Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Do prevention and control measures work? Evidence from the outbreak of COVID-19 in China

Ruofei Lin, Shanlang Lin, Na Yan, Junpei Huang

School of Economics and Management, Tongji University, China

ARTICLE INFO

JEL code: I18
Keywords: COVID-19 Mobility restrictions Non-pharmacological interventions Targeted epidemic prevention

ABSTRACT

In the face of COVID-19, an emerging infectious disease, in addition to the classic non-pharmaceutical interventions such as isolation, quarantine, social, China also adopted strict mobility restrictions including inter-administrative districts travel restrictions, which severely affect residents’ lives and almost completely stopped production activities at cost of a huge economic and social cost. In this paper, we develop the model of Dirk Brockmann and Dirk Helbing (2013) to theoretically explain the impact mechanism of prevention and control measures on the spread of the epidemic. Then, we divide the measures taken in China into two categories: mobility restrictions and other non-pharmacological interventions (O-NPI), and apply econometric approach to empirically test the effects of them. We find that although both of the two measures play a good role in controlling the development of the epidemic, the effect shows significant difference in different regions, and both the two measures had no significant effects in low-risk regions; Further, we prove that measures taken in a low-risk region is mainly against the imported cases, while a high-risk region has to defend against both imported cases and spread from within; The rapid and accurate transmission of information, a higher protection awareness of the public, and a stronger confidence of residents can promote the implementation of the measures.

1. Introduction

Same as other emerging infectious disease, there is no pharmacological intervention available at the beginning of COVID-19 outbreak in Wuhan, China in December 2019. In the absence of vaccines and antivirals, only strict implementation of old-style public health measures can effectively control the development of the epidemic (Wilder-Smith and Freedman, 2020). Compared with SARS, the mortality rate of COVID-19 is lower, but it has a larger reproductive number and a wider transmission range (Liu et al., 2020). In the measures, compared with rural areas, the higher population density in urban areas also promotes the transmission of the virus (Rocklov & Sjödin, 2020). Therefore, especially before effective pharmacological interventions have been popularized, it is crucial to evaluate the efficacy and applicability of various non-drug interventions, discuss how to implement targeted public health measures, and explore how to effectively control the spread of epidemic in city through urban prevention and control policies.

In the COVID-19 epidemic, China has taken comprehensive, strict and rapid prevention and control measures. Within one week, all provinces adopted the highest level of emergency response, i.e. the level I response according to the National Public Health Emergency Preparedness of China formulated by the Chinese central government in 2006, including isolation, quarantine, shelter-in-place, cordon sanitaire, protective sequestration, social distancing, and so on. More importantly, China adopted measures of “extremely strict mobility restrictions”. In contrast to travel restrictions and border controls in foreign countries, the measures implemented in China include restrictions on mobility between provinces, prefecture-level cities, county-level regions, towns and villages, which is unprecedented. Even during SARS in 2003, only a few of cities with severe outbreaks were lockdown. This is a measure given the right to adopt to local governments according to the National Public Health Emergency Preparedness of China formulated in 2006 after

© Geolocation information: China.
* Corresponding author at: School of Economics and Management, Tongji University, China.
E-mail address: 1830263@tongji.edu.cn (J. Huang).
1 Equal contribution.
2 This is the highest-level emergency response adopted in accordance with the National Public Health Emergency Preparedness of China, which classifies public health emergencies into particularly major (level I), major (level II), and large (level III) and general (level IV). According to the Level I response, the provincial government is responsible for emergency response, adopting prevention and control measures in a timely manner.

https://doi.org/10.1016/j.cities.2021.103347
Received 29 September 2020; Received in revised form 19 April 2021; Accepted 13 July 2021
Available online 16 July 2021
0264-2751/© 2021 Elsevier Ltd. All rights reserved.
SARS, and it is also the first time to take this measure. The adoption of strict mobility restrictions, which mean that urban and rural residents are restricted in their lives and all productive activities are disrupted, known as pressing the “pause button”, carries a huge social and economic cost. However, the epidemic in more than half of the country is very mild, and Tibet has only one imported case, but they all have adopted a Level I emergency response without exception. Therefore, when the epidemic in China is effectively controlled, we also need to weigh the health benefits and economic costs of these policies, reflect on whether it is necessary to implement comprehensive control in the areas with no infected cases, Which measures are effective and necessary in epidemic regions with different conditions, and how to make a region-specific, multi-level targeted approach to epidemic prevention and control. There is a need to discuss whether such strict mobility restrictions taken for the first time in China are necessary, especially for low-risk regions (Fig. 1).

In this paper, in order to answer the question of whether the strict mobility restrictions taken first time and other non-pharmaceutical interventions (O-NPI) is necessary, we develop the model of Dirk Brockmann and Dirk Helbing (2013), which theoretically explains the influence mechanism of mobility restrictions and other non-pharmaceutical interventions (O-NPI) on the spread of the epidemic. Then, based on the data mining technology, we collected city-daily COVID-19-related panel data mainland China collected from January 1 to February 19, 2020 including confirmed cases, specific content and start date/time of the control measures, Baidu migration data, etc. According to the various measures against COVID-19 taken in China, we divide them into mobility restrictions and other non-pharmaceutical interventions (O-NPI). We quantify the measures by calculating scores to construct indicators of prevention and control measures, and empirically test their efficacy and applicability using econometrics approach.

Firstly, we analyze the effects of the two types of measures implemented in China, and we find that on average, both mobility restrictions and other non-pharmaceutical interventions (O-NPI) have made great impact on prevention and control of COVID-19. Nationally, mobility restrictions are more effective than other non-pharmaceutical interventions (O-NPI). Despite the inevitable huge costs, the implementation of strict mobility restrictions is still desirable. In robustness checks, we try to remove data of Hubei province from the whole sample, which is most affected by the epidemic in China; change identification strategy to difference-in-differences (DID) approach; adjust the assumption of incubation period length in the calculation of actual cumulative case growth rate; considering the possible endogeneity, we take the first-order lag of the main explanatory variables as an instrument variable for second-stage regression, which proves the robustness of the empirical results. In addition, we find that mobility restrictions and other non-pharmaceutical interventions (O-NPI) shows complementary relationship, and the combined effect of the two measures will play a better role.

Secondly, we divide cities across the China into high, medium, and low according to their level of economic development (GDP per capita) and population size. Regression analysis is conducted on samples, and effects of mobility restrictions and other non-pharmaceutical interventions (O-NPI) were found to be distinctly different in various regions. The two measures play the best in areas with high level of economic development, and effect in turn decrease in areas with medium and low level of economic development. Different from the result on average, areas with low level of economic development, other non-pharmaceutical interventions (O-NPI) work better than mobility restrictions. Similarly, the effects of the two measures are better in areas with high population size than that of medium-population areas, and medium-population areas are better than low-population areas.

Thirdly, since we’d like to see how well the various measures are implemented in areas with different epidemic severity and what measures are necessary in different conditions, we divided cities into high-risk, medium-risk and low-risk areas according to the severity of COVID-19. The results show that although mobility restrictions and other non-pharmaceutical interventions (O-NPI) have played a huge role in COVID-19 control on average, these two measures made no significant effect in low-risk areas. In order to discuss what specific measures are effective in different risk regions, we further subdivided these measures into four categories: prevent from imported cases, internal traffic restrictions, internal activity restrictions, quarantine and monitoring. Interestingly, we find that prevention of imported cases is effective in low-risk areas, while in medium- and high-risk areas, not only are this measure effective, but measures to prevent spread of COVID-19 within the city (internal traffic restrictions, internal activity restrictions) are also indispensable. In other word, in low-risk areas, measures to keep from imported cases should be adopted, while in medium- and high-risk areas, both external import and internal spread prevention should be taken. In the meantime, monitoring and quarantine are essential regardless of epidemic situation.

Finally, we want to know whether the reaction of public can affect the effectiveness of prevention and control measures. We use the Baidu search index of “COVID-19” to represent degree of the information transmission among the public; “the correct way to wear masks” to show protection awareness of the public; “Zhong Nanshan” to illustrate the citizens’ confidence against the COVID-19. It can be seen that rapid and accurate information transmission, higher public awareness of prevention and residents’ confidence in anti-coronavirus can promote the effect of mobility restrictions and other non-pharmaceutical interventions (O-NPI).

Fig. 1. Confirmed cases and mortality in China (up to 25 February 2020).
2. Outbreak of COVID-19 and response of China

On December 31, 2019, 27 confirmed cases were first reported by the Wuhan municipal government. On January 23, 2020, Wuhan announced the “lockdown” of the city, and the city’s urban bus, subway, ferry, and long-distance passenger transportation were suspended; for no special reason, citizens should not leave Wuhan, and the passages out of Wuhan in the airport and railway station are temporarily closed. In the same day, Zhejiang, Guangdong, and Hunan provinces launched Level I emergency response over the Coronavirus. Since January 25, all provinces except Qinghai and Tibet have launched the response. On January 30, Tibet is the last province to launch it. The epidemic grew rapidly in just one month, with more than 70,000 confirmed cases nationwide by 16 February. In particular, the week starting on January 24, the Chinese Spring Festival holiday, is the period with the largest passenger flow in a year. In 2019, more than 421 million people, equivalent to 30.1% of China's total population, were transported by commercial transportation agencies, including trains, cars and aviation, which brings difficulties to COVID-19 prevention and control.

According to National Public Health Emergency Preparedness of China formulated by the Chinese government, the measures taken by provinces for Level I emergency response can be summarized into several aspects: the first is to inter-administrative travel restriction, which including provincial-level, prefecture-level and county-level to townships and villages. Vehicles and individuals are not allowed to enter or leave except for the transportation of necessities for urban residents and medical supplies; the second is to stop all or part of bus transportation operations in the city, and there are vehicles and personnel designated by the government to be responsible for the transportation of essential supplies; the third is to stop the operation of commercial institutions that are not essential for the basic livelihood of residents, including entertainment, sports, public culture and leisure places, and delay the opening of all schools; the fourth is to isolate urban and rural communities affected by the epidemic, which means non-community residents are not allowed to enter. It also includes performing temperature surveillance on individuals who enters and leaves the community and institutions, and conducting medical examination and screening on the febrile. In hard-hit communities, where residents are not allowed to leave their homes, supplies are pre-ordered online or over the phone and distributed by community managers and volunteers; the fifth is to trace the confirmed and suspected cases, which means mandatorily isolating and treating the confirmed cases, quarantining the suspected cases centralized, and quarantining the contacts centralized or at home; the sixth is to mobilize medical and protective equipment. Each province sends medical and health personnel and mobilizes medical equipment to support Hubei province, distributes or quantitative sales of masks to...

---

**Fig. 2.** New cases in China from January 20 to March 20.

---

**Fig. 3.** New cases in each province of China from Jan. 20 to Mar. 3 (except for Hubei).
residents, and requires residents to wear a face mask when they go out; the seventh is information disclosure. From the central government to the local area, regular reports of confirmed and suspected cases of COVID-19 are made daily, and epidemiological follow-up investigation reports are released, including their whereabouts and all possible contacts; the eighth is to quarantine cross-administrative personnel for 14 days. Since March 14, some areas require overseas entrants to be conducted centralized quarantine for 14 days. After the end of the Chinese Spring Festival holiday on Feb. 2, no local enterprises were allowed to produce and operate. Most provinces stipulated that production operations could only be carried out after February 10 with the approval of the government. Specifically, individuals who came from hardest-hit area should be quarantined at a designated location for 14 days, as for those from non-hardest-hit area, they also should be quarantined at home for 14 days.

Measures such as syndromic surveillance, prompt isolation of patients, strict enforcement of quarantine of all contacts, and in some areas top-down enforcement of community quarantine taken in 2003 SARS effectively contained the epidemic by means of interrupting all human-to-human transmission. Although the COVID-19 has many similarities with SARS, it is more infectious and less likely to be diagnosed (Wilder-Smith et al., 2020). Therefore, compared with the SARS, China has taken more strict measures in the COVID-19 epidemic; Different from the western countries, China adopted isolation measures for all cases, including mild cases (Dickens et al., 2020). By March 18, it is first time that there were no new cases in China, and the stick of confirmed cases had dropped to 7263.

On February 12, the number of confirmed cases reached the peak in China, that is, 15,152 cases (see Fig. 2), and most provinces reached the peak around February 10 (see Fig. 3). As can be seen in Fig. 3, the number of confirmed cases in different provinces varies greatly. Of the 32 province-level administrative regions in mainland China, the lowest number of cases occurred in Tibet, with only 1 case, 5 provinces have cases of 2-100, 13 are between 100 and 500 cases, accounting for 59.4% of all provincial-level administrative regions. Only 5 have more than 1000 cases, namely Hubei, Guangdong, Henan, Zhejiang, and Hunan. In fact, there are greater differences between prefecture-level administrative regions and county-level administrative regions. By February 12, 2020, when the number of confirmed cases of COVID-19 is the largest in China, there are still 19 prefecture-level administrative regions (accounting for 5.7% of all prefecture-level administrative regions) and 1110 counties (accounting for 39% of all county-level administrative regions) in China without the occurrence of the epidemic.

3. Literature review

The decision of controlling emerging infectious diseases is a complex process, which means decision-makers must analyze a large amount of uncertain information in a short period of time, and make effective decisions to deal with crises timely. This is an extremely difficult process. Missing that stage, it can form a “butterfly effect”, which causes a huge impact (Morse et al., 2012). As an emerging infectious disease, with no immediate effective pharmaceutical intervention for COVID-19 and limited health-care resources to treat all cases, non-pharmaceutical interventions (NPI) become the primary means of controlling the epidemic at this stage (Dickens et al., 2020; Lai et al., 2020). These measures aim to reduce transmission of the virus by reducing personal contact among individuals within or between populations, thereby slowing the spread of COVID-19 to a manageable rate (Hsiang et al., 2020). Literature on the control of emerging infectious disease, in addition to research on the process and method of handling infectious disease by medical staff, such as Kisting et al. (2010), Chen et al. (2015), Barbish et al. (2015), Koenig (2015), mainly focuses on two aspects:

The first is about the effectiveness of public health measures. Huremović (2019), Wilder-Smith and Freedman (2020) analyze and compare the clear definition and scope of common public health policies, including isolation, quarantine, Shelter-in-place, cordon sanitaire, protective sequestration, social distancing, travel restriction and so on. Combining epidemiological-relevant models and assessments, Rotthstein and Talbott (2007), Jefferson et al. (2008), Chong and Zee (2012), Wang et al. (2012), Sakaguchi et al. (2012), Mao (2013), Folayan and Brown (2015), Rashid et al. (2015), Rotthstein (2015), Huremović (2019) study the effect and suitable condition of different public health measures.

The second is the legal and ethical relationship of public health policy. Kapucu and Van Wart (2006), Fidler et al. (2007), Rotthstein (2015), Gostin and Wiley (2016) and Lewnard and Lo (2020) study legal and ethical issues facing public health measures such as imposed isolation, quarantine and social distancing in response SARS-CoV and MERS-CoV epidemic. Most of them believe that these old-style measures is still a valuable public health strategy, but led to a serious legal and ethical concerns, because its restrictions on civil liberties results in sorts of social harm, including economic disruptions, physical isolation and even violence, so adopting these measures must be carefully. There are four basic factors to consider: efficacy and scientific basis, minimum tort, humanitarian support service and public reason.

Existing literature analyze and verify the positive effects of measures such as lockdown of Wuhan, border control, social distancing, quarantine, isolation, community containment, the construction of Fangcang shelter hospitals in the prevention and control of COVID-19 (Wilder-Smith and Freedman, 2020; Lau et al., 2020; Thu et al., 2020; Zhang et al., 2020; Li et al., 2020; Chen et al., 2020; Tomar & Gupta, 2020; Fang et al., 2020; Hsiang et al., 2020; Sjdin et al., 2020; Qian et al., 2020; Heymann & Shindo, 2020; Gao et al., 2020). However, most of these literatures used numerical simulation and simple statistical methods, or only theoretically explained the impact mechanism of epidemic prevention policies. In particular, there is still a lack of identification, comparison and evaluation of the effect of “strict mobility restrictions” which is taken for the first time in China.

Compared with the existing literature, the contributions of this paper mainly include: first, we take the strict mobility restrictions which is taken for the first time in China as a separate variable to identify, compare and evaluate, and classify all other non-pharmaceutical interventions into one category, which is represented by O-NPI, which is the first time that this approach is tried; Second, we quote the concept of effective distance proposed by Brockmann and Helbing (2013), which breaks through the previous practice of estimating epidemic transmission scale based on geographical distance; Third, we collect the prevention and control measures adopted by local administrative region of China, and construct scoring indicator of mobility restrictions and non-pharmaceutical interventions (O-NPI) as explained variable. At the same time, we utilize data mining technique, collect and sort out the Baidu Search Index of “COVID-19”, “the correct wearing of masks”, “Zhong Nanshan” to explores the moderated effect of public reaction on the policy implementation effect; Fourth, from the perspectives of economic development level, population size and epidemic risk, we take into account the city heterogeneity, and empirically test the effects of mobility restriction measures and non-pharmaceutical interventions (O-NPI) on the prevention and control of COVID.

4. Theoretical framework

The outbreak of infectious diseases is a complex process of spreading that occurs in a population. There is a long history of modeling infectious disease epidemics (Anderson et al., 1992), and various modeling specifications have been developed. Kermack and McKendrick (1927) proposed the classic SIR model, which is a compartmental model. In the SIR model, it is assumed that each individual is the same, the population is homogeneous mixing, the contact is instant and independent of history, infection rate, and recovery rate is constant. Individuals in the same state form a compartment, and as the state changes, they move among the compartment. With the growth of urban population and the
development of transportation networks, social mobility has increased, and the spatial expansion of infectious diseases has shown a new pattern, especially when people move among different regions, the spread of the epidemic is common. Understanding the impact of population flow patterns on the prevalence of infectious diseases has attracted considerable attention (Gonzalez et al., 2008), and a meta-population model derived from ecology has been applied in the field of the epidemic. With the rise of complexity science, the micro-modeling specification has been developed and combined with social networks, a network-based micro-individual modeling method has been proposed, which provides a new approach to understand the spread of infectious diseases. These models enable epidemiologists and health authorities to understand the transmission process, predict its impact on healthy populations, and assess the effectiveness of different mitigation and prevention strategies. But, in any case, the epidemic of infectious diseases is inseparable from two key factors, namely, person-to-person contact and population mobility. When infectious disease outbreaks, various countries adopt public health intervention policies, in which one is to control human contacts, such as isolation, quarantine, and social distancing; the other is to control population mobility, such as travel restrictions.

The factors affecting the spread of the epidemic are extremely complex, which is closely related to the carrier, environment, weather, the contact and so on. If a city is abstracted into a node beyond the scale of micro-individuals, the population flow between cities is the key factor affecting the scale of virus transmission among cities, which is related to urban density and transportation. The meta-population model is a commonly used model for analyzing the spread of epidemics, which nodes are used to represent the city, and the linings are used to represent the traffic between cities, such as the plane, high-speed rail, bus and so on. Within each node, a certain number of people are set. Colizza et al. (2007) used a meta-population model to characterize human behavior on a global scale. They found that a large-scale epidemic would only erupt when the population density exceeded a certain threshold. When the scale of the network is infinite, a few large nodes (namely, important cities) in the network will cause an epidemic to outbreak globally. Regarding transportation, Brockmann and Helbing (2013) found that the spread of disease is closely related to the “effective distance” between cities rather than geographical distance. If the probabilistically motivated effective distance is used instead of conventional geographic distances, then complex spatiotemporal patterns can be reduced to surprisingly simple, homogeneous wave propagation patterns. It can also reliably predict the arrival time of the disease, and even if epidemiological parameters are unknown, we can still get the relative arrival times and the spatial origin of the propagation process by the approach.

The effective distance is defined as the best mode of transportation between two cities, depending on the probabilistic traffic flow. Assuming that \( p_{mn} \) is the conditional probability of the connectivity matrix \( P \), \( p_{mn} = F_{mn}/F_n \sum_m P_{mn} = 1 \). Weighted links \( F_{mn} \) quantify direct air traffic (passengers per day) from node \( m \) to node \( n \), \( F_n = \sum_m F_{mn} \). Then, the relationship between effective and \( p_{mn} \) is given as:

\[
d_{mn} = (1 - \log p_{mn}) \geq 1
\]  

On the basis of Brockmann and Helbing (2013) and combining the hypothesis of Aron and Schwartz (1984), we explore an epidemic diffusion model on the transportation network, which the equations are as follows:

\[
\frac{dS_m}{dt} = -\alpha_1 S_m I_m + \alpha_2 S_m E_m + \delta \sum_n P_{mn} (S_m - S_n)
\]

\[
\frac{dE_m}{dt} = \alpha_1 S_m I_m + \alpha_2 S_m E_m - \gamma E_m + \delta \sum_n P_{mn} (E_m - E_n)
\]

\[
R_e = 1 - S_n - E_n - I_n
\]

where, \( I_m \) and \( I_n \) are the local fractions of the infected of city \( m \) and city \( n \), \( S_n \) and \( S_m \) are the local fractions of the susceptible, \( E_m \) and \( E_n \) are the local fractions of the exposed, \( r_0 \) is recovered population of city \( n \), \( \alpha \) is infection rate, \( \beta \) is removal rate, progression rate is \( \gamma \).

In order to analyze the effect when adopting public health policies to intervene in the spread of infectious diseases, referring to the approach in Brockmann and Helbing (2013) and Zhang (2020), we introduce a term of the effective invasion threshold \( \zeta \):

\[
\frac{dS_m}{dt} = \zeta(t, t_0, t_m, \eta)(-\alpha_1 S_m I_m - \alpha_2 S_m E_m) + \delta \sum_n P_{mn} (S_m - S_n)
\]

\[
\frac{dE_m}{dt} = \zeta(t, t_0, t_m, \eta)(\gamma E_m + \delta \sum_n P_{mn} (E_m - E_n)) - \gamma E_m - \beta E_m
\]

\[
R_e = 1 - S_n - E_n - I_n
\]

where, \( \zeta \) is the human intervention factor of public health policy, \( \eta \) is the minimum intensity of intervention, \( t_0 \) is the time point of human intervention, \( t_m \) is the point at which an infectious disease is completely eliminated. Therefore, \( \zeta \) is a function of time and human intervention, at the same time \( t \), the more stringent the prevention and control measures, the smaller the \( \zeta(t, t_0, t_m, \eta) \). According to Eq. (3), the scale and speed of COVID-19 transmission are related to factors such as infection rate, recovery rate, and migration rate, as well as effective distance and public health policy intervention. According to equation:

\[
\frac{dI_m}{dt} = \zeta(t, t_0, t_m, \eta)(\alpha_1 S_m I_m + \alpha_2 S_m E_m) + \gamma E_m - \beta E_m + \delta \sum_n P_{mn} (I_m - I_n)
\]

It can be seen that in the case that infection rate \( \alpha \), removal rate \( \beta \), progression rate \( \gamma \) and effective distance among cities are all constant, prevention and control measures aimed at reducing human contact can reduce the proportion of new cases by reducing \( \zeta(t, t_0, t_m, \eta) \). So as to effectively control the epidemic.

Any public health policy intervention requires costs, and the cost of different interventions varies. In this paper, the various measures to prevent and control the spread of COVID-19 in China are divided into two categories: One is mobility restrictions, which not only affects the movement of people across regions and even across the country, but also affects the transportation of goods. The price of this is to force companies and other institutions to stop operations, which is at huge cost; Another is pharmaceutical interventions (O-NPI), including closure of public places in the city, community containment, isolation of the infected, and quarantine of the suspected, which affects the operation of some urban institutions, and the cost is less than the mobility restrictions. Based on the analysis above, we then propose the hypothesis:

A. mobility restrictions and other non-pharmaceutical interventions (O-NPI) can effectively contain the spreads of COVID-19 epidemic.

B. In regions with different economic development level and population size, mobility restrictions and other non-pharmaceutical interventions (O-NPI) perform differently.
5. Empirical specification

5.1. Empirical model and variable

We have analyzed the effect of prevention and control measures using theoretical model and put forward the hypothesis. In order to verify whether the hypothesis is consistent with reality, we apply econometrics approach and empirically test the theory using data of China. Econometric approach is commonly used to measure the effects of a factor on economic growth. Similar to early COVID-19 infections, economic output generally increases exponentially with a variable rate that can be affected by policies and other conditions (Hsiang et al., 2020). Therefore, it is appropriate to apply econometrics techniques to analyze the impact of prevention and control measures on the development of the epidemic. Compared with statistical methods such as Pearson correlation coefficient to identify the correlation relationship, econometric pay more attention to identify the causal relationship between variables (Angrist & Pischke, 2008), that is, whether the prevention and control measures lead to the containment of the epidemic. Compared with statistical methods such as econometrics approach and empirically test the theory using data of China. Econometric approach is commonly used to measure the effects of a factor on economic growth. Similar to early COVID-19 infections, economic output generally increases exponentially with a variable rate that can be affected by policies and other conditions (Hsiang et al., 2020). Therefore, it is appropriate to apply econometrics techniques to analyze the impact of prevention and control measures on the development of the epidemic.

According to the classification of prevention and control measures of COVID-19 in China, the baseline estimation strategy is as follows:4

\[ y_{it} = \alpha + \beta_1 \text{ intervention}_{it} + \sum_{k} \beta_k X_{it} + \gamma t + \delta_i + \epsilon_{it} \]  

(4)

where, \( y_{it} \) is the actual cumulative case growth rate of city i in date t. Given that average incubation period of COVID-19 is 5.2 days (Li et al., 2020), we use the 5th lead of the reported case to proxy the actual case, that is:

\[ \text{reported case}_{it} = \text{actual case}_{it+5} \]

Taking Chengdu, China as an example, 73 cases were reported in Chengdu on February 1, 2020. Considering the existence of an average incubation period of 5 days, 73 should be the actual cumulative number of cases on January 27, 2020, five days earlier; The actual cumulative number of cases on February 1 should be the reported number on February 6 (see Fig. 4).

\textit{Intervention} is the main explanatory variable, namely mobility restrictions and other non-pharmaceutical interventions (O-NPI). \( \beta_1 \) is the coefficient estimated, if \( \beta_1 < 0 \), then it indicates that the prevention and control measures have effectively reduced the growth of cumulative cases and mitigated the outbreak of the epidemic. \( X_k \) is control variable, including population size (pop), GDP per capita (pergdp), number of medical institutions (hospital), number of beds in medical institutions (bed), effective distance from Wuhan (distance) to control the city characteristics on the spread of the epidemic. \( \beta_k \) is coefficient of control variable. Although the data structure is a wide panel, the time span is relatively long, and the development of the epidemic itself has a time trend, so we introduced the time trend “\( t \)” to control the variation trend of the explained variable over time. It is common in econometric studies to consider time trend in modeling. For example, when exploring the influence of economic development on the degree of democracy, Brückner and Ciccone (2011) also introduced t into the econometric model considering that democratic development itself has time trend. \( \delta_i \) is a region fixed effect to control the characteristics of provinces constant over time. \( \delta_i \) is a time fixed effect to control the time factors that do not vary from individual to individual. \( \epsilon_{it} \) is an error term, we use cluster-robust standard error to estimate the standard deviation (Cameron & Miller, 2015). In addition, we also set some classified variable: GDP per capita (PerGDP), Baidu Index of “COVID-19” (Information), Baidu Index of “the correct way to wear a mask” (Awareness), Baidu Index of “Zhong Nanshan” (Confidence) to explore more interesting findings.

5.2. Data

5.2.1. Construction of the measure scoring indicator

We construct scoring data as proxy variable for prevention and control measures. Mobility restrictions and other non-pharmaceutical interventions (O-NPI) in each city are classified and scored according to the preventive and control measures taken by prefecture-level administrative regions in China. We have summarized 15 items of measures (see Table 1), each with a score of 1. Scoring starts until the measure is canceled. For example, on January 21, Shanghai began to implement “quarantining the contacts for 14 days.” Since this measure is under “O-NPI”, then the score of O-NPI in Shanghai from January 21 was 1. On January 24, Shanghai began to implement “closing part of the indoor urban public places”, since this measure is also under “O-NPI”,

| date   | reported | actual |
|--------|----------|--------|
| 24-Jan | 16       | 59     |
| 25-Jan | 22       | 69     |
| 26-Jan | 33       | 72     |
| 27-Jan | 37       | 73     |
| 28-Jan | 46       | 77     |
| 29-Jan | 59       | 87     |
| 30-Jan | 69       | 92     |
| 31-Jan | 72       | 97     |
| 1-Feb  | 73       | 102    |
| 2-Feb  | 77       | 109    |
| 3-Feb  | 87       | 120    |
| 4-Feb  | 92       | 123    |
| 5-Feb  | 97       | 124    |
| 6-Feb  | 102      | 125    |

**Table 1**

Scores for mobility restrictions and O-NPI

| Mobility restrictions | Other non-pharmaceutical interventions (O-NPI) |
|-----------------------|-----------------------------------------------|
| Launching level 1 response | Closing all the public places               |
| Suspending all the cross-city passenger transport | Closing part the public places             |
| Suspending part of the cross-city passenger transport | Closed management of all the community       |
| Monitoring all the cross-city passenger transport | Closed management of part of the community   |
| Suspending all the public transport | Quarantining returnees from key epidemic area (Hubei) for 14 days |
| Suspending all the public transport | Quarantining all the returnees for 14 days |
| Suspending all the public transport | Quarantining the contact for 14 days |

Fig. 4. Conversion of reported cases to actual cases.

---

4 Linear model is the most classical modeling paradigm of econometrics model. We linearize the nonlinear relationship by taking logarithm to facilitate parameter estimation in the next step, instead of assuming that the relationship between \( Y \) and \( X \) is linear.
then “O-NPI” in Shanghai will be added another 1 point since January 24, and so on, and finally, the points for mobility restrictions and O-NPI will be added up separately. It can be seen that since the lockdown of Wuhan on January 23, all provinces and cities across the country quickly took relatively strict and complete measures (see Fig. 5).

5.2.2. Data source
As to the data used in this paper, the specific content and implementation time of the prevention and control measures came from the information or announcements issued by the prevention and control headquarters of the prefecture-level administrative districts; the cumulative confirmed case of came from the official release of the National Health and Health Commission; population size, GDP per capita, number of medical institutions, and number of beds in medical institutions are from the China City Statistical Yearbook. Baidu search index data comes from the Baidu Index website. We refer to the approach of Brockmann and Helbing (2013) to calculate the effective distance from Wuhan to each city. The inter-city passenger flow data used in the calculation are from Baidu Migration website. The time span of the data we use is from January 1, 2020 to February 19, 2020. The explanation of each variable is shown in Table 2.

The data samples in this paper consist of the balance panel data of 279 prefecture-level cities from January 1 to February 19, 2020, and the descriptive statistics of related variables are shown as follows (Table 3).

6. Result

6.1. Are the measures effective?

6.1.1. Baseline regression

Table 4 reports the baseline regression results. The explanatory variable is the actual cumulative cases growth rate. The explanatory variables in column (1) and column (2) are the total score total score of prevention and control measures, in column (3) and column (4) are the score of mobility restrictions measures, in column (5) and column (6) are the score of O-NPI. Column (2), (4), and (6) introduce control variables on the basis of columns (1), (3), and (5). The regression results show that the coefficients of the total score, mobility restrictions, and O-

![Fig. 5. Scores for mobility restriction and O-NPI on Jan. 23 and Feb. 19, 2020.](image-url)
### Table 4
Result of baseline regression.

| (1)        | (2)        | (3)        | (4)        | (5)        | (6)        |
|------------|------------|------------|------------|------------|------------|
| Total score | -0.0255*** | -0.0257*** | -0.0465*** | -0.0466*** | -0.0322*** | -0.0330*** |
|             | (0.0025)   | (0.0025)   | (0.0048)   | (0.0047)   | (0.0039)   | (0.0039)   |
| Mobility restrictions | -0.0255*** | -0.0257*** | -0.0465*** | -0.0466*** | -0.0322*** | -0.0330*** |
|             | (0.0025)   | (0.0025)   | (0.0048)   | (0.0047)   | (0.0039)   | (0.0039)   |
| O-NPI      |            |            |            |            | -0.0121*** | -0.0116*** |
|             |            |            |            |            | (0.0038)   | (0.0038)   |
| Pop        | 0.0304***  |            | 0.0327***  |            | 0.0297***  |
|             | (0.0111)   |            | (0.0111)   |            | (0.0111)   |
| Bed        | -0.0135*   | -0.0160**  | -0.0120*   |            |            |
|             | (0.0070)   | (0.0070)   | (0.0070)   |            |            |
| Distance   | -0.0121*** | -0.0116*** | -0.0120*** |            |            |
|             | (0.0038)   | (0.0038)   | (0.0038)   |            |            |
| Constant   | -0.0653*** | 0.1593**   | -0.0606*** | -0.0008    | -0.0504*** |
|             | (0.0105)   | (0.0624)   | (0.0104)   | (0.0620)   | (0.0105)   |
| Observations | 12.555      | 12.555      | 12.555      | 12.555      | 12.555      |
| R-squared  | 0.046       | 0.048       | 0.045       | 0.047       | 0.043       |
| Time trend | Yes         | Yes         | Yes         | Yes         | Yes         |
| Province FE| Yes         | Yes         | Yes         | Yes         | Yes         |
| Time FE    | Yes         | Yes         | Yes         | Yes         | Yes         |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

### Table 5
Result of robustness.

#### Panel A without Hubei Province

| (1)        | (2)        | (3)        | (4)        | (5)        | (6)        |
|------------|------------|------------|------------|------------|------------|
| Total score | -0.0208*** | -0.0211*** | -0.0360*** | -0.0361*** | -0.0276*** | -0.0284*** |
|             | (0.0019)   | (0.0019)   | (0.0038)   | (0.0038)   | (0.0030)   | (0.0030)   |
| Mobility restrictions |            | -0.0360*** | -0.0361*** | -0.0276*** | -0.0284*** |
|             |            | (0.0038)   | (0.0038)   | (0.0030)   | (0.0030)   |
| O-NPI      |            |            |            |            | -0.1369*** | -0.1369*** |
|             |            |            |            |            | (0.0155)   | (0.0155)   |
| Observations | 12.015      | 12.015      | 12.015      | 12.015      | 12.015      |
| R-squared  | 0.056       | 0.060       | 0.054       | 0.058       | 0.053       |
| Control variables | No         | Yes         | No         | Yes         | No         |
| Time trend | Yes         | Yes         | Yes         | Yes         | Yes         |
| Province FE| Yes         | Yes         | Yes         | Yes         | Yes         |
| Time FE    | Yes         | Yes         | Yes         | Yes         | Yes         |

#### Panel B DID approach

| (1)        | (2)        | (3)        | (4)        | (5)        | (6)        |
|------------|------------|------------|------------|------------|------------|
| Total Score_dummy | -0.1440*** | -0.1440*** | -0.1369*** | -0.1369*** | -0.1102*** |
|             | (0.0155)   | (0.0155)   | (0.0155)   | (0.0155)   | (0.0155)   |
| Mobility Restrictions_dummy |            | -0.1369*** | -0.1369*** | -0.1102*** |
|             |            | (0.0155)   | (0.0155)   | (0.0155)   | (0.0155)   |
| O-NPI_dummy |            |            |            |            | -0.1102*** |
|             |            |            |            |            | (0.0150)   |
| Observations | 12.555      | 12.555      | 12.555      | 12.555      | 12.555      |
| R-squared  | 0.045       | 0.045       | 0.044       | 0.044       | 0.042       |
| Control variables | No         | Yes         | No         | Yes         | No         |
| Time trend | Yes         | Yes         | Yes         | Yes         | Yes         |
| Province FE| Yes         | Yes         | Yes         | Yes         | Yes         |
| Time FE    | Yes         | Yes         | Yes         | Yes         | Yes         |

#### Panel C adjust incubation period

| Incubation period = 4 | Incubation period = 6 |
|-----------------------|-----------------------|
| Total score           | -0.0179***            | -0.0307***            |
|                       | (0.0024)              | (0.0025)              |
| Mobility restriction  | -0.0290***            | -0.0582***            |
|                       | (0.0047)              | (0.0048)              |
| O-NPI                 | -0.0251***            | -0.0376***            |
|                       | (0.0038)              | (0.0040)              |
| Observations          | 12.834                | 12.834                |
| R-squared             | 0.045                 | 0.045                 |
| Control variables     | Yes                   | Yes                   |
| Time trend            | Yes                   | Yes                   |
| Province FE           | Yes                   | Yes                   |
| Time FE               | Yes                   | Yes                   |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
coefficient of population size was significantly positive. Large population size would make it more difficult to isolate person-to-person contact, which had a negative impact on preventing the further spread of infectious diseases. Both the coefficient of effective distance and the number of beds in medical institutions is significantly negative. The number of beds represents the medical resources of a city, and cities with rich medical resources are more capable of mitigating the worsening of the epidemic. The shorter the effective distance between Wuhan and other places, the more severe the outbreak of infectious diseases there will be, which is in line with theoretical expectations.

### 6.1.3. Endogenous treatment
Since the spread of the epidemic may be affected by some unobservable factors, the problem of omitting variables may not be avoided in the regression. At the same time, the places with severe epidemic situation are more inclined to take more vigorous prevention and control measures. If the score of the city’s prevention and control level is higher than the average value, it is 1; otherwise, it is 0. In baseline regression, we assume an incubation period of five days, here we re-estimate the results by assuming an incubation period of 4 and 6 days respectively.

Table 5 panel A reports the result of subsample without Hubei province, panel B reports the result of DID approach, and panel C reports the result after adjusting incubation period. It can be seen that all the coefficients are significantly negative, and the conclusion is still robust after changing the sample selection, identification strategy and basic assumptions.

#### 6.2. Comparison of the two measures
We have proved the effectiveness of the two measures, but which measures work better? To ensure that the coefficients of the two variables are comparable, we introduce the dummy variables of whether the

\[ y_i = \alpha + \beta_{\text{intervention}} H_i + \sum_{k=1}^{n} \gamma_k X_{it} + \rho t + \delta_i + \epsilon_i \]  

(5)

where, \( \text{intervention} H \) is dummy variable of whether city \( i \) in date \( t \) take high prevention and control level measures. If the score of the city’s prevention and control level is higher than the average value, it is 1; otherwise, it is 0.

### Table 6
Result of instrumental variable.

| Panel A. Total score | (1) 2SLS | (2) Reduced form | (3) First stage |
|----------------------|----------|-----------------|----------------|
| Total score          | -0.031*** (0.0031) |                 |                |
| Total Score_IV       | -0.0293*** (0.0026) | 0.9435*** (0.0046) |               |
| Kleibergen-Paap F statistic | 42,581.1 |                 |                |
| Observations         | 12,276 12,276 12,276 | 12,276 12,276 12,276 | 12,276 12,276 12,276 |
| R-squared            | 0.048 0.050 0.971 |                 |                |

| Panel B. Mobility restriction |
|-------------------------------|
| 2SLS | Reduced form | First stage |
| Mobility restrictions | -0.0560*** (0.0069) | | |
| Mobility restrictions_IV | -0.0528*** (0.0050) | 0.9451*** (0.0044) | |
| Kleibergen-Paap F statistic | 46,394.7 | | |
| Observations | 12,276 12,276 12,276 | 12,276 12,276 12,276 | 12,276 12,276 12,276 |
| R-squared | 0.047 0.048 0.962 | | |

| Panel C. O-NPI |
|----------------|
| 2SLS | Reduced form | First stage |
| O-NPI | -0.0400*** (0.0036) | | |
| O-NPI_IV | -0.0368*** (0.0040) | 0.9190*** (0.0052) | |
| Kleibergen-Paap F statistic | 31,144.9 | | |
| Observations | 12,276 12,276 12,276 | 12,276 12,276 12,276 | 12,276 12,276 12,276 |
| R-squared | 0.045 0.046 0.960 | | |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

\( y_i = \alpha + \beta_{\text{intervention}} H_i + \sum_{k=1}^{n} \gamma_k X_{it} + \rho t + \delta_i + \epsilon_i \)

(5)
score of measure is high into the empirical model for further comparative analysis. Table 7 reports the results. Columns (1) and (2) report the result of the comparison between the two measures. It can be seen that the effect of mobility restrictions on epidemic prevention and control is better than O-NPI. Further, we introduce the interaction terms of mobility restrictions and O-NPI (Interaction terms) in columns (3) and (4) to explore the substitutive and complementary relationship between the two measures. It shows that the interaction terms are negative, which is the same sign as the main explanatory variable. That is, the two measures have a complementary relationship and the joint effort of the two measures will be more effective in prevention of the spread.

6.3. Different effects in different regions

China is a vast territory, and there is obvious heterogeneity in many characteristics among cities (see Fig. 6). In order to further explore the regional heterogeneity of effect of the measures, we divide the sample into three groups: high, medium, and low according to the economic development level of the city (GDP per capita) and population size. The sub-sample regression results are reported in Table 8. Panel A presents the results of subsample divided according to per capita GDP, and panel B presents the results subsample divided according to population size. We find that mobility restrictions and O-NPI work best in high-GDP areas, and weaken in turn in low- and medium-GDP areas. The effect of mobility restrictions is better than O-NPI in high GDP areas, while in middle and low GDP areas the effect of O-NPI exceeds that of mobility restriction. We know from the previous theoretical analysis that although mobility restriction measures effectively restrict population movement, it also makes it more difficult to deliver materials, equipment, and humanitarian assistance to affected areas, as well as increasing the difficulty of dealing with the epidemic while controlling the spread of it. Therefore, for cities with low economic development level (low GDP per capita), the implementation of mobility restrictions cannot achieve as good results as in cities with higher economic development level.

Panel B presents the results of subsample divided according to population size. Similarly, mobility restrictions and O-NPI work best in areas with large populations, and decreases in turn in areas with medium and low population sizes. Whether it is mobility restrictions or O-NPI, the measures are to reduce physical contact between people, so the effect of these measures can be better reflected in larger population cities. With respect to smaller population cities, originally human

Table 8
Different effects in different regions.

Panel A by GDP per capita

|               | Pergdp_H | Pergdp_M | Pergdp_L | Pergdp_H | Pergdp_M | Pergdp_L |
|---------------|----------|----------|----------|----------|----------|----------|
| Mobility restrictions | 0.2688*** | 0.1097*** | 0.0402** | 0.2202*** | 0.0704*** | 0.0522*** |
| O-NPI         | (0.0400)  | (0.0168)  | (0.0166)  | (0.0389)  | (0.0164)  | (0.0158)  |
| Observations  | 4275     | 4140     | 4140     | 4275     | 4140     | 4140     |
| R-squared     | 0.045    | 0.083    | 0.058    | 0.042    | 0.077    | 0.059    |
| Control variables | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Time trend    | Yes      | Yes      | Yes      | Yes      | Yes      | Yes      |
| Province FE   | Yes      | Yes      | Yes      | Yes      | Yes      | Yes      |
| Time FE       | Yes      | Yes      | Yes      | Yes      | Yes      | Yes      |

Panel B by population size

|               | pop_H    | pop_M    | pop_L    | pop_H    | pop_M    | pop_L    |
|---------------|----------|----------|----------|----------|----------|----------|
| Mobility restrictions | 0.2436*** | 0.1215*** | 0.0555*** | 0.1620*** | 0.1081*** | 0.0545*** |
| O-NPI         | (0.0308)  | (0.0299)  | (0.0191)  | (0.0294)  | (0.0296)  | (0.0183)  |
| Observations  | 4365     | 4050     | 4140     | 4365     | 4050     | 4140     |
| R-squared     | 0.054    | 0.044    | 0.047    | 0.049    | 0.043    | 0.047    |
| Control variables | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Time trend    | Yes      | Yes      | Yes      | Yes      | Yes      | Yes      |
| Province FE   | Yes      | Yes      | Yes      | Yes      | Yes      | Yes      |
| Time FE       | Yes      | Yes      | Yes      | Yes      | Yes      | Yes      |

Standard errors in parentheses , *** p<0.01, ** p<0.05, * p<0.1
contact there is less than that of high-population cities, so the effect of these measures is not so obvious. In conclusion, the effect of the two measures is not the same across the country and depends on the city's own situation. Therefore, the local situation should be fully considered when making the epidemic prevention and control policies, and the scientific and targeted prevention and control measures should be formulated so as to be tailored to the city.

### 6.4. What is necessary?

In more than half of the country is not serious about COVID-19, and there is only one imported case in Tibet, but all provinces activated first-level public health emergency responses without exception. The implementation of most prevention and control measures will have to pay huge social and economic costs. Consequently, it is necessary to discuss whether such strict prevention and control are necessary to be implemented throughout the country. We divided the samples into three groups: high-risk, medium-risk, and low-risk according to the severity of the epidemic, and estimated them separately. Table 9 reports the results of the sample regression, from which we can see that mobility restriction measures and O-NPI measures are most effective in high-risk areas, followed by medium-risk areas, and both measures are ineffective in low-risk areas. If these measures are not implemented in the light of specific situation, it will violate cost-effective principle. Therefore, differentiated measures should be taken and apply a region-specific, multi-level targeted approach to epidemic prevention and control.

### 6.5. Prevent from imported cases or internal spread?

Compared with failure of mobility restrictions and O-NPI in low-risk areas, we pay more attention to the specific measures that have failed in these areas, and the implementation of which measures are scientific and necessary. To explore this problem, we further subdivided these measures into four categories. The specific classification principles are

---

### Table 9

Necessity of the measures in areas with different severity of epidemic.

|                    | High-risk area | Medium-risk area | Low-risk area | High-risk area | Medium-risk area | Low-risk area |
|--------------------|----------------|------------------|---------------|----------------|------------------|---------------|
| Mobility restrictions | $-0.2616^{***}$ | $-0.1481^{***}$ | $-0.0358$     | $-0.2012^{***}$ | $-0.0987^{***}$ | $0.0012$     |
| O-NPI              |                |                  |               |                |                  |               |
| Observations       | 7298           | 3076             | 2181          | 7298           | 3076             | 2181          |
| R-squared          | 0.051          | 0.149            | 0.105         | 0.048          | 0.140            | 0.144         |
| Control variables  | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time trend         | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Province FE        | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time FE            | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| R-squared          | 0.051          | 0.149            | 0.105         | 0.048          | 0.140            | 0.144         |
| Control variables  | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time trend         | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Province FE        | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time FE            | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |

Standard errors in parentheses, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

### Table 10

Further classification of prevention and control measures.

| Prevent from imported cases | Suspending all the cross-city passenger transport |Suspending part of the cross-city passenger transport | Monitoring all the cross-city passenger transport | Monitoring part of the cross-city passenger transport | Quarantining returnees from key epidemic area (Hubei) for 14 days |
|----------------------------|--------------------------------------------------|-----------------------------------------------|-----------------------------------------------|---------------------------------------------------|
| Internal traffic restrictions | Suspending all the public transport |Suspending part of the public transport | Monitoring all the public places | Monitoring part of the public places | Quarantining all the returnees for 14 days |
| Internal activity restrictions | Closing all the public places |Closing part of the public places | Closed management of all the community | Closed management of part of the community | Quarantining the contact for 14 days |
| Quarantine and monitoring | Isolating and testing the suspected |   |   |   |   |

### Table 11

Prevent from imported cases or internal spread?

| Prevent from imported cases | High-risk area | Medium-risk area | Low-risk area | High-risk area | Medium-risk area | Low-risk area |
|-----------------------------|----------------|------------------|---------------|----------------|------------------|---------------|
|                            | $-0.2551^{***}$ | $-0.1253^{***}$ | $-0.0564^{***}$ | $-0.0917^{***}$ | $-0.0186^{*}$ | $-0.0037$ |
| Internal traffic restrictions |                |                  |               |                |                  |               |
| Observations                | 7298           | 3076             | 2181          | 7298           | 3076             | 2181          |
| R-squared                   | 0.050          | 0.144            | 0.107         | 0.046          | 0.133            | 0.140         |
| Control variables           | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time trend                  | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Province FE                 | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time FE                     | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| R-squared                   | 0.050          | 0.144            | 0.107         | 0.046          | 0.133            | 0.140         |
| Control variables           | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time trend                  | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Province FE                 | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |
| Time FE                     | Yes            | Yes              | Yes           | Yes            | Yes              | Yes           |

Standard errors in parentheses, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. 

---

R. Lin et al.
The effective control of the epidemic depends not only on the selection of prevention and control measures of the authority but also on the performance of the public. Therefore, in this section, we further use Baidu Search Index to explore the influence of the public’s access to information, protection awareness, and public confidence on the implementation effect of mobility restrictions and O-NPI. Fast and effective information dissemination can greatly reduce the information asymmetry of the public and raise public awareness of the epidemic. We use the Baidu search index of “COVID-19” to characterize the degree of information spread among the public. A higher search index means that the public has learned about the novel coronavirus earlier and paid more attention to it; the public’s protection awareness and positive attitude will allow them to better carry out the measures, which can absolutely improve the effectiveness of policy implementation. Here, we use the Baidu search index of “the correct way of wearing a mask” to characterize protection awareness of the public. A higher search index indicates that people have a better sense of protection; we use Baidu search index of “Zhong Nanshan” to characterize people’s confidence about fighting the epidemic. A high search index indicates that the public has more confidence to fight the epidemic, and it is even more convinced that the epidemic problem will be overcome.

We divide these three indexes into high, medium, and low, respectively, generate dummy variables, and construct the interaction terms between dummy variables and the measures. The results are shown in Table 12. Column (1) in Panel A constructs the interaction between mobility restrictions and high O-NPI. High information (M_information_H) and medium information (M_information_M), and column (2) constructs the interaction between O-NPI and the two items; similarly, Panel B presents the results of protection awareness, and Panel C presents the results of public confidence. It can be seen that, whether it is mobility restrictions or O-NPI, the coefficient of the interaction with high information dissemination (information_H) and high protection awareness (awareness_H) is significantly positive, while high public confidence (emotion_H) is significantly negative, that is, mobility restrictions and O-NPI have played a better role in cities with better information dissemination, high protection of the public, and strong confidence in epidemic prevention. It emphasizes the importance of paying attention to the public. While adopting mobility restrictions and O-NPI, the government should also increase the transparency of information disclosure, improve protection awareness of the public, and properly channel the public sentiment, strengthening public confidence.

7. Conclusion and discussion

The conclusions of this article are: ① In the prevention and control of the COVID-19 epidemic, mobility restrictions and O-NPI have played a very good role in controlling the spread of the epidemic. ② On average, the effect of mobility restrictions is better than O-NPI. The two measures are complementary, and their combined effect will play a better role in epidemic prevention; ③ The effect of prevention measures in different regions is distinct. These measures work best in areas with high GDP per capita and high population size. The effect in lower regions weakens in turn. Different from national average, O-NPI works better in low GDP areas; ④ Mobility restrictions and O-NPI are only effective in areas where the epidemic is more serious, while in low-risk areas, both measures are ineffective; ⑤ By dividing measures further, we find that strategies to prevent imported cases in low-risk areas are necessary, while in medium- and high-risk areas, both imported cases prevention and internal spread prevention are required. Regardless of the epidemic situation, monitoring and quarantine are necessary; ⑥ The rapid and accurate information transmission, higher public awareness of prevention and higher confidence in anti-epidemic can promote the effect of mobility restrictions and O-NPI.

The conclusions above have important implications for urban epidemic prevention policy. Despite the high economic and social costs,
the adoption of strict mobility restrictions for the first time in China is generally effective. Considering the complementary relationship between mobility restrictions and O-NPI, these two should be coordinated when formulating policies; considering the regional heterogeneity of the two measures, the epidemic prevention measures should be made in accordance with the city’s own situation. It should be carefully weighed what measures to take, making targeted measures according to the city’s own situation; considering some measures may fail in low-risk areas, tailored and scientific prevention and control policies should be implemented precise and differentiated epidemic control strategies should be adopted. Considering the contribution of better information dissemination, high protection awareness and strong public confidence on the effect of the measures, we should increase the transparency of information, improve protection awareness of the public, guide emotions of the public in a proper way, enhancing public confidence.

CRediT authorship contribution statement

Conceptualization, J.H. and S.L.; data curation, N.Y. and J.H; formal analysis and writing—original draft preparation, J.H. and R.L.; writing—review and editing, S.L. and J.H. All authors read and approved the manuscript.

Declaration of competing interest

The authors declare there is no conflicts of interest regarding the publication of this paper.

Acknowledgements

The authors gratefully acknowledge the financial support of the National Social Science Fund of China (Grant No. 13BJY091) and the National Natural Science Foundation of China (Grant No. 71773083).

Appendix A. Baidu Index

The data used in Section 6.6 is from Baidu Search Index of Baidu Index (http://index.baidu.com). Baidu Index is a data analysis platform based on massive Internet user behavior data in Baidu (The world’s largest Chinese search engine https://www.baidu.com/). It is one of the most important statistical analysis platforms in the current Internet and even the whole data era. Since its release, Baidu Index has become an important basis for many enterprises’ marketing decisions.

Baidu Index is based on massive data in Baidu. On the one hand, it carries out keyword search heat analysis, on the other hand, it deeply excavates data features of public opinion information, market demand, user characteristics and other aspects. Baidu Index can tell users: how big is the search scale of a keyword in Baidu, the rise and fall trend in a period of time and the changes of relevant news and public opinion, what kind of netizens are concerned about these words, where they are distributed, and what relevant words they have searched at the same time. Baidu search index is based on the search volume of Internet users in Baidu, with keywords as the statistical object, scientifically analyzes and calculates the weighted sum of search frequency of each keyword in Baidu web search.6

Appendix A. Baidu Index

Fig. 1. Baidu search trends of “新型冠状病毒”.

The following three figures are all downloaded from the official website of the Baidu Index: http://index.baidu.com.
Fig. 2. Baidu search trends of “口罩的正确戴法”.

Fig. 3. Baidu search trends of “钟南山”.

References

Anderson, R. M., Arshed, A., Anderson, B., & May, R. M. (1992). Infectious diseases of humans: Dynamics and control. Oxford university press.

Angrist, J. D., & Pischke, J.-S. (2008). Mostly harmless econometrics: An empiricist’s companion. Princeton Univ. Press.

Aron, J. L., & Schwartz, I. B. (1984). Seasonality and period-doubling bifurcations in an epidemic model. Journal of Theoretical Biology, 110(4), 665–679.

Barbisch, D., Koenig, K. L., & Shih, F. Y. (2015). Is there a case for quarantine? Perspectives from SARS to Ebola. Disaster Medicine and Public Health Preparedness, 9(5), 547–553.

Brockmann, D., & Helbing, D. (2013). The hidden geometry of complex, network-driven contagion phenomena. Science, 342(6164), 1337–1342.
Koenig, K. L. (2015). Health care worker quarantine for Ebola: To eradicate the virus or
Rokitnv, J., & Sjdin, H. (2020). Only strict quarantine measures can curb the coronavirus disease (covid-19) outbreak in Italy, of novel coronavirus
(2019-ncov) outbreak. The Lancet Infectious Diseases, 20(3), Article taaa139.

Lau, H., Khosrawipour, V., Kobrba, P., Mihalajczuk, A., Schubert, J., Bania, J., &
Khosrawipour, T. (2020). The positive impact of lockdown in Wuhan on containing
the COVID-19 outbreak in China. Journal of Travel Medicine, 27(3), Article taa037.

Lewnard, J. A., & Lo, N. C. (2020). Scientific and ethical basis for social-distancing
interactions against COVID-19. The Lancet Infectious Diseases, 20(6), 631–633.

Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., et al. (2020). Early transmission
dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. New England
Journal of Medicine, 382(13), 1199–1207.

Liu, Y., Gayle, A. A., Wilder-Smith, A., & Rocklov, J. (2020). The reproductive number
of COVID-19 is higher compared to SARS coronavirus. Journal of Travel Medicine, 27(2).
https://doi.org/10.1093/jtm/taaa021. taaa021

Mao, L. (2013, November). Cost-effectiveness of workplace closure and travel restriction
for mitigating influenza outbreaks: A network-based simulation. In Proceedings of the
second ACM SIGSPATIAL international workshop on the use of GIS in public health (pp.
77–84).

Morris, S. S., Mazet, J. A., Woolhouse, M., Parrish, C. R., Carroll, D., Kares, W. B., et al.
(2012). Prediction and prevention of the next pandemic zoonosis. Lancet, 380(9857).

Qian, M., Wu, Q., Wu, P., Hou, Z., Liang, Y., Cowling, B. J., & Yu, H. (2020).
Psychological responses, behavioral changes and public perceptions during the early
phase of the COVID-19 outbreak in China: A population based cross-sectional survey.
medRxiv.

Rashid, H., Rida, I., King, C., Begum, M., Tekin, H., Wood, J. G., et al. (2015). Evidence
compendium and advice on O-NPI and other related measures for response to an
influenza pandemic. Paediatric Respiratory Reviews, 16(2), 119–126.

Rocklov, J., & Sjdin, H. (2020). High population densities catalyze the spread of covid-19.
Journal of Travel Medicine, 27(3).

Rothstein, M. A. (2015). From SARS to Ebola: Legal and ethical considerations for
modern quarantine. Ind. Health Law Rev., 12, 227.

Rothstein, M. A., & Talbott, M. K. (2007). Encouraging compliance with quarantine: A
proposal to provide job security and income replacement. American Journal of Public
Health, 97(Supplement 1), S49–S56.

Sakaguchi, H., Tsuomura, W., Wada, O., Ohta, H., Kawashima, M., Yoshino, Y., &
Iizawa, Y. (2012). Assessment of border control measures and community
containment measures used in Japan during the early stages of pandemic (H1N1)
2009. PloS One, 7(2).

Sjdin, H., Wilder-Smith, A., Osman, S., Farooq, Z., & Rocklov, J. (2020). Only strict
quarantine measures can curb the coronavirus disease (covid-19) outbreak in Italy, in
2020. Eurosurveillance, 25(13).

Thu, T. P. B., Ngoc, P. N. H., & Hai, N. M. (2020). Effect of the social distancing measures
on the spread of COVID-19 in 10 highly infected countries. Science of the Total
Environment, 742, 140430.

Tomar, A., & Gupta, N. (2020). Prediction for the spread of covid-19 in India and
effectiveness of preventive measures. Science of the Total Environment, 728, Article
138762.

Wang, L., Zhang, Y., Huang, T., & Li, X. (2012). Estimating the value of containment
strategies in delaying the arrival time of an influenza pandemic: A case study of
tavel restriction and patient isolation. Physical Review E, 86(3), Article 032901.

Wilder-Smith, A., & Chiew, C. J., & Lee, V. J. (2020). Can we contain the covid-19 outbreak
with the same measures as for sars? The Lancet Infectious Diseases, 20(5).

Wilder-Smith, A., & Freedman, D. O. (2020). Isolation, quarantine, social distancing and
community containment: pivotal role for old-style public health measures in the
novel coronavirus (2019-nCoV) outbreak. Journal of Travel Medicine.

Zhang, J. (2020). How much control can we do to curb the development of the epidemic?
Network dynamics deduction gives you the answer. Working paper, https://www.th
epaper.cn/newsDetail_forward_5677940.

Zhang, Z. B., Li, L., Qin, P. Z., Li, K., Huang, Y., Luo, L., & Ou, C. Q. (2020). Countries of
origin of imported COVID-19 cases into China and measures to prevent onward
transmission. Journal of Travel Medicine, 27(8), Article taa139.