial period. This may be due to the fact that when Alpha & Beta variant waves were trending, the overall infection situation in

TABLE 2 The impact of "Zero Covid" policy on China's export, at province-HS4-destination level.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Δln(1 + Value)							
Normalized new infections (in lag 1 month)	−0.0813***	−0.0832***	−0.0888***	−0.0901***				
	(0.004)	(0.004)	(0.005)	(0.005)				
Normalized new infections (in lag 2 months)		−0.0152***		−0.0213***				
		(0.005)		(0.005)				
Inflow restriction (in lag 1 month)					−0.0086	−0.0151	−0.0232	−0.0281
					(0.047)	(0.043)	(−0.048)	(−0.043)
Inflow restriction (in lag 2 months)						−0.0485		−0.053
						(0.049)		(−0.051)
ln (1 + new infections in the destination)	−0.0046***	−0.0053***			−0.0033	−0.0099***		
	(0.002)	(0.002)			−0.002	−0.003		
Observations	8,207,094	7,152,001	7,524,226	6,527,534	4,052,302	2,962,370	3,711,277	2,698,737
R-squared	0.250	0.254	0.423	0.429	0.261	0.271	0.433	0.445
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-Year FE	Yes	Yes	—	—	Yes	Yes	—	—
Year-Month-HS4 FE	Yes	Yes	—	—	Yes	Yes	—	—
Year-Month-HS4-Destination FE	—	—	Yes	Yes	—	—	Yes	Yes

Note: Observations are by year-month-province-product (HS 4-digit)-destination level. Data of Panel A (Infection Shock) are for each of the 12 months from 2019 to 2021 (columns 1–4). Data of Panel B (Mobility Restriction Shock) are for the months of January to April and October to December from the years 2019 to 2021 (columns 5–8). The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The infection shock and mobility restriction shock as the independent variables in 2019 are set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 3 Interacted with main variant waves trending in China.

	(1)	(2)	(3)	(4)
Sample dimension	**Year-Month-Province-HS4**		**Year-Month-Province-HS4-Destination**	
Variables	**Δln(1 + Value)**			
Normalized new infections × Initial (both in lag 1 month)	−0.0875***	−0.0877***	−0.0810***	−0.0876***
	(0.009)	(0.009)	(0.003)	(0.004)
Normalized new infections × Initial (both in lag 2 months)	−0.0419***	−0.0420***	−0.0151***	−0.0209***
	(0.007)	(0.007)	(0.005)	(0.005)
Normalized new infections × AlphaBeta (both in lag 1 month)	−2.6495***	−2.7562***	−1.2934***	−1.3305**
	(0.894)	(0.925)	(0.468)	(0.518)
Normalized new infections × AlphaBeta (both in lag 2 months)	0.0868	0.0128	0.7086*	0.6968*
	(0.376)	(0.388)	(0.376)	(0.374)
Normalized new infections × Delta both (in lag 1 month)	−1.2317	−1.3806	−0.4466	−0.6626
	(1.663)	(1.690)	(0.417)	(0.450)
Normalized new infections × Delta (both in lag 2 months)	−2.5393*	−2.6798*	−0.1629	−0.3968
	(1.428)	(1.515)	(0.471)	(0.535)
ln (1 + new infections in the destination)			−0.0053***	
			(0.002)	
Observations	604,785	603,223	7,152,001	6,527,534
R-squared	0.257	0.312	0.254	0.429
Province-Year FE	Yes	Yes	Yes	Yes
HS4-Year FE	Yes	—	—	—
Year-Month FE	Yes	—	—	—
Year-Month-HS4 FE	—	Yes	Yes	—
Destination-Year FE	—	—	Yes	—
Year-Month-HS4-Destination FE	—	—	—	Yes

Note: Observations are by year-month-province-product (HS 4-digit)-destination level. The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The data of SARS-CoV-2 variants of concern is sourced from GISAID Initiative, based on Elbe and Buckland-Merrett (2017). The trending and perishing time of each variant that trending in mainland China is as follows: Initial (Jan 2020–Nov 2020), Alpha & Beta (Dec 2020–Jun 2021), Delta (Apr 2021–Nov 2021), Omicron (Dec 2021 till now). Since the sample period of this table is 2019–2021, the Omicron period is not included, and the infection variable in 2019 is set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

mainland China were actually eased, leading to a relatively relaxed lockdown restriction in most regions, during which the lockdown measures might exert a greater impediment on exports if a region still had serious increasing infections. Moreover, during the Delta variant waves (Apr 2021 to Nov 2021), after controlling for the severity of the pandemic in the importing economy, the impact of local new infections on China's exports was no longer significant. This result is reasonable, given that the pandemic in most foreign countries is seriously worse than that in mainland China during this period.

4.4 | Heterogeneity effects

China is known as the world's manufacturing factory, with processing trade accounting for about one third of its total exports. The inputs and final products in processing trade regime are mostly sourced from and flowing to economies outside mainland China. Therefore, in Table 4, we conduct sub-sample regressions according to different trade regimes. Results show that the increase of one-month lagged new infections of the region exerts a significantly negative impact on local export growth, in both ordinary (non-processing) and processing trade regimes (columns (1) to (4)), more so for the latter in the short run. One possible reason is that processing firms tend to be bigger and more labor-intensive, requiring more workers and thus are more likely to be impacted from the labor shortage due to Covid or its related travel restrictions.[2] As Table A4 in the Appendix A reports, these results hold when the destination dimension is collapsed.

In contrast, for exports under the ordinary trade regime, the negative impact of new infections still persists for at least 2 months (as seen in columns (2) and (4)). Similar to the baseline results, the impact of local inflow restrictions on exports is still not significant for both ordinary and processing trade regimes (as seen in columns (5) to (8)). However, the negative impact of infection severity in importing economies still exists (as seen in columns (5) and (7)). This suggests that the demand side plays an important role in China's Covid-related export downturn.

In Tables 5 and 6, we investigate the potential heterogeneous effects of "Zero Covid"-related policies (using new infections as proxies in Table 5 and inflow restriction in Table 6) on China's export growth, depending on product or industrial characteristics. To accomplish this, we estimate Equation (5). Firstly, to control the spread of Covid-19, the Chinese government, like many other countries, promotes "working from home" during the pandemic. Therefore, for both Tables 5 and 6, in column (1), we analyze the diverse performance of export products under the influence of "Zero Covid"-related policies, using an above median dummy interaction based on the home work index provided in Dingel and Neiman (2020). A higher index implies that the industry is more flexible in adopting the "working from home" approach. We generate a dummy variable if the index is above the median across HS 3-digit categories. Secondly, in column (2), we use the interaction term that takes the value 1 if the import demand elasticity, provided by Broda and Weinstein (2006), is below the median across HS 3-digit categories. Thirdly, in column (3), we examine the potential differential effects among inputs and final goods (including capital goods and consumption goods). The interaction term takes the value of 1 if the HS 4-digit product is an input, according to the UN BEC classification, and zero otherwise. Finally, in column (4), we use the interaction term that takes the value 1 if the upstreamness index, proposed by Antràs et al. (2012), is above the median across HS2-digit categories, and zero otherwise.

The results in Table 5 show that the negative effects of new infections are more significant for exports from industries that rely less on remote working (column (1)), products that are more substitutable (column (2)), final goods (column (3)), or products produced in the downstream

TABLE 4 Heterogeneity test: Sub-sample with different trade regimes.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trade regime	**Ordinary**		**Processing**		**Ordinary**		**Processing**	
Variables	**Δln(1 + Value)**							
Normalized new infections (in lag 1 month)	−0.0737***	−0.0810***	−0.1191***	−0.1327***				
	(0.004)	(0.005)	(0.006)	(0.005)				
Normalized new infections (in lag 2 months)	−0.0162***	−0.0196***	−0.0105*	−0.0053				
	(0.004)	(0.006)	(0.006)	(0.011)				
Inflow restriction (in lag 1 month)					−0.0203	−0.0340	−0.0277	−0.0549
					(0.052)	(0.056)	(0.051)	(0.057)
Inflow restriction (in lag 2 months)					−0.0500	−0.0536	0.0534	0.0365
					(0.060)	(0.067)	(0.055)	(0.057)
ln (1 + new infections in the destination)	−0.0070***		−0.0074***		−0.0138***		−0.0117***	
	(0.002)		(0.002)		−0.003		−0.003	
Observations	6,120,746	5,625,548	809,597	626,398	2,535,120	2,320,337	350,236	270,639
R-squared	0.264	0.441	0.200	0.423	0.279	0.454	0.209	0.428
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-Year FE	Yes	—	Yes	—	Yes	—	Yes	—
Year-Month-HS4 FE	Yes	—	Yes	—	Yes	—	Yes	—
Year-Month-HS4-Destination FE	—	Yes	—	Yes	—	Yes	—	Yes

Note: Observations are by year-month-province-product (HS 4-digit)-destination level. Data of Panel A (Infection Shock) are for each of the 12 months from 2019 to 2021 (columns 1–4). Data of Panel B (Mobility Restriction Shock) are for the months of January to April and October to December from the years 2019 to 2021 (columns 5–8). The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The infection shock as the independent variables in 2019 is set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 5 Heterogeneity test: New infections interacted with product characteristics.

		(1)	(2)	(3)	(4)
	Types of interaction terms (Dz)	**Teleworkable**	**Low elasticity**	**BEC input**	**Upstreamness**
Coeff.	**Variables**	**$\Delta\ln(1 + \text{Value})$**			
*b*1	Normalized new infections (in lag 1 month)	−0.0944***	−0.0756***	−0.1104***	−0.0947***
		(0.016)	(0.004)	(0.007)	(0.004)
*b*2	Normalized new infections (in lag 1 month) × Dz	0.0292	0.0066	0.0732***	0.0564***
		(0.024)	(0.006)	(0.013)	(0.009)
*b*3	Normalized new infections (in lag 2 month)	−0.0545***	−0.0318***	−0.0326***	−0.0170***
		(0.017)	(0.005)	(0.006)	(0.006)
*b*4	Normalized new infections (in lag 2 month) × Dz	0.0586**	0.0383***	0.0467***	0.0195
		(0.026)	(0.004)	(0.012)	(0.012)
	Observations	7,092,349	7,348,420	7,412,024	7,421,733
	R-squared	0.298	0.297	0.297	0.297
	Province-Year FE	Yes	Yes	Yes	Yes
	Year-Month-Destination FE	Yes	Yes	Yes	Yes
	HS4-Destination FE	Yes	Yes	Yes	Yes
	Joint significance test: b1 + b2	−0.0652***	−0.0690***	−0.0372***	−0.0383***
	Joint significance test: b3 + b4	0.0041	0.0065	0.0142	0.0025

Note: Observations are by year-month-province-product (HS 4-digit)-destination level, for each of the 12 months from 2019 to 2021. The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The infection shock as the independent variables in 2019 is set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. The interaction terms of product characteristics are dummy variables that take the value 1 if the HS4-digit product is an input (not belonging to capital or consumption goods), according to the UN BEC classification; or if the upstreamness index, provided by Antràs et al. (2012), is above the median across HS2-digit categories; or if the work from home index, provided by Dingel and Neiman (2020), is above the median across HS 3-digit categories; or if the import demand elasticity, provided by Broda and Weinstein (2006), is below the median across HS 3-digit categories, and zero otherwise. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE 6 Heterogeneity test: Mobility restrictions interacted with product characteristics.

Coeff.	Types of interaction terms (Dz) / Variables	(1) Teleworkable	(2) Low elasticity	(3) BEC input	(4) Upstreamness
		$\Delta\ln(1+\text{Value})$			
*b*1	Inflow restriction (in lag 1 month)	0.0120	0.0112	−0.0124	−0.0121
		(0.042)	(0.042)	(0.042)	(0.041)
*b*2	Inflow restriction (in lag 1 month) × Dz	−0.0180***	−0.0107**	0.0373***	0.0456***
		(0.006)	(0.005)	(0.008)	(0.010)
*b*3	Inflow restriction (in lag 2 month)	−0.0486	−0.0587	−0.0283	−0.0270
		(0.052)	(0.051)	(0.050)	(0.049)
*b*4	Inflow restriction (in lag 2 month) × Dz	0.0242***	0.0450***	−0.0048	−0.0100
		(0.009)	(0.006)	(0.008)	(0.007)
	Observations	2,875,105	2,979,666	3,005,242	3,008,859
	R-squared	0.324	0.323	0.323	0.323
	Province-Year FE	Yes	Yes	Yes	Yes
	Year-Month-Destination FE	Yes	Yes	Yes	Yes
	HS4-Destination FE	Yes	Yes	Yes	Yes
	Joint significance test: b1 + b2	−0.0060	0.0005	0.0249	0.0335
	Joint significance test: b3 + b4	−0.0244	−0.0138	−0.0331	−0.0369

Note: Observations are by year-month-province-product (HS 4-digit)-destination level, for the months of January to April and October to December from the years 2019 to 2021. The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The mobility restriction shock as the independent variables in 2019 are set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. The interaction terms of product characteristics are dummy variables that take the value 1 if the HS4-digit product is an input (not belonging to capital or consumption goods), according to the UN BEC classification; or if the upstreamness index, provided by Antràs et al. (2012), is above the median across HS2-digit categories; or if the work from home index, provided by Dingel and Neiman (2020), is above the median across HS 3-digit categories; or if the import demand elasticity, provided by Broda and Weinstein (2006), is below the median across HS 3-digit categories, and zero otherwise. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

of supply chains (column (4)). Similarly, when using mobility restrictions as a proxy for "Zero Covid"-related policies, the results in columns (3) and (4) of Table 6 suggest that compared to final goods and downstream products, inputs and upstream products are less adversely affected by local inflow restrictions. Tables A5 and A6 in the Appendix A show consistent results when the destination country dimension is collapsed.

5 | CONCLUDING REMARKS

This paper investigates the impact of the "Zero Covid"-related policy on export performance across provinces in China. By analyzing monthly export data at the product-destination level for China's 31 provinces and municipality cities for each month between 2019 and 2021, we find that spikes in new infections in a Chinese region is significantly negatively correlated with the region's export growth. This impact is more pronounced for exports in the non-processing trade regime and for industries that depend less on remote working, final goods, and products that are more substitutable and used mostly in the downstream of supply chains. Additionally, the severity of the pandemic in the export destination is negatively correlated with China's export growth, highlighting the significant role of demand during China's Covid-related export downturn.

Despite China's efforts towards economic development and industrial upgrading, it remains the world's largest manufacturing center and is heavily focused on downstream manufacturing, such as assembly, which requires significant labor inputs. While China has been reducing its dependence on processing trade regimes and moving towards skill and capital-intensive products, its current trade regime composition and product portfolio make its exports highly vulnerable to the negative impact of population restrictions under the "Zero Covid" policy.

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DATA AVAILABILITY STATEMENT

All data used in this study were obtained from the following public sources: Trade data from China Customs official website (http://stats.customs.gov.cn/). Health data from WHO Website of Covid-19 (https://covid19.who.int/data). Mobility data from Baidu Qianxi web platform (https://qianxi.baidu.com/). Data on different Covid variants by country from the GISAID Initiative (https://covariants.org/per-country). The data about the numbers of Covid-19 confirmed cases and other aggregated data at the province and province-sector levels can be made available from the corresponding author upon request.

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ENDNOTES

[1] According to the real-time statistics of Johns Hopkins University, as of 5:30 am on March 16, 2020, the total number of confirmed Covid-19 cases in the world reached 162,687, of which the total number of confirmed cases outside China reached 81,625. According to the report from China's National Health Commission on the same day, as of 24:00 on March 15, 2020, confirmed cases in China reached 80,860, which means that the total number of confirmed cases abroad has exceeded that of China.

[2] However, when controlling for the severity of the pandemic in the importing economies, the impact of two-month lagged new infections on processing exports is no longer significant.

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APPENDIX A

TABLE A1 Summary statistics.

1. Summary of sample statistics in baseline regressions										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	***N***	**Mean**	**p50**	**SD**	**Min**	**p10**	**p25**	**p75**	**p90**	**Max**
Panel A: at Year-Month-Province-HS4 Level, 2019–2021 (Table 2, *col 3)*										
Δln(1 + Value)	640,749	0.15	0.10	1.55	−18.57	−1.31	−0.44	0.69	1.68	18.42
Normalized new infections (in lag 1 month)	640,749	13.22	13.36	2.76	0	9.70	11.54	15.11	16.61	23.13
ln(1 + Value)_lag	640,749	0.02	0	0.35	0	0	0	0	0.03	11.19
Panel B: at Year-Month-Province-HS4 Level, Jan–Apr and Oct–Dec, 2019–2021 (Table 2, *col 7)*										
Δln(1 + Value)	324,645	0.15	0.10	1.58	−18.57	−1.34	−0.45	0.71	1.73	18.42
Inflow restriction (in lag 1 month)	324,645	0.13	0	0.54	−2.14	−0.28	0	0.40	0.65	2.48
ln(1 + Value)_lag	324,645	13.21	13.36	2.75	0	9.71	11.55	15.09	16.58	23.13

2. Summary of product characteristics										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	***N***	**Mean**	**p50**	**SD**	**Min**	**p10**	**p25**	**p75**	**p90**	**Max**
At HS2 level (converted to HS v2017)										
Upstreamness (above median dummy, based on upstreamness index)	99	0.51	1	0.50	0	0	0	1	1	1
At HS3 level (converted to HS v2017)										
Teleworkable (above median dummy, based on work from home index by employment)	147	0.48	1	0.50	0	0	0	1	1	1
Low elasticity (below median dummy, based on elasticity index)	175	0.52	1	0.50	0	0	0	1	1	1
At HS4 level (converted to HS v2017)										
BEC Input (dummy)	1203	0.61	1	0.49	0	0	0	1	1	1
Skill intensive (above median dummy, based on skill intensive index)	1196	0.48	0	0.50	0	0	0	1	1	1
Capital intensive (above median dummy, based on capital intensive index)	1196	0.62	1	0.49	0	0	0	1	1	1

Note: The Covid shock variables in 2019 are set to be 0, assuming that there is no change from 2018 to 2019.

TABLE A2 Impact of new infections on China's export performance at the province level.

Variables	(1) Δln(1 + Value)	(3) Δln(1 + no. HS4)	(4) Δln(1 + no. Destinations)
Normalized new infections (in lag 1 month)	−0.0701***	0.0066	−0.0060
	(0.016)	(0.008)	(0.004)
Normalized new infections (in lag 2 month)	0.0060	0.0071	0.0014
	(0.018)	(0.007)	(0.004)
ln(1 + Value) (in lag 1 year)	−0.9800***		
	(0.063)		
ln(1 + no. HS4) (in lag 1 year)		−1.0944***	
		(0.153)	
ln(1 + no. Destinations) (in lag 1 year)			−1.1167***
			(0.048)
Constant	21.0412***	7.0174***	5.5789***
	(1.350)	(0.980)	(0.240)
Observations	744	744	744
R-squared	0.739	0.574	0.636
Province FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes

Note: Observations are by year-quarter-province level. Data are for each of the four quarters from 2019 to 2021. The dependent variables in all the columns are the log difference in the variable of interest from the same quarter a year ago. The infection shock of independent variable in 2019 is set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes between 2018 and 2019 correspond to the pre-treatment period, and 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE A3 Robustness check: Using quarterly sample.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample dimension	**Province-HS4-Year-Quarter**				**Province-HS4-Year-Quarter-Destination**			
Variables	**$\Delta \ln(1 + \text{Value})$**							
Normalized new infections	−0.0134***	−0.0056			−0.0023	−0.0015		
	(0.003)	(0.004)			(0.002)	(0.002)		
Inflow restriction			−0.7753***	−0.6513***			−0.5243***	−0.2885
			(0.191)	(0.218)			(0.144)	(0.225)
ln (1 + new infections in the destination)					0.0160***		0.0101	
					(0.004)		(0.008)	
Observations	269,884	269,884	134,939	134,939	5,553,847	5,553,846	2,747,772	2,747,772
R-squared	0.225	0.227	0.244	0.246	0.212	0.215	0.211	0.213
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HS4-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	—	Yes	—	Yes	Yes	—	Yes	—
Destination-Year FE	—	—	—	—	Yes	—	Yes	—
Destination-Year-Quarter FE	—	—	—	—	—	Yes	—	Yes

Note: Observations in columns (1)–(4) are by year-quarter-province-product (HS 4-digit) level, and observations in columns (5) and (8) are by year-quarter-province-product (HS 4-digit)-destination level. Data of Panel A (Infection Shock) are for each of the 4 quarters from 2019 to 2021 (columns 1, 2, 5, 6). Data of Panel B (Mobility Restriction Shock) are for Q1 & Q4 from the years 2019 to 2021 (columns 3, 4, 7, 8). The dependent variable in all the columns is the log difference in the variable of interest from the same quarter a year ago. The infection shock and mobility restriction shock as the independent variables in 2019 are set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE A4 Heterogeneity test: Sub-sample with different trade regimes, at Year-Month-Province-HS4 level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trade regime	**Ordinary**		**Processing**		**Ordinary**		**Processing**	
Variables	**Δln(1 + Value)**							
Normalized new infections (in lag 1 month)	−0.0924***	−0.0920***	−0.1322***	−0.1383***				
	(0.015)	(0.013)	(0.004)	(0.004)				
Normalized new infections (in lag 2 months)		−0.0475***		−0.0123**				
		(0.008)		(0.005)				
Inflow restriction (in lag 1 month)					−0.1033	−0.1033	−0.0686	−0.0854
					(0.122)	(0.113)	(0.092)	(0.098)
Inflow restriction (in lag 2 months)						−0.1003		−0.0027
						(0.106)		(0.092)
Observations	602,208	566,159	132,479	124,690	304,738	243,353	67,407	54,252
R-squared	0.315	0.322	0.293	0.299	0.341	0.36	0.302	0.314
Province-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month-HS4 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Observations are by year-month-province-product (HS 4-digit) level. Data of Panel A (Infection Shock) are for each of the 12 months from 2019 to 2021 (columns 1–4). Data of Panel B (Mobility Restriction Shock) are for the months of January to April and October to December from the years 2019 to 2021 (columns 5–8). The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The infection shock as the independent variables in 2019 is set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE A5 Heterogeneity test: New infections interacted with product characteristics, at Year-Month-Province-HS4 level.

Coeff.	Types of interaction terms (Dz)	(1) Teleworkable	(2) Low elasticity	(3) BEC input	(4) Upstreamness
	Variables	**Δln(1 + Value)**			
*b*1	Normalized new infections (in lag 1 month)	−0.0986***	−0.0785***	−0.1143***	−0.1090***
		(0.010)	(0.007)	(0.010)	(0.010)
*b*2	Normalized new infections (in lag 1 month) × Dz	0.0031	−0.0195***	0.0455***	0.0396***
		(0.005)	(0.003)	(0.005)	(0.005)
*b*3	Normalized new infections (in lag 2 month)	−0.0596***	−0.0450***	−0.0560***	−0.0496***
		(0.006)	(0.008)	(0.012)	(0.010)
*b*4	Normalized new infections (in lag 2 month) × Dz	0.0175**	0.0018	0.0208	0.0119
		(0.007)	(0.005)	(0.014)	(0.011)
Observations		541,702	594,767	601,574	602,587
R-squared		0.249	0.237	0.239	0.239
Province-Year FE		Yes	Yes	Yes	Yes
Year-Month FE		Yes	Yes	Yes	Yes
HS4 FE		Yes	Yes	Yes	Yes
Joint significance test: b1 + b2		−0.0956***	−0.0981***	−0.0689***	−0.0694***
Joint significance test: b3 + b4		−0.0421***	−0.0433***	−0.0352***	−0.0377***

Note: Observations are by year-month-province-product (HS 4-digit), for each of the 12 months from 2019 to 2021. The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The infection shock as the independent variables in 2019 is set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. The interaction terms of product characteristics are dummy variables that take the value 1 if the HS4-digit product is an input (not belonging to capital or consumption goods), according to the UN BEC classification; or if the upstreamness index, provided by Antràs et al. (2012), is above the median across HS2-digit categories; or if the work from home index, provided by Dingel and Neiman (2020), is above the median across HS 3-digit categories; or if the import demand elasticity, provided by Broda and Weinstein (2006), is below the median across HS 3-digit categories, and zero otherwise. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

TABLE A6 Heterogeneity test: Mobility restrictions interacted with product characteristics, at Year-Month-Province-HS4 level.

		(1)	(2)	(3)	(4)
	Types of interaction terms (Dz)	**Teleworkable**	**Low elasticity**	**BEC input**	**Upstreamness**
Coeff.	**Variables**	**Δln(1 + Value)**			
*b*1	Inflow restriction (in lag 1 month)	−0.1236	−0.1039	−0.1743*	−0.1595*
		(0.093)	(0.089)	(0.092)	(0.089)
*b*2	Inflow restriction (in lag 1 month) × Dz	−0.0138	−0.0248	0.1008***	0.0866***
		(0.012)	(0.015)	(0.013)	(0.012)
*b*3	Inflow restriction (in lag 2 month)	−0.0508	−0.0611	−0.0400	−0.0437
		(0.060)	(0.058)	(0.057)	(0.055)
*b*4	Inflow restriction (in lag 2 month) × Dz	0.0053	0.0174*	−0.0194	−0.0155
		(0.012)	(0.010)	(0.013)	(0.015)
	Observations	233,375	256,400	259,309	259,720
	R-squared	0.291	0.276	0.278	0.278
	Province-Year FE	Yes	Yes	Yes	Yes
	Year-Month FE	Yes	Yes	Yes	Yes
	HS4 FE	Yes	Yes	Yes	Yes
	Joint significance test: *b*1 + *b*2	−0.1374	−0.1287	−0.0735	−0.0729
	Joint significance test: *b*3 + *b*4	−0.0455	−0.0437	−0.0594	−0.0591

Note: Observations are by year-month-province-product (HS 4-digit)-destination level, for the months of January to April and October to December from the years 2019 to 2021. The dependent variable in all the columns is the log difference in the variable of interest from the same month a year ago. The mobility restriction shock as the independent variables in 2019 is set to be 0, assuming that there were no Covid-related shocks from 2018 to 2019. Changes in 2019 correspond to the pre-treatment period, and after 2020 to the treatment period after the Covid-19 outbreak in China (in Wuhan) was announced. The interaction terms of product characteristics are dummy variables that take the value 1 if the HS4-digit product is an input (not belonging to capital or consumption goods), according to the UN BEC classification; or if the upstreamness index, provided by Antràs et al. (2012), is above the median across HS2-digit categories; or if the work from home index, provided by Dingel and Neiman (2020), is above the median across HS 3-digit categories; or if the import demand elasticity, provided by Broda and Weinstein (2006), is below the median across HS 3-digit categories, and zero otherwise. One-year lagged exports and constant term are always included in the regressions. Standard errors clustered by province are reported in parenthesis. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

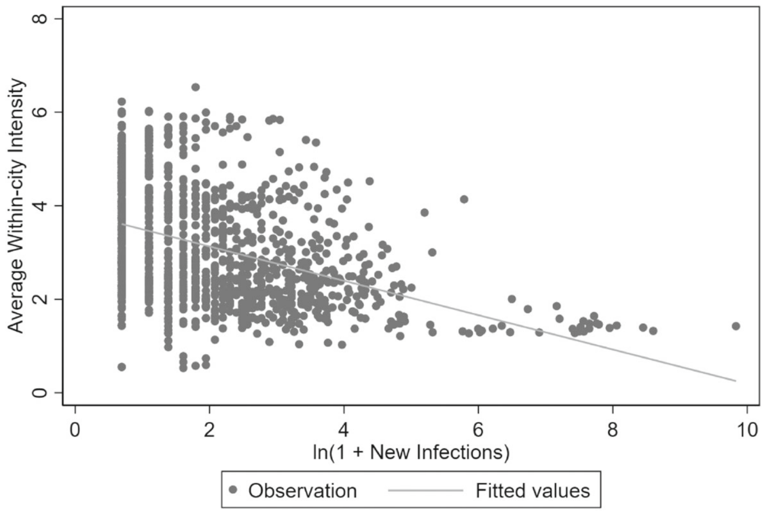

FIGURE A1 The correlation between within-city intensity and new infections. In this figure, the indicator on the Y-axis (average within-city intensity) is calculated by the weighted average of the city-level within-city intensity index, with weights being the proportion of its proportion in that of the province. The indicator on the X-axis (ln(1 + new infections)) is the log form of the number of newly confirmed Covid-19 cases per 10,000 people. Limited to data availability, the sample period in this figure is from Jan to April, 2020, the most severe period of the Covid-19 pandemic in China, and the dimension is by daily province level. The figure shows that there is a negative correlation between within-city intensity and the number of new infections, and the correlation is significant under the 1% significance level, as in the following Table A7.

TABLE A7 Correlation coefficients between the variables.

	Within-city intensity	**Ln(1 + new infections)**
Within-city intensity	1.000	
ln(1 + new infections)	−0.418***	1.000

Note: The results is based on the variables of the above sample in in Figure A1, obtained using the "pwcorr_a" command in Stata.