The Economic Impacts of COVID-19 and City Lockdown: Early Evidence from China

Jianxin Wu[a], Xiaoling Zhan[a], Hui Xu[b], Chunbo Ma[c]*

[a]School of Economics, Institute of Resource, Environment and Sustainable Development Research, Jinan University, No.601 Huangpu West Road, Guangzhou, Guangdong Province, China
[b]School of Economics, Institute of Resource, Environment and Sustainable Development Research, Jinan University, No.601 Huangpu West Road, Guangzhou, Guangdong Province, China
[c]Department of Agricultural and Resource Economics, UWA School of Agriculture and Environment, University of Western Australia, 35 Stirling Highway, Crawley 6009, Western Australia, Australia

*E-mail address: chunbo.ma@uwa.edu.au

31 October 2022
Working Paper 22XX
UWA Agricultural and Resource Economics
http://www.are.uwa.edu.au

Citation: Wu, J.X., Zhan, X.L., Ma, C. (2022) *The Economic Impacts of COVID-19 and City Lockdown: Early Evidence from China*, Working Paper 22XX, Department of Agricultural and Resource Economics, The University of Western Australia, Crawley, Australia.

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Abstract

China adopted the world's most stringent lockdown interventions to contain the COVID-19 spread. Using macro- and micro-level data, this paper shows that the pandemic and lockdown both had negative and significant impacts on the economy. Gross regional product (GRP) fell by 9.5 and 0.3 percentage points in cities with and without lockdown, respectively, representing a dramatic recession from China's average growth of 6.74% before the pandemic. The results indicate that lockdown explains 2.8 percentage points of the GDP loss. We document significant spill-over effects the pandemic but no such effects of lockdown. Reduced mobility, land supply, and entrepreneurship are significant mechanisms underpinning the impacts. Cities with higher share of secondary industry, higher traffic intensity, smaller population, lower urbanization, and lower fiscal capacity suffered more. However, these cities have recovered well and quickly closed the economic gap in the aftermath of the pandemic and city lockdown.

Key words

Economic impact; COVID-19; pandemic; city lockdown; China

JEL classifications

I18 R11 R38

1. Introduction

With the wide spread of the COVID-19, the pandemic has led to significant health and economic losses worldwide. Many countries experienced significant economic slowdown and are still struggling to recover from the COVID pandemic. Various non-pharmaceutical intervention measures, including social distancing, extension of public holiday, school closure, stay-at-home orders, large-gathering bans, non-essential business closures, transportation restrictions, and even more drastic measures such as complete city lockdown, have been adopted. However, the stringency of these restrictions varies significantly across countries and regions. Concerned about possible impacts on the economy, many governments are reluctant to implement the most drastic interventions or remove restrictions as soon as the pandemic is considered under control. An important and challenging question is how much of the impacts resulted from the pandemic versus government-imposed interventions (Goolsbee and Syverson, 2020). These impacts may also depend on the structure of the economy. A sound understanding of such heterogeneity will provide vital and timely input to the challenging policy tradeoff between intervening to reduce disease transmission and maintaining economic growth.

However, gauging and disentangling the impacts of the pandemic and interventions on economic growth are always challenging because traditional data are rarely reported at high-enough frequencies and at the treatment levels (e.g. city, county) where most intervention measures are implemented (Kong and Prinz, 2020). Most recent studies examined the impact of the pandemic using indirect proxies, such as online search data on unemployment insurance claims (Kong and Prinz, 2020; Forsythe et al., 2020; Brodeur et al., 2021a), mobility variations from Facebook (Bonaccorsi et al., 2020), or mobile phone records data on customer visits to businesses (Goolsbee and Syverson, 2020), and job vacancy postings (Forsythe et al., 2020; Campello et al., 2020).

As the first country heavily struck by the COVID-19 pandemic, China has seen its economy shrink by 6.8% in the first quarter of 2020 quarter on quarter. In Hubei province, which has the largest number of confirmed cases and deaths of COVID-19 among all Chinese provinces, the gross provincial product fell by 39.2%. China responded with fast and stringent interventions to avoid catastrophic virus transmission. Many interventions were implemented at the city level. Almost one-third of Chinese cities were locked down in the first quarter of 2020. The Chinese governments collected and reported quarterly city-level socioeconomic data (Au and Henderson, 2006) as well as confirmed COVID-19 cases and death data, making Chinese cities an excellent case to study the economic impacts of the pandemic and related interventions.

China's strict interventions proved to be effective. By the end of the first quarter, most lockdown restrictions were repealed. The number of additional local confirmed cases of COVID-19 declined to almost zero in the second quarter. While many economies are still struggling in the economic downturn of the pandemic, the Chinese economy seems to have recovered rapidly with 3.2%, 4.9% and 6.5% growth in the second, third and fourth quarters in 2020 and 8.1% growth in 2021. This also provide us a unique opportunity to examine the recovery process of a major pandemic-hit economy.

This paper employs quarterly data for China's prefectural-and-above (PAA) level cities to evaluate the impacts of COVID-19 and intervention polices on cities' gross regional product (GRP). We use city-level confirmed cases and deaths of COVID-19 to measure the severity of the pandemic, and focus on the most stringent intervention – city lockdown. This paper takes the advantage of the spatial and temporal variation of the pandemic and city lockdown and uses a difference-in-difference approach to quantify the causal effects. Specifically, we compare the before-and after variation and cross-city variation of the outcome variable.

The analyses yield three sets of results. First, the results show that both the pandemic and lockdown policies have negative impacts on economic growth. An increase of confirmed cases and deaths of the COVID-19 by 1% led to a decline of gross regional product (GRP) by 0.024 and 0.022 percentage point, while city lockdown resulted in a GRP loss of 2.8 percentage points[1]. The results document significant spillovers from the pandemic but no spillover effects for city lockdown. The findings also show that COVID-19 had a continuing but much reduced economic impact during the immediate post-pandemic periods whereas city lockdown had no dynamic impact beyond the intervention period.

Second, we examined the main mechanisms through which the pandemic and city lockdown affected the economy. The analyses of microeconomic activities show that reduced input supplies including labour, land and entrepreneurship are among the most significant channels. We find that the pandemic, and city lockdown in particular have much larger impacts on these microeconomic activities than on overall economy.

Third, the study also examined the heterogeneous effects of the pandemic and lockdown on cities with different characteristics. Analyses of the recession period show that cities with higher share of secondary industry and higher passenger traffic intensity suffered more from the pandemic and lockdown policies indicating larger impacts on manufacturing and mobility. The results also show larger economic decline in less developed regions with smaller population, lower urbanization rate, and lower fiscal

[1] To put these numbers into perspective, one should compare China's average growth of 6.74% during the five years prior to the pandemic to a fall of 6.8% in the first quarter of 2020.

capacity. However, results from the post-pandemic periods also show that the economy has recovered well from the recession. Although those cities hit harder in the pandemic still lag behind, they seem to have recovered faster and quickly closed the economic gap.

This paper contributes to the rapidly growing literature studying the economic impacts of COVID-19 and related interventions (see Brodeur et al. (2021b) for a review of this literature). Many existing studies focus on the impacts on the job market (Adams-Prassl et al., 2020; Forsythe et al., 2020; Rojas et al., 2020; Bartik et al., 2020; Hensvik et al., 2020; Gupta et al., 2020; Couch et al., 2020; Montenovo et al., 2020; Baek et al., 2020; Kong and Prinz, 2020; Lin and Meissner, 2020; Green and Loualiche, 2020; Crossley et al., 2020; Binder, 2020; Ascani et al., 2021). Another strand of literature examines the impacts on income distribution and consumer behavior (Goolsbee and Syverson, 2020; Chetty et al., 2020; Brewer and Gardiner, 2020; Carvalho et al., 2021). A few other studies use various economic approaches to simulate the macroeconomic impacts and calibrate the effects of potential policies (Atkeson, 2020; Altig et al., 2020; Eichenbaum et al., 2020; Krueger et al., 2020; Jordà et al., 2020; Gregory et al., 2020; Aum et al., 2021; Capello and Caragliu, 2021; Yang et al., 2021; Yilmazkuday, 2021). The present paper extends the literature in several ways.

First, most existing studies on the economic impacts of the pandemic focus on the developed countries, particularly the USA. Few efforts have been made to evaluate the pandemic and intervention effects in developing countries. The economic structure, medical treatment capacity and interventions taken in developing countries can differ greatly from developed countries. China makes an excellent case. As the largest developing country with perhaps the most sophisticated economic structure, China is the first major economy heavily struck by the COVID-19 pandemic. However, the severity of the pandemic and its associated economic impacts vary significantly across different regions of the country. There has been an emerging literature on the social and environmental effects of the COVID-19 in China (Fang et al., 2020; He et al., 2020; Matthew et al., 2020; Liu et al., 2020). Rigorous micro and macro studies on the economic effects of the pandemic are surprisingly limited (Zhang et al., 2020; Dai et al., 2021).

Second, this paper examines the economy-wide impacts. Compared with indirect proxies such as mobile phone records or online search data, the economy-wide economic growth data provides straightforward and more comprehensive account of the economic impacts. A couple of studies have examined the economic impact of the pandemic in China. Dai et al. (2021) provides micro evidence of the impacts on small and medium-sized enterprises. To our knowledge, our study is among the first to conduct an economy-wide economic analysis. Zhang et al. (2020) also investigates the macro-economic impact of the COVID-19 in China but largely focuses on agri-food system.

Third, we address the often-asked question about the relative impacts resulted from the pandemic versus government-imposed interventions (Goolsbee and Syverson, 2020). The analysis separately identifies the economic effects of the pandemic and the city lockdown interventions. More importantly, this is done by controlling for possible spillover effects from both the pandemic and city lockdowns. As many Chinese cities adopted complete lockdown restrictions, a study of China's city lockdown also complements the existing studies of interventions in the developed countries that are typically much less stringent. We also explore how these effects differ across cities with different economic structure, which could be of interest for making tailored intervention as well as recovery policies.

Fourth, China is the first major economy that has seen swift and strong post-pandemic recovery. Differing from the existing studies which mostly focus on the pandemic and intervention effects during the economic recession, the present study examines both the decline and recovery processes.

The remainder of the paper is organized as follows. We described the data in Section 2. The empirical strategy is presented in Section 3. Section 4 presents and discusses the results. The last section concludes the paper.

2. Data

Data for the empirical analyses presented in this section were collected various official statistical publications and public databased. Using this dataset, we constructed a quarterly data set for 296 Chinese PAA level cities over the period from the first quarter of 2019 to the third quarter of 2020.

2.1 Outcome variables

We use quarterly GRP as the outcome variable to quantify the economy-wide impact of the pandemic and city lockdown. The GRP data for 296 cities from the first quarter of 2019 to the third quarter of 2020 were collected manually from the local governmental websites and deflated to the constant price in the first quarter of 2019. [2]Table 1 presents the detailed variable definition and summary statistics of the main variables for China

[2] In the fourth quarter of 2020, China experienced a second wave of pandemic due to imported cases. To clearly identify the recovery process, our dataset is limited to the third quarter of 2020.

and for the lockdown and the non-lockdown cities separately.

We also use real-time inter-city migration data from the internet services company Baidu, total land supply data, and new firm registration data as outcome variables in the mechanism analysis. The migration data is based on real-time location records for every smartphone using the company's mapping app and other location services. The Baidu migration dataset covers all Chinese cities 24 days before and 51 days after the Spring Festivals in 2019 and 2020, which correspond to the period between January 12 and March 27 in 2019, and the period between January 1 and March 15 in 2020. Baidu out-migration and in-migration index are sourced from *Baidu Migration Platform*[3]. Total land supply include land supply for all commercial, residential, industrial and public infrastructure uses. The data are sourced from *China Land Market Network*[4] and are aggregated to city-month level. New firm registration data are sourced from the State Administration for Market Regulation database that covers the universe of registered firms in China, which provides details of each registered firm, includes registration time, location, capital and shareholders. New firm numbers and capital are aggregated to city-quarter level in the regression.

2.2 City characteristics

We consider five dimensions of city heterogeneity: industry structure (the share of second industry in GRP), passenger traffic intensity (the ratio of passenger traffic to population), population size, urbanization (the ratio of urban population relative to total population), and fiscal capacity (the ratio of fiscal revenue to GRP). To explore how the impacts of COVID-19 and city lockdown differ by each of these dimensions, we split

[3]Source: https://qianxi.baidu.com/#/
[4] Source: https://www.landchina.com/landSupply

the sample of cities into two groups using the medium value of each characteristic variable and perform analyses for each of the groups. The data on city characteristics are sourced from *The China City Statistic Yearbook* 2019.

2.3 City lockdown and confirmed COVID-19 cases and deaths

The data on confirmed cases and deaths of COVID-19 is sourced from "Resources for COVID-19"[5]. The data was originally collected from http://www.dxy.cn/, China's authorized publishing platform for COVID-19 cases and deaths. The stringency and terms of city lockdown differ greatly across cities. Following He et al. (2020), we identify a lockdown city if it imposes all three preventive measures including: 1) bans on nonessential commercial activities in people's daily lives; 2) bans on any types of gathering by residents; and 3) restrictions on public and private transportation. Lockdown information was manually collected from local governmental announcements. Among the total of 296 cities, 88 cities are identified as the locked-down cities. It is worth noting that all the city lockdown interventions were imposed in the first quarter of 2020 but then repealed by the end of the first quarter. Figure 1 shows the spatial distribution of the lockdown and non-lockdown cities.

2.4 Control variables

We control for city-level heterogeneity including hospital beds, doctors, R&D expenditure as a share of government fiscal expenditure, trade openness, FDI intensity, and per capita income. The data was collected from *the China City Statistical Yearbook* for the pre-treatment year of 2019. We also control for population mobility (the ratio of

[5] Source：https://projects.iq.harvard.edu/chinadatalab/resources-covid-19

migrant population to local population) and collected the data from the most recent population census in 2010. All control variables are interacted with quarter dummies in the regressions.

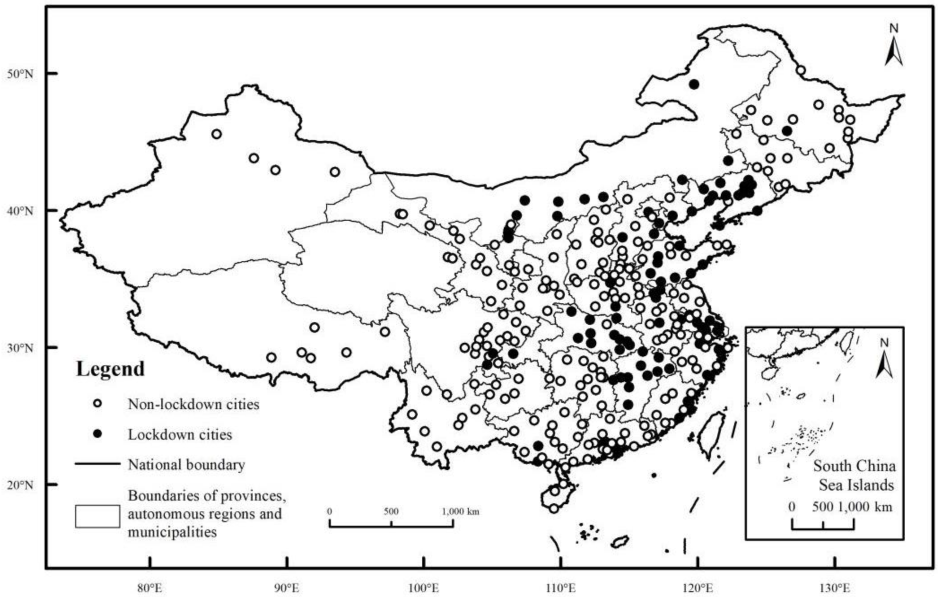

Figure 1. The spatial distribution of lockdown cities and non-lockdown cities

Table 1. Summary statistics

	Lockdown		Non-lockdown		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Description
Confirmed cases	119.88	2026.18	5.27	20.56	Number of confirmed cases
Death cases	7.25	154.83	0.05	0.33	Number of deaths
GRP	148263	188797	71647	65805	Gross regional product (Million RMB)
Death_neighbor	41.96	296.28	0.62	5.92	Number of deaths in neighboring cities
Firms_new	9920	14705.91	5138	6921.306	Number of new registered firms
Investment	33690.71	47150.74	17616.61	25151.51	Capital of new registered firms (Million RMB)
Share of 2nd industry	43.41	8.82	43.26	9.82	Share of second industry in GRP(%)
Passenger traffic intensity	1.01	0.62	1.90	5.25	Ratio of passenger traffic to population
Population	6068.23	5013.50	4038.39	2473.04	Population size (1,000)
Urbanization	0.62	0.15	0.58	0.14	Ratio of urban residents in population
Fiscal capacity	0.09	0.03	0.08	0.03	Ratio of fiscal revenue to GRP
Income level	77035.21	42677.56	64791.42	29277.59	GRP per capita (RMB)
Population mobility	214.16	131.07	200.16	122.03	Ratio of migrant population to local population (per 1,000 people)
Doctors	2.84	1.82	3.01	2.29	Doctors per 1000 people
Hospital beds	5.17	3.34	5.35	4.03	Hospital beds per 1000 people
R&D intensity	0.02	0.02	0.75	4.13	Ration of R&D expenditure to government fiscal expenditure
Trade openness	0.22	0.27	0.19	0.29	Ratio of total import and export value to GRP
Industrial structure	0.96	0.33	0.96	0.37	Ratio of the added value of the secondary industry to the tertiary industry
Distance to Wuhan	777.57	463.94	802.08	349.37	Distance to Wuhan (km)
FDI intensity	0.02	0.01	0.02	0.02	Ratio of FDI to GRP
Number of observations	616		616		
Land	138.78	160.34	99.76	130.52	Land supply area (hectare)
Number of observations	528		528		
Moveout	1.53	2.29	1.11	1.43	Baidu out-migration index
Movein	1.51	2.02	1.12	1.30	Baidu in-migration index
Number of observations	13200		13200		

Notes: The upper panel of the table presents the mean and standard deviation for each variable at either city-quarter or city-year level, focusing on the comparison between the treated lockdown cities and the matched control non-lockdown cities. There are 88 cities in the treated group and 88 in the control for the period 2019.Q1-2020.Q3. The quarterly GRP data were collected manually from the local governmental websites and deflated to constant price in the first quarter of 2019. The data on confirmed cases and deaths of COVID-19, city characteristics, Baidu migration index, and land supply area are sourced, respectively, from "Resources for COVID-19", *The China City Statistic Yearbook 2019, Baidu Migration Platform*, *China Land Market Network,* and *the State Administration for Market Regulation database*.

3. Empirical method

3.1 Difference-in-differences (DID) strategy

The first confirmed case of COVID-19 in China were identified at the end of 2019, but city lockdown and most confirmed cases and deaths were concentrated in the first quarter of 2020[6]. The spatial and temporal variations allow us to employ a difference-in-differences (DID) model to quantify the impacts of the pandemic and city lockdown on economic growth. The specification takes the form:

$$Y_{it} = \beta Pandemic_{it} + \gamma Lockdown_{it} + \alpha X_{it} + \mu_i + \eta_t + \varepsilon_{it} \qquad (1)$$

where Y_{it} is Log(*GRP*) in city *i* at quarter *t*. $Pandemic_{it}$ denotes the log form of the number of confirmed COVID-19 cases (Log($Cases_{it}$)) or deaths (Log ($Deaths_{it}$)) in city *i* at quarter *t*. To facilitate taking logarithm, we added 0.01 to reported $Cases_{it}$ and $Deaths_{it}$. $Lockdown_{it}$ is a dummy taking the value of 1 if for lockdown cities and 0 for non-lockdown cities. Thus, the coefficient of interest β is expected to capture the effect of the pandemic while γ capture the impact of city lockdown. β and γ are expected to be negative, as production activities were restricted in the cities with pandemic and lockdown policies. X_{it} is a vector of controls previously described. The city fixed effects, μ_i which are a set of city-specific dummy variables, capture time-invariant city characteristics such as geographical location, short-term industrial and economic structure, income and natural endowments. The quarter fixed effects, η_t, are a set of dummy variables that account for shocks that are common to all cities at quarter t, such as public holiday extension, macroeconomic conditions and restricted express

[6] Although there are small number of additional cases in a few cities such as Beijing and Shulan after the first quarter of 2020, dropping these cities from the sample does not significantly change the main results.

services, and ε_{it} is the error term. The standard errors are clustered at the city level.

3.2 Selecting the Control Regions Using Propensity Score Matching (PSM)

An accurate evaluation of the policy effects depends on a credible control group that has similar socioeconomic status and satisfies parallel trend and Stable Unit Treatment Value Assumption (SUTVA). Chinese cities differ greatly in many characteristics (such as geographical location, industrial structure, medical treatment capacity, and population mobility etc.). Therefore, we use the PSM approach developed by Rosenbaum and Rubin (1983) to select a control group from the 208 non-lockdown cities for the 88 lockdown cities. We use a logistic regression and data from 2018 on five matching variables to estimate the propensity score. The matching variables include industrial structure, hospital beds, distant to Wuhan, FDI intensity, and population mobility. These variables ensure that the control group have a socioeconomic status similar to that of the treatment cities. We match treatment and control cities through 1:1 nearest neighbor matching without replacement. This provides us with the same number of control cities for the 88 treatment cities. For robustness, we also provide the results using the full sample and alternative numbers of nearest neighbor.

Table A1 in the appendix presents the mean difference for each of the five covariates between the treatment and control groups before and after matching, along with p-values for the t-statistics. We observe apparent lack of balance between the treatment and control counties before matching. After matching, none of the differences between the treatment and matched control counties are statistically significant. For example, the difference in distance to Wuhan between the treatment and control groups drops from -37.3 (p-value=0.01) before matching to -4.8 (p-value=0.694) after matching.

4. Results

4.1 Baseline results using matched sample

Table 2 shows the results from Specification (1) using different pandemic indicators and sample periods. Columns 1, 3, 5 and 7 use data from the first quarter of 2019 to the first quarter of 2020. Data for the second and third quarter of 2020 are dropped in these regressions. Although the number of new cases declined to almost zero after the first quarter of 2020 and city lockdowns were also repealed by the end of the first quarter, there may be lagged impacts of the pandemic and lockdowns, making cities in the second and third quarters of 2020 contaminated controls in a DID setting. China celebrates the Spring Festival in the first quarter and celebration activities can extend well beyond the official 7-day holiday period. The GDP in the first quarter is typically lower than other quarters. This may bias the estimates of the impacts of the pandemic and lockdown interventions, both also occurring in the first quarter in 2020. We control for such quarterly heterogeneity using quarterly fixed effects. Alternatively, in Columns 2, 4, 6 and 8, we use data including only the first quarters of 2019 and 2020. In Columns 1-4, we only consider the pandemic (cases or deaths). However, one may be concerned that these estimates are biased upwards if cities with more severe pandemic are also likely to adopt more stringent city lockdown which also affects the economy. In Columns 5-8, the specifications include both the pandemic and lockdown intervention.

The estimates using different pandemic measures, model specifications and data samples vary only slightly. The estimated coefficients across all specifications provide robust evidence that the pandemic and city lockdown had negative and statistically significant impact on the economy. As the results using confirmed cases or deaths are similar, following Kong and Prinz (2020) and Goolsbee and Syverson (2020), we focus on results using deaths as the indicator of the pandemic in following discussions.

4.2 Robustness

For robustness, we also estimated the results using the full unmatched sample. Similarly, Table 3 only reported the results using the specifications including both the pandemic and lockdown intervention for brevity. We first provide the results using full unmatched sample in Columns 1 and 2. The results are similar to our baseline analysis shown in Table 2. Nevertheless, we also examined the sensitivity of our results to samples generated from alternative matching algorithms. We alter to the 2-, 4-, and 6-nearest neighbor matching with replacement. The coefficients of interest remain statistically significant with a very minor change in magnitude from our baseline estimates (Table 2), indicating that our results are not sensitive to the choice of matching algorithms. Similarly, results using data from the first quarter of 2019 to the first quarter of 2020 are presented in Columns 1, 3, 5 and 7, and those using only first quarters of 2019 and 2020 presented in Columns 2, 4, 6 and 8. Taken together, bias due to lack of overlap is not a concern in our case, which is perhaps not surprising given we are using a very dense sample.

Table 2. The impacts of pandemic and city lockdown on GRP†

Variables	(1) Log(GRP)	(2) Log(GRP)	(3) Log(GRP)	(4) Log(GRP)	(5) Log(GRP)	(6) Log(GRP)	(7) Log(GRP)	(8) Log(GRP)
Log(*Cases*)	-0.036***	-0.026***			-0.033***	-0.024***		
	(0.009)	(0.007)			(0.008)	(0.006)		
Log(*Deaths*)			-0.032***	-0.023***			-0.030***	-0.022***
			(0.005)	(0.004)			(0.005)	(0.004)
Lockdown					-0.050***	-0.030**	-0.048***	-0.028***
					(0.019)	(0.012)	(0.018)	(0.011)
Constant	15.747***	15.502***	15.850***	15.492***	15.844***	15.542***	15.940***	15.532***
	(0.263)	(0.113)	(0.212)	(0.088)	(0.248)	(0.108)	(0.207)	(0.088)
Observations	880	352	880	352	880	352	880	352
R-squared	0.993	0.998	0.993	0.998	0.993	0.998	0.993	0.998
Cov*Q.Dummy	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Period	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,

† Robust standard errors clustered at the city level and reported in the parentheses; *, ** and *** denote significance at 10%, 5% and 1%.

Table 3 Robustness check using different samples †

	Unmatched full sample		2-Nearest neighbor		4-Nearest neighbor		6-Nearest neighbor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(GRP)	Log(GRP)	Log(GRP)	Log(GRP)	Log(GRP)	Log(GRP)	Log(GRP)	Log(GRP)
Log(*Deaths*)	-0.028***	-0.017***	-0.031***	-0.022***	-0.030***	-0.020***	-0.030***	-0.020***
	(0.005)	(0.003)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Lockdown	-0.053***	-0.036***	-0.055***	-0.030***	-0.055***	-0.032***	-0.055***	-0.032***
	(0.016)	(0.010)	(0.017)	(0.010)	(0.017)	(0.010)	(0.016)	(0.009)
Constant	15.692***	15.119***	15.898***	15.471***	15.818***	15.344***	15.760***	15.296***
	(0.162)	(0.059)	(0.202)	(0.084)	(0.182)	(0.071)	(0.171)	(0.066)
Observations	1,480	592	905	362	1,115	446	1,215	486
R-squared	0.991	0.999	0.993	0.998	0.992	0.998	0.992	0.999
Cov*Q.Dummy	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES
Period	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,	2019.Q1-2020.Q1	2019.Q1, 2020.Q1,

† Robust standard errors clustered at the city level and reported in the parentheses; *, ** and *** denote significance at 10%, 5% and 1%.

4.3 Parallel trends

A potential concern regarding the DID estimation of the impacts of the pandemic and city lockdown is that the changes in the GRP was caused by a differential pre-existing trend. A necessary condition for satisfying our identification assumption is that the city groups separated by the severity of the pandemic or lockdown policies have similar time trends in the outcome variable. We test this assumption for the pre-treatment period. Specifically, we estimate the following:

$$Y_{ct} = \sum_{t=1}^{6} \beta_t \, Pandemic_i * Quater_t + \sum_{t=1}^{6} \gamma_t \, Lockdown_i * Quarter_t + \alpha X_{it} + \mu_i + \eta_t + \varepsilon_{it} \tag{2}$$

where $Quarter_t$ represents the quarterly dummies, and the fourth quarter in 2019 is the omitted category. $Lockdown_i$ takes the value of 1 if the city is a lockdown city in the first quarter of 2020 and 0 otherwise. Similarly, the pandemic measure (Log ($Deaths_i$)) take the values in the first quarter of 2020. For this test, we include data for all periods from the first quarter in 2019 to the third quarter in 2020. This also allow us to examine the marginal effects of the pandemic and intervention policies by quarter.

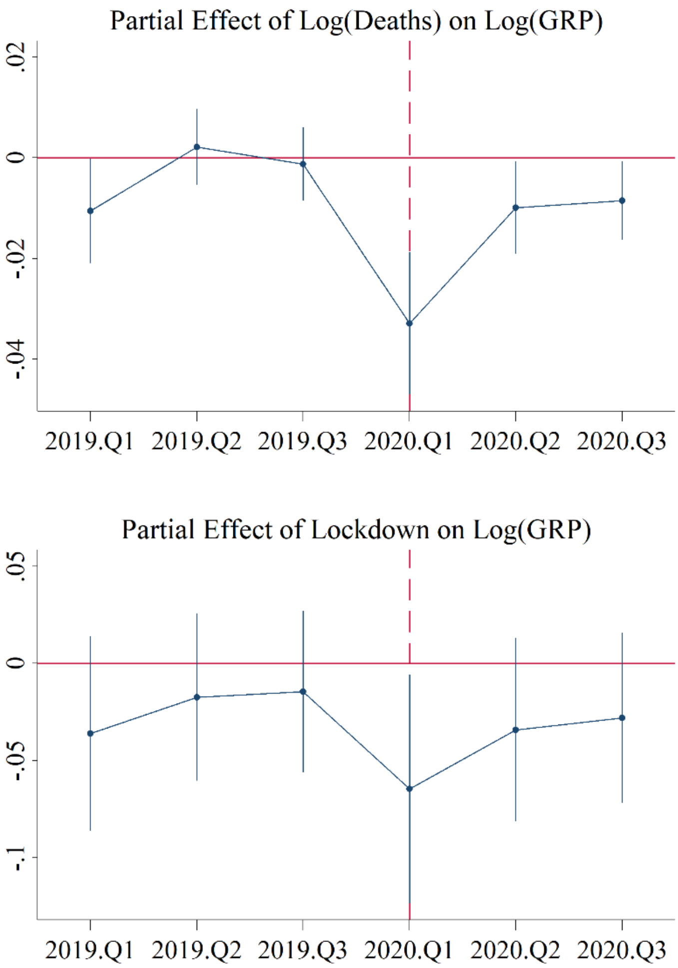

Figure 2. Parallel trend tests for $\mathrm{Log}\,(Deaths_i)$ and $Lockdown_i$

Figure 2 plots the quarterly estimates for $Pandemic_i$ (i.e. $\mathrm{Log}\,(Deaths_i)$) and $Lockdown_i$ along with the 95% confidence intervals. The estimates show no consistent pre-treatment trend between the cities with different pandemic severity or cities with different lockdown status. Figure 2 also suggests that city lockdown had only immediate impacts as the estimates became insignificant in the post-pandemic periods. On the other hand, the negative impact of pandemic remained significant in the second and third quarter although declined substantially. Parallel trend tests were also conducted for cities above or below the median values of chosen city characteristics. The results are provided in the Appendix. Overall, the results do not suggest violation of the parallel trend assumption.

4.4 City lockdown

The pandemic is largely exogenous but lockdown interventions were not randomly assigned. The validity of the identification depends on the assumption that the outcome variable is independent of the lockdown assignment, conditional on selected controls. Following Chetty et al. (2009) and La Ferrara et al. (2012), we conduct a robustness check by randomly assigning treatment (lockdown) status to cities. Specifically, we randomly draw and assign 88 cities out of the matched 176 cities as the lockdown cities. We then construct a false regressor of $Lockdown_{it}^{false}$ and replace $Lockdown_{it}$ in Specification (1). For this robustness check, we use data including only the first quarters of 2019 and 2020, as the baseline results using different sample periods do not differ significantly (Table 2). The necessary condition for satisfying conditional independence is that the falsified treatment regressor should have no effect on Log(GRP). We conduct the random sampling and assignment process 500 times to avoid possible impacts of incidental events.

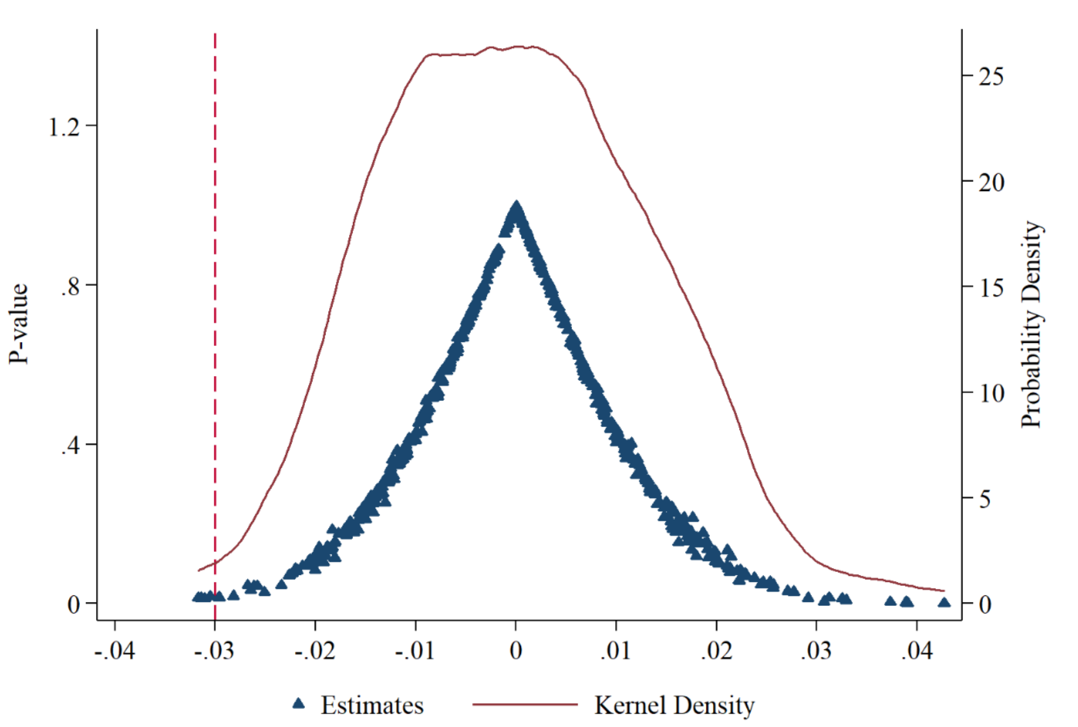

Figure 3. The placebo test for the city lockdown policies

Figure 3 presents the distribution of the estimates of $Lockdown_{it}^{false}$ and corresponding p-values controlling for COVID-19 deaths. The distribution centers around zero and most estimates are statistically insignificant. The baseline estimate (-0.028, from Column (8) in Table 2) indicated by the dashed vertical line in Figure 3, is clearly beyond a critical value of a 1% rejection region in the placebo test. These results provide stronger support for our identification strategy.

4.5 Pandemic and lockdown spillovers

The economic performance in a city may be affected by the severity of pandemic and lockdown policies in neighboring cities, which leads to biased estimate of the causal effects. Because the pandemic spillover can occur in both ways between adjacent cities, its impact is a matter of empirical investigation. The impact of the lockdown spillover is also ambiguous. Lockdown may temporarily affect input-output linkages and restrict market access but it also helps to enhance consumer confidence and maintain normal production in neighboring cities.

Our first strategy here is to employ a spatial exclusion approach. Adjacent areas proximate to the treatment boundary are potentially most affected by the spillover effects (Kline and Moretti, 2014; Ehrlich and Seidel, 2018). We dropped all the neighboring cities of the lockdown cities and re-estimate Equation (1). The results are presented in Columns (1) and (2) in Table 4. The estimates for city lockdown are slightly lower (in absolute value) than those of the baseline (Columns (7)-(8) in Table 2). This may suggest a small positive spillover effect that the economy of adjacent areas benefits from a city's lockdown intervention. The estimates for the pandemic are larger than those of the baseline; however, the exclusion approach does not specifically address possible pandemic spillovers. Given the nature of the virus spread, it is possible that the pandemic is also more severe in the neighboring areas of lockdown cities. The larger estimates may be a result of the exclusion of these areas.

A disadvantage of the spatial exclusion approach is that it does not differentiate and consider the nature of the pandemic and lockdown interventions of these adjacent areas. In Columns (3) and (4), we take an alternative approach by specifically controlling for the pandemic and lockdown intervention in the neighboring cities. *Deaths_Neighbor* is total new COVID-19 deaths in all neighboring cities. *Lockdown_Neighbor* takes the value of 1 if a city borders at least one lockdown city and 0 otherwise. The results on Log(*Deaths_Neighbor*) indicate significant spillovers of the pandemic. The economic impact of the pandemic on surrounding areas is more than half of the impact of the pandemic on the city itself. Once the pandemic spillover is controlled for, the main estimates of Log(*Deaths*) become slightly smaller than those of the baseline in Table 2. Specifically, a 1% increase in the number of confirmed deaths corresponds to a decline of GRP in the lockdown city and the neighboring cities by 0.017% and 0.009%, respectively (Column 4).

The results on *Lockdown_Neighbor* suggest no significant lockdown spillovers. For lockdown cities, our data show that the economy fell by 9.5% on average in the first quarter compared with the same period in 2019. The results in Column 4 indicate that city lockdown caused reduction in GRP by 2.8 percentage points, which explains 29% of the nominal decline, or 17.2% of the overall recession from the 5-year average growth of 6.74% prior to the pandemic. This is largely consistent with existing studies (Kong and Prinz, 2020; Forsythe et al., 2020; Lin and Meissner, 2020; Goolsbee and Syverson, 2020). The pandemic is a common shock and has broader economic impacts whereas the interventions explain a smaller part of the impacts. Other factors, such as the decline of consumer demand due to fears of virus spread and contagion, may play more important roles in the economic slowdown.

Nevertheless, our estimate of the lockdown impact is much larger than those reported in other studies. Goolsbee and Syverson (2020) found that the shelter-in-place order explained 12% of the nominal traffic fall in the USA. Similarly, Kong and Prinz (2020) found that six NPIs can only explain 12.4% of UI claims filed. The difference may be a result of the different economic outcome variable used in the analysis. Previous studies mostly rely on indirect proxy data and may have only captured partial effects. We use GRP and the estimate therefore reflects the economy-wide impacts. A second explanation could be the stringency of intervention measures. Restrictions imposed in many developed countries are often much less stringent than the complete city lockdowns implemented in China. However, a more likely interpretation for the higher estimate of lockdown impact may be China's unique economic structure. Intra-regional and inter-regional migrant workers contribute significantly to Chinese economy. China has the world's largest migrant population (mostly migrant workers) accounting for over one sixth of the national population (Department of Floating Population, National Health and Family Planning Commission, 2016). The largest seasonal migration also occurs in the first quarter of the year when migrant workers return home before the Spring Festival and then to the work place afterwards. The impact of lockdown restrictions may therefore be much greater in China than in other economies. Infrastructure investment and entrepreneurship have also been key drivers of China's economy growth. Impacts of pandemic and intervention measures on capital supply and new firm investment may also exact a heavier toll on the economy. We explore some of these mechanisms in the next section.

Table 4. Test for spillover effects

Variables	(1) Log(GRP)	(2) Log(GRP)	(3) Log(GRP)	(4) Log(GRP)
Log(*Deaths*)	-0.038***	-0.027***	-0.024***	-0.017***
	(0.005)	(0.004)	(0.004)	(0.003)
Log(*Deaths_Neighbor*)			-0.012***	-0.009***
			(0.003)	(0.002)
Lockdown	-0.042*	-0.030**	-0.048**	-0.028**
	(0.025)	(0.015)	(0.021)	(0.013)
Lockdown_Neighbor			-0.002	-0.002
			(0.022)	(0.013)
Observations	600	240	880	352
R-squared	0.994	0.998	0.994	0.999
Period	2019.Q1-2020.Q1	2019.Q1&2020.Q1	2019.Q1-2020.Q1	2019.Q1&2020.Q1

† Robust standard errors clustered at the city level and reported in the parentheses; *, ** and *** denote significance at 10%, 5% and 1%; all specifications control for covariates interacted with quarterly dummies, pandemic spillover, city FEs and quarter FEs.

4.6 Impacts on labor migration, land supply, new firm entry and investment

The pandemic and city lockdown interventions can affect the economy through various microeconomic channels, such as restricting access to input and output markets (Fang et al., 2020; Bartik et al., 2020) and new infant firm entry and investment. We are particularly interested in the impacts on labor mobility, private and public investment activities, and new firm entries as these are among the most important drivers of Chinese economy. Examination on the variations of these microeconomic activities can help us understand the mechanisms through which the pandemic and city lockdown interventions affect economy. Specifically, we estimate Equation (1) using five alternative outcome variables: 1) outgoing labor migration; 2) incoming labor migration; 3) total land supply for industrial, commercial, residential and public infrastructure uses; 4) new firm registrations; 4) new firm investment. The results are presented in Table 5. All estimates are statistically significant and much larger in magnitude than baseline estimates of the impacts on the overall economy. In addition, the magnitude of the coefficients on city lockdown is more than four times than those of the pandemic in human mobility, new firm registration and investment regressions (Columns 1, 2, 4 and 5 in Table 5), and more than three times in the land supply regression (Column 3), indicating much larger impact of lockdown intervention on human mobility, land supply, new firm entries and investment than the pandemic. Taken together, our results suggest that the unique characteristics of Chinese economy (and perhaps also more stringent lockdown intervention) may help explain our much larger estimates of lockdown impacts than those reported in other studies.

Table 5. The impacts of pandemic and lockdown on human mobility, land supply, new firm registration, and investment

Variables	(1) Log(Moveout)	(2) Log(Movein)	(3) Log(Land)	(4) Log(Firms_new)	(5) Log(Investment)
Log(*Deaths*)	-0.054***	-0.037***	-0.105***	-0.032***	-0.031***

	(0.007)	(0.007)	(0.026)	(0.007)	(0.006)
Lockdown	-0.243***	-0.172***	-0.330**	-0.139***	-0.128***
	(0.055)	(0.049)	(0.144)	(0.034)	(0.033)
Observations	26,400	26,400	1,056	352	352
R-squared	0.900	0.917	0.611	0.991	0.992
City FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Period	2019.Jan 1st-2019, Mar 15th, 2020.Jan 1st-2020, Mar 15th,	2019.Jan 1st-2019, Mar 15th, 2020.Jan 1st-2020, Mar 15th,	2019. Jan-Mar, 2020. Jan.-Mar.,	2019.Q1, 2020.Q1,	2019.Q1, 2020.Q1,

† Intercity daily data are used in the human mobility regressions, monthly data are used for land supply regression, and quarterly data are used in the new firm and investment regressions; all specifications control for covariates interacted with time dummies, pandemic spillover, city FEs and time FEs. robust standard errors clustered at the city level and reported in the parentheses; *, ** and *** denote significance at 10%, 5% and 1%.

4.7 Heterogeneity in economic slowdown and recovery

He et al. (2020) and Bonaccorsi et al. (2020) both found that the effects of city lockdown policies can vary across cities with different characteristics. Note that our heterogeneity analyses do not have causal interpretations but help us to understand the channels through which the pandemic and city lockdown affect economy. As described in Section 2.2, we examine five city characteristics: industrial structure, passenger traffic intensity, population size, urbanization, and fiscal capacity. Panels A and B in Table 6 only use data for the first quarters of 2019 and 2020 and therefore examine the heterogeneous effects of the pandemic and city lockdown at the recession stage. In contrast, Panels C and D use data for the second and third quarters of 2019 and 2020 and examine recovery relative to the same periods in the previous year. Panels E and F further compare the second and third quarters of 2020 to the first quarter of 2020 and therefore reflect how cities differ in recovery from the recession. In all specifications, the pandemic measure and lockdown indicator are as defined in Specification (2). We also control for the pandemic spillover.

Columns (1) and (3) in Panel A show that cities with higher share of secondary industry and smaller cities were more affected by the pandemic and city lockdown. These results are generally consistent with national statistics. For example, in the first quarter of 2020, the national GDP declined by 6.8% whereas the secondary industry declined by 9.6%. Data from the National Statistical Bureau of China (NBSC) also indicate that the unemployment rate was higher in smaller cities than larger cities in the first quarter of 2020.[7]

The fear for virus contagion reduces people's willingness to travel (Goolsbee and Syverson, 2020). City lockdown policies further impose more stringent restrictions on travel. Therefore, cities depend more on passenger transportation may suffer more from the pandemic and related countermeasures. As expected, the pandemic and city lockdown policies had greater economic impacts on cities with higher passenger traffic intensity (Column (2), Panels A and B). In particular, the estimates for the lockdown in cities with low traffic intensity is not significant.

Column (4) in Panel A and B shows that less urbanized regions suffered significantly more from lockdown interventions, while the difference in the impacts of the pandemic is much less pronounced between the two groups of cities. Disposable income of the rural residents and urban residents was reported to have declined 4.7% and 3.9% respectively in the first quarter of 2020 compared with the previous year.[8] A substantial proportion of China's migrant labor force come from rural areas. The migrant workers' remittance to their rural homes is the dominant income source for most rural families

[7] Source: http://www.gov.cn/xinwen/2020-04/17/content_5503698.htm
[8] Sources: http://www.stats.gov.cn/tjsj/zxfb/202004/t20200417_1739334.html.

and makes an important contribution to the rural economy. However, lockdown interventions significantly restricted migrant workers' mobility and access to jobs. On the other hand, compared with urban residents, migrant workers more likely to take jobs that cannot be done at home. These jobs typically pay less than work-from-home jobs which have been somewhat sheltered from immediate unemployment (Dingel and Neiman, 2020; Forsythe et al., 2020). This may lead to increases in poverty incidence in the rural area. Our results are broadly consistent with Bonaccorsi et al. (2020) and Chetty et al. (2020) which also indicate that low-income population are more affected by lockdown restrictions.

The last column in Panel A and B has results for cities with different government fiscal capacity. Cities with greater fiscal capacity were more resilient to the shocks of the pandemic and city lockdown policies. The results also suggest that regions with weak government resources should be prioritized for fiscal transfers from the central government to mitigate the negative impacts. Bonaccorsi et al. (2020) found that mobility contraction is more severe in municipalities with stronger fiscal capacity in Italy. Our interpretation is that stronger fiscal capacity can help implement and enforce lockdown restrictions (hence greater mobility reduction). However, fiscal resources can also help to cushion the negative impacts and make cities more resilient during the pandemic and lockdown.

While many economies are still struggling in the economic shock of the pandemic and intervention measures, Chinese national statistics show that the country's economy has already started recovery with positive growth in the second to fourth quarters of 2020. Firm-level surveys also show that most small and medium-sized enterprises that have temporarily closed in the first quarter of 2020 have reopened by May (Dai et al., 2021).

Due to data limitation, we focus on the short-term recovery in the second and third quarters of 2020. We offer two perspectives: recovery relative to the same periods in 2019 and recovery from the recession in the first quarter of 2020. The results in Panels C and D indicate that those city groups hit harder by the pandemic and lockdown (i.e. smaller, less urbanized cities, and those with higher share of secondary industry, higher passenger traffic intensity, and lower fiscal capacity) were still lagging behind by the end of the third quarter in 2020 compared with the same periods in the previous year. However, when compared to the recession in the first quarter, the results in Panels E and F show that the same groups of cities recovered faster than those groups less affected by the pandemic and lockdown. For example, Column (1) in Panels E and F show that the cities with higher shares of secondary industry recovered twice as fast as those with lower shares secondary industry during the post-pandemic periods. Zhang et al. (2020) also find economic recovery is heterogeneous across economic sectors in China. Specifically, the employment recovery in the agri-food system is slower than that of other sectors largely due to the sluggish recovery of restaurants.

Taken together, the results suggest cities were quickly closing the gap in the economic performance induced by the pandemic and lockdown interventions. This may be explained partially by the immediate recovery interventions targeted at the most affected regions. For example, the People's Bank of China established lending facilities with a capacity of over 2 trillion RMB to fund loans for small businesses and poverty alleviation. However, we are unable to unpack the causal link due to lack of data. As we are providing the first analysis on the immediate recovery from the pandemic, the results are only suggestive. Further research and comparisons to other recovering economies would be very useful when data becomes available in the near future.

Table 6. The heterogeneous impacts of the pandemic and city lockdown policies†

	(1) Share of 2nd industry	(2) Passenger traffic intensity	(3) City size	(4) Urbanization	(5) Fiscal capacity
Recession / Panel A: Above Median					
Log(Deaths)	-0.027***	-0.021***	-0.016***	-0.010**	-0.010*
	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)
Lockdown	-0.043***	-0.047***	-0.023	0.001	-0.003
	(0.016)	(0.016)	(0.017)	(0.011)	(0.011)
Recession / Panel B: Below Median					
Log(Deaths)	-0.013***	-0.014***	-0.020***	-0.023***	-0.023***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)
Lockdown	-0.020	-0.006	-0.029**	-0.060***	-0.056***
	(0.012)	(0.012)	(0.013)	(0.016)	(0.015)
Sample	N. Obs.: 176 / Period: 2019.Q1 & 2020.Q1				
Recovery / Panel C: Above Median					
Log(Deaths)	-0.012***	-0.009***	-0.006***	-0.006***	-0.003
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Lockdown	-0.016**	-0.018**	-0.001	-0.003	-0.005
	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Recovery / Panel D: Below Median					
Log(Deaths)	-0.004**	-0.005***	-0.011***	-0.009***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lockdown	-0.012**	-0.004	-0.023***	-0.023***	-0.023***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Sample	N. Obs.: 352 / Period: 2019.Q2-2019.Q3 & 2020.Q2-2020.Q3				
Recovery / Panel E: Above Median					
Log(Deaths)*Post	0.040***	0.025**	0.023***	0.013	0.011
	(0.006)	(0.012)	(0.007)	(0.011)	(0.010)
Lockdown*Post	0.090***	0.081***	0.051**	0.043**	0.009
	(0.030)	(0.027)	(0.022)	(0.022)	(0.013)
Recovery / Panel F: Below Median					
Log(Deaths)*Post	0.016**	0.020***	0.028***	0.040***	0.034***
	(0.008)	(0.005)	(0.005)	(0.006)	(0.006)
Lockdown*Post	0.024	0.024	0.047	0.069**	0.112***
	(0.019)	(0.023)	(0.031)	(0.029)	(0.032)
Sample	N. Obs.: 264 / Period: 2020.Q1-Q3				

† Robust standard errors clustered at the city level and reported in the parentheses; *, ** and *** denote significance at 10%, 5% and 1%.; all specifications control for covariates interacted with quarterly dummies, pandemic spillover, city FEs and quarter FEs.

5. Conclusions

The COVID-19 crisis has had significant impacts on the economy of most countries. However, different countries experienced heterogeneous decline and recovery trajectories. Combining a city-level dataset and a microeconomic dataset on labor mobility, total land supply, and entrepreneurship, this study examines the economic impacts of the pandemic and city lockdown polices in a major developing country during both the recession and the recovery stages. Our findings complement existing studies and have important implications for policies adopted to contain the spread of COVID-19 and to reduce its impact on the economy and residents.

Our results indicate that both the pandemic and strict city lockdown implemented in China play important roles in explaining the economic recession. However, we document much larger impact of lockdown interventions than those reported for developed countries. This could be a result of differences in data used, stringency of intervention measures or economic structure. Our findings also reveal significant pandemic spillover but no lockdown spillover, which may be of interest for intervention coordination in adjacent areas and simulation of regional economic impacts.

The findings also reveal significant heterogeneity in cities' economic responses to the pandemic and lockdown measures. The greater impacts on rural and poorer population as well as less developed regions may enlarge the existing inequality and increase the incidence of poverty. Although these cities were quickly closing the pandemic-induced economic gap, they still hadn't fully caught up with the better performed areas. These heterogeneous effects have important implications for government to prioritize resources to mitigate possible impacts on poverty and inequality, and to facilitate economic recovery.

Further research is desirable to extend our investigation of economic impact of the COVID-19 pandemic and its related policies. First, our results are limited to the short-run effects of the pandemic and intervention policies. It remains unknown whether the impacts are just a one-time shock or have changed some industries permanently. Future research could provide evidence on the long-run effects on economy and its structural change. Second, China implemented more strict intervention measures compared with most other countries and achieved a rapid recovery from the recession. Studies of different intervention measures and comparisons with other recovering economies would also be promising research areas.

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Appendix

Table A1 Balance tests

Variables	Sample	Bias(%)	P-value
Industrial structure	Unmatched	-7.50	0.567
	Matched	-0.60	0.966
Hospital beds	Unmatched	-0.70	0.958
	Matched	-5.30	0.744
Distance to Wuhan	Unmatched	-37.30	0.005
	Matched	-4.80	0.694
FDI Intensity	Unmatched	13.90	0.313
	Matched	-5.30	0.708
Population mobility	Unmatched	53.50	0.000
	Matched	11.90	0.466

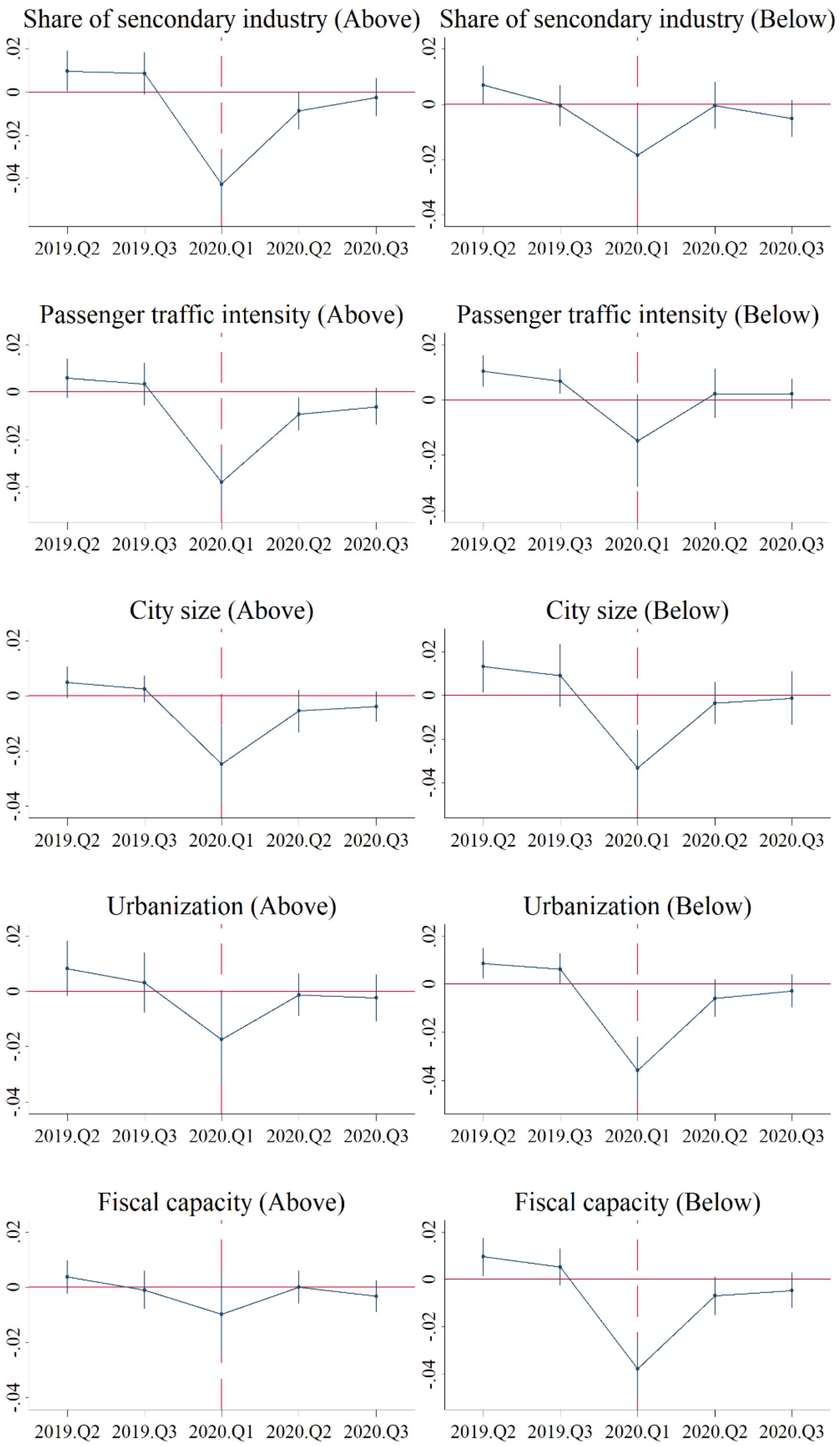

Figure A1 Parallel trend tests for Log ($Deaths_i$) by city characteristic

Figure A2 Parallel trend tests for $Lockdown_i$ by city characteristic