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The effectiveness and costs of nonpharmaceutical interventions for COVID-19 containment: A border discontinuous difference-in-difference approach

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ARTICLE INFO

JEL codes:
R5
H7
I1
O5

Keywords:
COVID-19
Nonpharmaceutical interventions
Effectiveness
Costs
Spatial spillover

ABSTRACT

We examine the effectiveness and costs of alternative nonpharmaceutical interventions (NPIs) for COVID-19 containment. Using a border discontinuous difference-in-difference approach, we find that the enforcement of rigid NPIs reduces the number of new COVID-19 cases by 10.8% in China, compared with cities with less NPIs. Among the three NPIs, contact tracing is much more effective than the other two NPIs, namely, public information provision and social distancing. The connections of mayors to the upper-level politicians reinforce the city's implementation of rigid NPIs. These networks also serve as an informal signaling channel to the neighboring cities, encouraging the adjacent cities to impose strict NPIs to curb the spread of COVID-19. We further estimate the long-term costs of the NPIs – a net present value of 2153 yuan per child in the human capital loss attributed to more prolonged school closure alone.

1. Introduction

With >9.28 billion doses of vaccine have been administered across 183 countries since January 14, 2022,¹ the world expects to see a glimmer of light at the end of the tunnel – or at least a cautiously optimistic view – that the pandemic might recede to the background. Some highly vaccinated countries, such as Israel, the U.K., and the U.S., started to ease the restrictions associated with coronavirus diseases (COVID-19), such as the mandatory mask rule and social distancing. However, the two recent variants of COVID-19, i.e., Delta and Omicron, appear to be breaking through the protective vaccines provided at a higher rate than previous strains in 2021. According to data from the U.S. Centers for Disease Control and Prevention (CDC), with a fully vaccinated rate of 62.9% in the nation, community transmission remains high throughout the United States. This trend is driven by the Omicron variant, which now accounts for approximately 98% of cases in the United States. The uneven distribution of vaccination worldwide is also taking its toll on some of the poorest and most vulnerable people in the world. The debate continues on the importance and effectiveness of nonpharmaceutical interventions (NPIs), such as social distancing, mask mandates, public information provision, and contact tracing, to curb the spread of new virus strains. Among alternative NPIs, people want to know which approach is more effective in containing pandemics, such as

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Data sources: WHO Coronavirus (COVID-19) Dashboard, https://covid19.who.int/.

https://doi.org/10.1016/j.chieco.2022.101849
Received 16 January 2022; Received in revised form 26 June 2022; Accepted 6 August 2022
Available online 11 August 2022
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COVID-19 and its variants, but less costly to the economy and society.

This paper provides a novel analysis of the pandemic containment policy by comparing the effectiveness and costs of alternative NPIs, including public information provision, contact tracing and social distancing. We hand-collected the official documents from both the provincial and city-level governments in China. We performed a textual analysis to measure the daily stringency of NPIs at the city level, which provides more information on the NPIs than other measures in the literature, such as the first date when a certain policy was introduced (Qiu, Chen, & Shi, 2020). Our measure extends the similar stringency measures of government response reported by the Oxford COVID-19 Government Response Tracker (OxCGRT), where OxCGRT only measures NPIs at the country level. Moreover, we use a border discontinuous difference-in-difference (DID) method, with exogenous variations in the stringency of NPIs to identify the causal effect of NPIs on COVID-19 spread. We also estimate the cost of these NPIs to the economy and human capital in cities with harsher NPIs.

Our paper contributes to the burgeoning literature on the public policy implemented to manage the global COVID-19 pandemic and mitigate the detrimental effects on the economy and society (Dave, 2021; Fang, Wang, & Yang, 2020; Kraemer, 2020; Pindyck, 2020). First, we find that, on average, NPIs significantly reduce the COVID-19 spread in China by 10.8% after 21 days of enforcement. Among the three NPIs, contact tracing is more effective than public information provision and social distancing for COVID-19 containment. Most of the literature focuses on the effect of social distancing, as measured by GPS-based human mobility, on the spread of COVID-19 (Allcott et al., 2020; Fang et al., 2020; Glaser, Gorbach, & Redding, 2022). Our study provides new insights to formulate effective public health policy designed to combat the current and future global pandemics. In particular, we extend the studies by Gupta (2021) and Ferretti et al. (2020) by causally quantifying the importance of contact tracing and public information provision on COVID-19 containment.

Second, we explore how government officials might impact the implementation of NPIs. Li (2022) find that officials’ profession-alism in public health or medicine affects their policy response and performance in combating the COVID-19 pandemic. We provide new evidence that the political connections of mayors to provincial leaders (including provincial governors and party secretaries) significantly increase the severity of the NPI implemented in the city. Political connections reduce information asymmetry through a communication channel (Jia, Kudamatsu, & Seim, 2015), which helps mayors with political connections execute their local NPIs more rigidly and effectively. These networks also serve as an informal signaling channel to encourage neighboring towns to impose rigid NPIs.

Third, we estimate the costs of alternative NPIs using approaches similar to those described by Fleisher and Wang (2004) and Adda (2016). A sharp reduction in the economy, an approximately 5.16% decrease in the economic growth rate, was observed in both the treatment and control groups during the first quarter of 2020. The loss of human capital associated with children due to school closure is significant. The primary schools of the adjacent treatment group were closed 4.58 days more than those in the control group. The net present value of loss in life cycle earnings is 2153 yuan per child due to more prolonged school closure, even after online learning is considered. This cost estimate is comparable to the 850 yuan loss per child who loses three days of schooling due to a flu-like illness in the study by Adda (2016). Our results provide empirical evidence that pandemic containment measures implemented during the COVID-19 pandemic have a costly long-term effect on human capital, which policy-makers should consider carefully.

Fourth, the border discontinuous DID approach provides better identification of the causal effects of NPIs, compared with the instrumental variable approach (Adda, 2016), DID estimation (Allcott et al., 2020; Fang et al., 2020), and the event-study method (Gupta, 2021) reported in the literature. Before the central government announced the Wuhan lockdown on January 23, 2020, the local governments employed different NPIs based on their local knowledge of the virus. The date of NPIs enforcement and the cities in which individuals reside jointly determine the intensity of their exposure to the NPIs. Inspired by Duflo (2001), the treatment cities are selected where the residual of the regression of NPIs intensity on the number of cumulative confirmed cases by January 23 is positive. We adopt the boundary discontinuous DID approach, i.e., restrict both types of cities that share the exact boundaries (Ambros, Field, & Gonzalez, 2020; Mangrum & Niekamp, 2022), to ensure the parallel trends between the treatment and control cities. To account for the confounding NPIs implemented simultaneously, we further employ a stacked DID to explore which NPIs are the most effective in curbing the spread of COVID-19.

The remainder of this paper is structured as follows. Section 2 describes the data used in our analysis. Section 3 presents the empirical design of DID estimations. Section 4 presents the results for the estimates of the causal effects of NPIs on COVID-19 containment. Section 5 explores the political determinants of the stringency of the NPIs. Section 6 provides the cost of COVID-19 containment using estimates from the literature. Section 7 describes the conclusions.

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2 The Oxford COVID-19 Government Response Tracker (OxCGRT) systematically collects publicly available information on several different common policy responses that the government has implemented to contain COVID-19, and quantifies them by measuring 17 indicators (e.g., stringency index, government response index, and school closure index). See the following website: https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker/data.

3 Gupta (2021) find that information-focused actions such as first case announcements have bigger effects on COVID-19 containment. Ferretti et al. (2020) model the effect of digital contact tracing on containing the epidemic spread, and report that it is an effective means to contain the epidemic if a sufficient amount of people use those contact tracing apps.

4 We converted the loss of €100 estimated by Adda (2016) into Chinese Yuan with an exchange rate of 8.5 CNY/€.
2. Data

2.1. Stringency of NPIs

China has a top-down political system. The central government generally sets the general guidelines to contain the spread of COVID-19. However, the local governments (including the provincial and city levels) are responsible for establishing the details and enforcing the NPIs. In particular, the central government uses official documents to mandate policy actions. These official documents identify the stringency of policy enforcement and transfer that responsibility to lower-level governments simultaneously. The cross-city level heterogeneity in the harshness of policy enforcement allows us to measure the daily stringency of local NPIs, based on the official documents released by the provincial governments and prefecture-level cities.

We consider the official documents from both levels of local governments (provincial and city) because the provincial governments form the official documents and deliver them to the lower level government. The city governments may create similar enforcement documents or only implement the policy provided by the provincial governments. However, city leaders with political connections to provincial leaders may know the political insights of the upper-level official documents issued by provincial governments through the informal communication channel (Jia et al., 2015). The information thus guides city leaders to formulate specific NPIs consistent with the aforementioned documents. Therefore, we weigh the provincial and city governments equally in measuring the official documents.

We hand-collected the daily official documents on the NPIs for COVID-19 published from January 3 to May 3, 2020, from the government’s website. We started on January 3, when the city government of Wuhan first released the information on pneumonia of unknown etiology.\(^5\) We use a dictionary-based method to measure the stringency of NPIs in each city, which is by far the most common method used in literature (Baker, Bloom, & Davis, 2016; Gentzkow, Kelly, & Taddy, 2019). First, we construct a dictionary of terms by performing a word frequency analysis of the official documents issued by the central government during the studied period, to measure particular categories of NPIs. Relative terms with top word frequencies, such as “disclosure”, “monitoring” and “face mask”, are classified into three categories: public information provision, contact tracing, and social distancing. We also consider terms that account for the easing of NPIs, such as “work and production resumption”. We ultimately define specifically a dictionary of terms that are classified into four categories as measurements of NPIs. The NPI dictionary with prespecified terms is summarized in Table A.1 in the Appendix. Second, we map the local document-token matrix C to predict NPIs. We define \(NPI^d = f(c^d)\) by performing a word frequency analysis:

\[
NPI^d_{it,g} = \frac{\sum_{j=0}^{d} w^d_{it,j} T^d_{it,j} + \sum_{j=0}^{d} \text{counts}_{it,j} T^d_{it,j}}{\sum_{j=0}^{d} \text{counts}_{it,j} T^d_{it,j}}
\]

where \(NPI^d_{it,g}\) is the stringency of the \(d\)th NPIs enforced by government \(g\) of city \(i\) on date \(t\). \(T\) is the calendar date of January 3, 2020, and \(j\) is the gap between dates \(t\) and \(T\). \(w^d_{it,j}\) is the word count of prespecified terms for the \(d\)th NPIs in the official documents, and \(\text{counts}_{it,j}\) is the total word count of the official documents imposed by city \(i\)’s government \(g\). We also calculate the stringency of the \(d\)th NPIs enforced by city \(i\)’s upper-level government \(p\) (i.e., provincial-level government). We use the sum of \(NPI^d_{it,g}\) and \(NPI^d_{it,p}\), weighted by 0.5 of each NPI, as the stringency of \(NPI^d_{it}\) in city \(i\).

We show the geographical difference in NPIs in Panels A and B of Fig. 1. Before the Wuhan lockdown on January 23, 2020, a few cities enforced NPIs to contain the spread of the epidemic. Some cities in Inner Mongolia and Ningxia Province have less infection risks; however, they enforce earlier and stricter NPIs (see Panels A and C). Two months after the epidemic outbreak, the cities with earlier and more rigid NPIs generally confirmed fewer COVID-19 cases (Panel D).

As a method to verify the accuracy of NPIs measured by Eq. (1), we calculate the stringency of NPIs by 1) considering the word frequency of prespecified terms in the official documents imposed by city \(i\)’s government \(g\); namely, we use \(NPI^d_{it,g}\) as city \(i\)’s stringency of \(NPI^d_{it}\); 2) including the prespecified terms measuring the easing of NPIs, which is calculated using Eq. (A.1) in the Appendix; and 3) using TF-IDF (term frequency-inverse document frequency) score to measure city \(i\)’s stringency of \(NPI^d_{it}\) (see Eq. (A.2 – A.4) in Appendix A for details). We use the three measures of NPIs in the robustness analysis. Moreover, we compare the stringency of NPIs calculated using Eq. (1) we proposed with those measured by OxCGRT. Fig. A.2 in Appendix A shows that the stringency of NPIs calculated with different measures increases over time, and their trends are also comparable.\(^6\)

2.2. Confirmed COVID-19 cases

The COVID-19 cases analyzed in this study refer to the laboratory-confirmed cases reported by the health departments of each provincial government.\(^7\) The information reports the daily asymptomatic carriers, confirmed positive cases, deaths, and recovered COVID-19 cases in each city of the province.\(^8\) The data cover 84,229 confirmed COVID-19 cases and 78,974 recovered cases in 321 cities in China from January 3 to July 30, 2020. Fig. A.3 in the Appendix shows the trends for daily new laboratory-confirmed cases in

\(^5\) Wuhan Municipal Health Commission, http://wjw.wuhan.gov.cn/xwzx_28/gsgg/202004/t20200430_1199588.shtml

\(^6\) We acknowledge potential measurement errors in the stringency of NPIs calculated by word frequency. The comparable trends for NPIs measured from different sources in Fig. A.2 in the Appendix provide a confidence to the stringency of NPIs we calculated.

\(^7\) For example, the website of The Hubei provincial health commission: http://wjw.hubei.gov.cn/bmdt/ztzl/fyxwzx/index.shtml

\(^8\) The confirm positive cases do not include asymptomatic cases.
A) Stringency of NPIs by Jan. 23

B) Stringency of NPIs by Mar. 28

C) Cumulated Cases by Jan. 23

D) Cumulated Cases by Mar. 28

Fig. 1. Geographic differences in the stringency of NPIs and COVID-19 infections.

Note: The figure shows the geographic differences in the stringency of NPIs and cumulative COVID-19 confirmed cases. Panel A shows the stringency of NPIs enforced by city governments by January 23, 2020. Cities in red indicate that the local government implemented the strictest NPIs by January 23, 2020. Panel B shows the stringency of NPIs enforced by city governments by March 28, 2020. Panel C shows cumulative COVID-19 confirmed cases as of January 23, 2020. Panel D shows the cumulative confirmed cases by March 28, 2020. The population inflow from Wuhan before the lockdown (January 23, 2020) is also included in each panel.

Many possible reasons exist to treat the official reported numbers of confirmed cases in Wuhan and other cities in Hubei Province with more caution. First, approximately half of the population outflow from Wuhan moved to other cities in Hubei Province (Panel A in Fig. A.4 in Appendix A). These moves increased the number of infection outbreaks in Hubei Province, and the health care systems in Hubei Province were overwhelmed. Therefore, conducting a sufficient number of laboratory tests was impossible, resulting in underreported confirmed cases in Hubei Province in the early stage of the COVID-19 outbreak. Second, all cities in Hubei Province have been strictly locked down since January 26, 2020. The government does not allow individuals to walk outside of their homes and shut down the public transportation system. The strictest control measures in Hubei Province are not comparable to those in other cities outside Hubei. Thus, we exclude cities in Hubei Province from our analysis.

2.3. Real-time population flow

We use real-time population flow to measure people's mobility and, thus, the potential risks of infections (Fang et al., 2020). The Baidu Inc. has only released the real-time population flow to the public by May 3, which is discussed in the next section.

\[ \text{Footnote:} \text{Baidu Inc. has only released the real-time population flow to the public by May 3, which is discussed in the next section.} \]
real-time population flow data are derived from China’s search engine Baidu,\textsuperscript{10} which provides the largest travel map apps in China. The Baidu Migration dataset provides two types of population mobility, the population flow within each city and the population flow across cities. The cross-city population flow covered 9,869,121 population mobility pairs (origins to destinations) from January 1 to May 3, 2020. Each of the 333 cities provides the indices of population flow from the top 100 departure cities and the top 100 destination cities (see Fig. A.4 in Appendix A).

We added the days since the first confirmed case and its square term in each city to control the temporal trends of the COVID-19 outbreak and the loading of the public health system. We also include the daily weather conditions, namely, the average temperature, relative humidity, and average wind speed, which may affect the transmission of COVID-19 (Adda, 2016). The weather variables are constructed based on the fifth-generation reanalysis of the global climate and weather variables (ERA5) released by the European Centre for Medium-Range Weather Forecasts (ECMWF).\textsuperscript{11} Table 1 presents the summary statistics of the data used in this study.

3. Empirical identification

3.1. Event study

Our goal is to measure the effect of NPIs on the spread of COVID-19. We first use an event-study framework to compare mobility behavior, and COVID-19 patterns before and after the city implemented NPIs. Our analysis sample is 313 prefecture cities in China from January 3 to March 28, 2020.

The basic specification is:

\[ Y_{it} = \sum_{j=1}^{35} \beta_j \text{Event}_{it,j} + \theta X_{it} + \gamma_i + \theta_i + \epsilon_{it} \]

where \( Y_{it} \) is one of the four outcomes: 1) internal mobility and 2) population outflow, both of which measure the mobility patterns before and after the NPIs are implemented in city \( i \) on date \( t \); 3) daily new confirmed COVID-19 cases; and 4) cumulative COVID-19 deaths, which measure the COVID-19 patterns before and after the NPIs are implemented. Event measures the event time for city \( i \), a dummy variable that equals 1 if city \( i \) enforced NPIs as of day gaps \( j \) and 0 otherwise. \( X \) is a vector of control variables, which has been described in the previous section. We include the city fixed effect \( \gamma_i \) to capture the time-constant heterogeneous characteristics within a city, and date fixed effects \( \theta_t \) to capture the time-varying trends that may affect COVID-19 cases.

Fig. A.1 in Appendix A shows the timeline of cities that started to enforce NPIs. Before January 20, 2020, when the Chinese government announced the risk of human-to-human transmission of COVID-19, no city realized the danger of epidemic spread, and the local governments enforced no NPIs. However, by the lockdown date on January 23, over half of the city governments (157 cities) had executed NPIs, including public information provision, contact tracing, and social distancing. Ten days after the lockdown in Wuhan’s, all cities in our sample have implemented NPIs to contain the COVID-19 spread. This flexible event-study approach allows us to explore whether reverse causality exists such that NPIs may be enforced in cities with worse COVID-19 cases (Goodman-Bacon & Marcus, 2020).

3.2. DID estimation

For our main analysis, we use a DID design to estimate the effects of NPI enforcement on COVID-19. The date of NPI enforcement and the cities in which individuals reside jointly determine the intensity of their exposure to the NPIs. Table 2 presents the regression results for NPI stringency in each city, which was calculated using Eq. (1), on the logarithmic cumulative confirmed cases and population inflow from Wuhan by January 23, 2020. The greater the number of cumulative confirmed cases and greater population inflow from Wuhan, the harsher the NPIs that are expected. The coefficients in Table 2 have the expected, significantly positive sign. According to Duflo (2001), the treatment cities are defined as cities where the residual of the regression of NPI stringency on the number of cumulative confirmed cases by January 23 is positive. The remaining cities are defined as the control cities (see Panel A in Fig. 2).\textsuperscript{12}

The basic idea of this identification is that before the central government announced the strictest lockdown policy, local governments adopted NPIs with different stringencies based on their known information on the virus. The number of COVID-19 infections in cities that received early and harsher NPIs is less than that in cities with late and looser NPIs (Alexander & Karger, 2021). The difference in confirmed COVID-19 cases related to the differences in NPI stringency might be interpreted as the effect of the NPIs, based on the assumption that in the absence of NPIs, the trends of COVID-19 cases would not be systematically different in harsher and looser cities. Panel A in Fig. 2 shows that the treatment cities are mostly clustered in the northern and southwestern regions and some in Henan and Jiangsu Provinces. The control cities are clustered in the northwestern and northern regions. The cluster of treatment and control cities implies that the other conditions, such as economic activities and public health systems, are not comparable between the two

\textsuperscript{10} Baidu Migration data, http://qianxi.baidu.com/.

\textsuperscript{11} Data source: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview

\textsuperscript{12} The cumulative confirmed COVID-19 cases and population inflow from Wuhan are strongly correlated by January 23, 2020. We also use the alternative definition of treatment cities as cities where the residual of a regression of NPI stringency on the number of cumulative population inflow by 23 January is positive in Appendix B.
Table 1
Summary statistics.

| Variable | N   | Mean | S.D. | P1   | P50  | P99  |
|----------|-----|------|------|------|------|------|
| Panel A: Treatment cities |     |      |      |      |      |      |
| Treatment cities          | 313 | 0.48 | 0.50 | 0    | 0    | 1    |
| Daily new confirmed cases | 27,606 | 0.48 | 2.45 | 0    | 0    | 9    |
| Cumulative confirmed cases | 27,606 | 25.21 | 58.23 | 0    | 6    | 337  |
| Enforcement of NPIs (Post) | 27,606 | 0.74 | 0.44 | 0    | 1    | 1    |
| Word counts               | 27,606 | 17.376 | 19.023 | 0    | 10,649 | 69,157 |
| Stringency of NPIs        | 27,606 | 1.90 | 1.31 | 0.00 | 2.19 | 4.95 |
| Public information provision | 27,606 | 0.65 | 0.47 | 0.00 | 0.76 | 1.75 |
| Contact tracing           | 27,606 | 0.43 | 0.34 | 0.00 | 0.47 | 1.30 |
| Social distancing         | 27,606 | 0.82 | 0.65 | 0.00 | 0.86 | 2.79 |
| Days since the first confirmed case | 27,606 | 21.66 | 21.56 | 0    | 16   | 65   |
| Temperature               | 27,606 | 10.77 | 9.37 | -12.84 | 11.04 | 29.26 |
| Relative humidity         | 27,606 | 62.25 | 21.42 | 16.42 | 64.31 | 98.20 |
| Wind speed                | 27,606 | 2.99 | 2.17 | 0.60 | 2.25 | 10.13 |
| Internal mobility         | 27,606 | 3.85 | 1.35 | 0.94 | 4.04 | 6.49 |
| Population outflow        | 27,606 | 0.75 | 1.34 | 0.01 | 0.45 | 6.33 |
| Population                | 267  | 9.07 | 0.59 | 7.90 | 9.05 | 10.16 |
| Doctors per ten thousand population | 267  | 2.40 | 0.68 | 1.24 | 2.33 | 4.90 |

Panel B: Adjacent Treatment cities

| Variable | N   | Mean | S.D. | P1   | P50  | P99  |
|----------|-----|------|------|------|------|------|
| Adjacent Treatment cities | 224 | 0.47 | 0.50 | 0    | 0    | 1    |
| Daily new confirmed cases | 19,436 | 28.95 | 62.30 | 0    | 7    | 346  |
| Cumulative confirmed cases | 19,436 | 0.75 | 0.43 | 0    | 1    | 1    |
| Word counts               | 19,436 | 18.476 | 19.681 | 0    | 12,998  | 72,782 |
| Enforcement of NPIs (Post) | 19,436 | 0.75 | 0.43 | 0.00 | 1.00 | 1.00 |
| Stringency of NPIs        | 19,436 | 1.92 | 2.10 | 0.00 | 2.19 | 4.79 |
| Public information provision | 19,436 | 0.64 | 0.43 | 0.00 | 0.75 | 1.61 |
| Contact tracing           | 19,436 | 0.44 | 0.34 | 0.00 | 0.47 | 1.34 |
| Social distancing         | 19,436 | 0.83 | 0.64 | 0.00 | 0.89 | 2.65 |
| Days since the first confirmed case | 19,436 | 22.66 | 21.65 | 0    | 18   | 65   |
| Temperature               | 19,436 | 10.01 | 8.92 | -12.77 | 10.22 | 26.37 |
| Relative humidity         | 19,436 | 62.45 | 21.48 | 16.16 | 64.45 | 98.16 |
| Wind speed                | 19,436 | 3.07 | 2.23 | 0.59 | 2.32 | 10.27 |
| Internal mobility         | 19,436 | 3.87 | 1.33 | 1.15 | 4.04 | 6.55 |
| Population outflow        | 19,436 | 0.81 | 1.45 | 0.01 | 0.48 | 6.74 |
| GDP per capita            | 187  | 8.31 | 0.67 | 6.64 | 8.38 | 10.09 |
| Population                | 179  | 8.31 | 0.67 | 6.64 | 8.38 | 10.09 |
| Doctors per ten thousand population | 179  | 2.40 | 0.66 | 1.22 | 2.31 | 4.90 |

Note: This table provides the summary statistics of the key variables from January 3 to March 28, 2020. Panel A includes treatment and control cities defined by the stringency of NPIs (Panel A in Fig. 2). Panel B restricts the treatment and control cities with adjacent boundaries (Panel B in Fig. 2). Daily new confirmed cases are the laboratory-confirmed cases reported by the provincial NHS in China. Enforcement of NPIs (used as the Post variable in the subsequent regressions) is a dummy variable that equals one if a city enforced a certain NPI to control the COVID-19 spread. The stringency of NPIs is the word frequency of prespecified terms in the local governments’ official documents. Public information provision, contact tracing, and social distancing are the corresponding words frequency of prespecified terms. Days since the first confirmed case measure the temporal trends of the COVID-19 outbreak. Temperature, relative humidity, and wind speed are the weather variables measured by the ERA5 reanalysis dataset. Internal mobility and population outflow are measured by real-time commuting data from Baidu Inc. Several city characteristics, including logarithmic gross domestic product (GDP) per capita, the logarithmic population in thousands, and doctors per thousand population, are included in the analysis.

Table 2
The NPI stringency by January 23, 2020.

| NPI stringency | Log(cumulative confirmed case × 100 + 1) | Population inflowed from Wuhan | Number of observations |
|----------------|----------------------------------------|---------------------------------|------------------------|
|                | 0.108***                               | 13.29***                        | 321                    |
|                | (0.023)                                 | (5.067)                         | (0.023)                |

Note: The dependent variable is the NPI stringency on January 23, as calculated using Eq. (1). We multiplied the cumulative confirmed cases on January 23 by 100 to maintain the sensibility of local governments’ response to the cumulative confirmed cases. Robust standard errors are shown in parentheses. *** significant at the 1% level.
groups. We thus define a better treatment-control group by referring to the studies by Ambrus et al. (2020) and Pinkovskiy (2017), namely border discontinuous DID. We match the treatment cities that share a border with the control cities called the adjacent treatment-control-cities (Panel B in Fig. 2).

We consider the dynamics of COVID-19 lags among the NPI enforcement, individual exposure, and laboratory-confirmed infections for the \( j \) lagged days window:

\[
\log(Y_{it}) = \sum_{j=0}^{7,14,21} \alpha_j \text{Treat}_i \times \text{Post}_{i,t-j} + \sum_{j=0}^{7,14,21} \beta_j \text{Post}_{i,t-j} + \mu X_{it} + \gamma_i + w_t + \epsilon_{it}
\]  

(3)

where \( Y_{it} \) is the daily laboratory-confirmed new COVID-19 cases in city \( i \) on date \( t \). The definition of \( \text{Treat} \) varies by the DID specification, as we have discussed previously. \( \text{Post} \) is a dummy variable that varies by the time of enforcing NPIs in each city. In particular, \( \text{Post} \) equals one if the city government started to implement NPIs to contain the COVID-19 spread, and zero otherwise. \( X_{it} \) is a set of control variables that are described in Section 2. \( \gamma_i \) represents the city fixed effect of controlling the time-unvarying city heterogeneities. \( w_t \) is the calendar week fixed effect to eliminate the time-varying effect. The estimated coefficient \( \alpha_j \) thus captures the effect of NPIs on virus spread with a time-lagged \( j \). We consider the dynamic effects of NPI enforcement for \( j \in \{0,7,\cdots,21\} \) days, which represent the periods following the 99th percentile thresholds in the incubation window for COVID-19 (Fang et al., 2020; Lauer, 2020). We replace the dummy of enforcement in Eq. (3), with the stringency of NPIs in the sensitivity analyses to explore the effects of variations in policy stringencies over time.

Several threats may violate the parallel trends assumption, which biased our DID estimation. First, Goodman-Bacon and Marcus (2020) argue that voluntary precautions among individuals may positively bias the DID estimation. As mentioned above, we control for the voluntary precautions by adding two time trends: the days since the first confirmed case in city \( i \) and its square term (Brzezinski, Kecht, & Van Dijcke, 2020; Gupta, 2021). In particular, the temporal trends in the announcement of the first case help capture the unobserved voluntary responses to the risk within a city.

Second, infectious diseases may spread across city borders through migrant travel. Harsher NPIs that help the treatment cities also help the control cities. To address this concern, we weigh all the DID regressions by performing propensity-score-matching of migrant inflows and characteristics that affect the spread of COVID-19 (Bertrand, Duflo, & Mullainathan, 2004; Dave, 2022).

Third, in the presence of the time-varying treatment effects (see Fig. A.1 in Appendix A), a two-way fixed effects model may bias the causal effects when some of the DID variations are driven by comparisons in which previously treated cities are used as controls for later treated cities. Following Goodman-Bacon (2021), we document that approximately 96% of the DID variations of our estimation are due to “good” comparisons (see Appendix B.2) and suggest very little scope (approximately 2.2% of the weights) for bias in the

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13 Variables used in propensity score matching are cumulative migrant inflow from other cities, GDP per capita, population size and doctors per ten thousand population.

14 Table B.1 in the Appendix B provides the baseline DID estimations without the propensity score reweighting, to gauge bias due to an imbalance in the exposure to inflowing migrants and other characteristics.
estimations obtained using Eq. (3) due to the “negative weights” (Goodman-Bacon, 2021). Nonetheless, we employ a fuzzy DID in Appendix B.2 to address bias in two-way fixed effects models (de Chaisemartin & D’Haultfouill, 2020).

We are also interested in what types of NPIs are the most effective in containing the spread of COVID-19. In China, governments typically implement a wide range of measures to curb the spread of COVID-19 in a short time, which may possibly confound the estimation obtained using Eq. (3). Using the method reported by Deshpande and Li (2019), we employ stacked DID to eliminate the confounding effects caused by other NPIs. Specifically, we create separate datasets for each of the 313 cities with NPIs. In each dataset, city \(i\) that started to implement the \(d_{t_i}\) NPIs on date \(D\), for example, “public information provision”, is labeled a Post-treated city. Event days are specified relative to date \(D\) of NPI implementation. The cities that implement the other NPIs at least 21 days later relative to date \(D\) are labeled control cities. We restrict the cities to event days of \(-14\) to 21 in each dataset. We then append the 313 datasets into a final dataset. Taking cities implementing “public information provision” as an example, the final dataset includes 313 Post-treated cities, which on average contain 10 control cities for each Post-treated city, resulting in 108 thousand city-event days sample. With the final stacked dataset in hand, we estimate the effects of the \(d_{t_i}\) NPIs on COVID-19 containment as follows:

\[
\text{Log}(Y_{it}) = \sum_{j=7,14,21} \alpha_{Treat_{ij}} \times \text{NPI}_{t-j} + \sum_{j=7,14,21} \beta_{\text{NPI}_{t-j}} + \theta \text{Treat}_{ij} + \mu X_{it} + \gamma_{t} + w_{i} + \epsilon_{it}
\]  

where \( \text{Treat}_{ij} \) is a dummy variable equal to if city \(i\) is a Post-treated city; NPIs are the stringency of NPIs implemented by city \(i\) on date \(t-j\), which are calculated using Eq. (1). Note that the same city can appear as a treated and control city in the final dataset, according to date \(t\) relative to \(D_{t_i}, t-j\). The definitions of the other variables are the same as in Eq. (3).

4. Results

4.1. Effects of policies on voluntary responses and COVID-19 infections

In this section, we employ an event study to analyze whether individuals adopt voluntary responses before the NPIs are implemented by the local governments. The results presented in Panel A of Fig. 3 show a statistically positive trend of internal mobility in the pre-NPI period. Nevertheless, no significantly different trend in human mobility is observed across cities (Panel B). In other words, no voluntary precautions are taken before NPI enforcement by city governments. The results in Panel C and Panel D also show little evidence of differential pre-NPI COVID-19 case trends in the period leading up to the enforcement of NPIs by the local governments. In China, city governments generally implemented joint interventions but with different stringencies to fight against COVID-19. We also observe that the estimated new case reduction accelerates over time, becoming largest after 14–21 days following the enforcement of NPIs by the city governments. A decreasing trend was observed at 21 days post-implementation (Panel C).

Together, our findings thus far suggest that individuals do not adopt voluntary responses to periods leading up to the implementation of NPIs. Little evidence of differential pre-NPI COVID-19 case trends is available in the period leading up to the enforcement of NPIs by the local governments. The results also highlight the value of employing a difference-in-differences model to analyze the effect of NPIs on COVID-19 cases.

4.2. Effects of NPIs on COVID-19 containment

Table 3 reports our estimates for two sets of treatment groups and various sets of control variables, based on Eq. (3). In our most parsimonious specification without any controls, we find that COVID-19 cases significantly decrease during the first 6 days following the NPI implementation. This result is slightly different from our expectation, as the infections may take several days to be laboratory-confirmed cases after an asymptomatic incubation period. A containment effect of NPIs on COVID-19 cases is observed after 21 days of enforcement, and the effect strengthens to be an 8.48% decrease in the number of COVID-19 cases after 21 days of enforcement (Column 1 of Table 3). We also find that the number of COVID-19 cases increases significantly after 7 to 20 days of NPI enforcement, although these effects are imprecisely estimated.

In Column (2), we add the time trends variables and other control variables in the estimates. On the one hand, city-specific days since the first confirmed cases and its square term control for the voluntary responses to the risk within a city. On the other hand, they may control the loading of the local public health system and the characteristics of virus spread (Brzezinski et al., 2020). A similar effect from 0 days to 21 days and later periods after NPI enforcement is found in Column (2).

In Column (3), we utilize both city fixed effects and week fixed effects to account for the city-specific time-unvarying characteristics and other time-varying trends in China, which significantly alter the effect of NPIs on COVID-19 cases. We now find little evidence that COVID-19 cases were affected during the 13 days following NPI enforcement, which is not surprising due to the incubation period of the virus. Additionally, the number of COVID-19 cases increases by 8.29% between 14 and 20 days following the enforcement of NPIs, and the effect is statistically significant at the 10% level. On the one hand, the nucleic acid testing capabilities may increase after the enforcement of NPIs. On the other hand, family–cluster infections may increase when a strict social distancing policy is enforced, as people spend more time at home (Dave, 2022). After controlling all the preferred variables and a series of fixed effects, we find that the

15 In China, many medical resources, including doctors, medical CT machines, and mobile testing stations, are sent to high risk areas to treat the infections. See: http://www.xinhuanet.com/politics/2020-06/07/c_11266083364.htm.
number of new confirmed COVID-19 cases is reduced by 6.32% at 21+ days after NPIs enforced (Column 3).

Symmetric differences between these loosely defined treatment and control cities may exist, which may be correlated with unobservable. Inspired by Ambrus et al. (2020) and Pinkovskiy (2017), we thus employ a border discontinuous DID method to identify the effect of NPIs on the spread of COVID-19. The specifications in Columns (4)–(6) are the same as those in the first three columns in Table 3. Using a border discontinuous DID with the preferred variables in the estimation, we find a 10.8% decrease in the number of new COVID-19 cases for 21 days or more after NPI enforcement, an effect that is a statistical difference from zero at the 1% level. This result is comparable to the study by Qiu et al. (2020), who found that a stay-at-home policy reduces the number of new COVID-19 cases by 12.4% after two weeks of enforcement. We thus use the results in Column (6) as our baseline findings, which provide a more credible estimate.

We replicate the baseline estimates using an alternative definition of treatment cities that cities as those where the residual of regression of NPI stringency on the number of cumulative population inflow from Wuhan by January 23 is positive. The results in Appendix Table B.4 are comparable to those in Table 3.

### 4.3. Sensitivity analyses

In Table 4, we explore the sensitivity of the baseline findings by extending our sample period as the data become available. The containment effect of NPIs on COVID-19 remains statistically significant when we extend the sample period to May 3 (see Table 4).

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16 Up to March 28, 2020, 13,306 COVID-19 cases were documented outside Hubei Province, representing approximately 16.4% of the total confirmed cases in China. The effects of NPIs on COVID-19 containment become much larger when we extend the sample cities to all cities except Wuhan in Column (7) of Table 4.
Table 3
The baseline estimations.

|                | Full sample | Adjacent cities sample |
|----------------|-------------|------------------------|
|                | (1)         | (2)        | (3)         | (4)         | (5)        | (6)         |
| Dependent variable: logarithmic daily new cases |             |             |             |             |             |             |
| Treatment      | -0.034***   | -0.049***   | 1.510***    | -0.030***   | -0.045***   | 1.641***    |
|                | (0.005)     | (0.006)     | (0.126)     | (0.005)     | (0.007)    | (0.125)    |
| Treatment × (0-6 days after NPIs) | -0.185***   | -0.149***   | -0.051      | -0.087**    | -0.060      | 0.040       |
|                | (0.036)     | (0.036)     | (0.032)     | (0.042)     | (0.042)    | (0.037)    |
| Treatment × (7-13 days after NPIs) | 0.150***    | 0.210***    | 0.048       | 0.152**     | 0.197***    | 0.053       |
|                | (0.055)     | (0.053)     | (0.048)     | (0.066)     | (0.063)    | (0.056)    |
| Treatment × (14-20 days after NPIs) | 0.169***    | 0.136***    | 0.083*      | 0.120*      | 0.083      | 0.051       |
|                | (0.056)     | (0.051)     | (0.048)     | (0.068)     | (0.062)    | (0.057)    |
| Treatment × (21+ days after NPIs) | -0.085**    | -0.129***   | -0.063**    | -0.132***   | -0.167***   | -0.108***   |
|                | (0.037)     | (0.033)     | (0.032)     | (0.045)     | (0.040)    | (0.037)    |
| Observations   | 21,414      | 20,169      | 20,169      | 15,910      | 14,985     | 14,985      |
| R-squared      | 0.286       | 0.344       | 0.476       | 0.283       | 0.346      | 0.480       |
| Time Trends    | No          | Yes         | Yes         | No          | Yes        | Yes         |
| Weather Controls | No        | Yes         | Yes         | No          | Yes        | Yes         |
| City FE        | No          | No          | Yes         | No          | No         | Yes         |
| Week FE        | No          | No          | Yes         | No          | No         | Yes         |

Note: Estimates are obtained using a weighted DID regression analysis. The sample period is from January 3 to March 28, 2020. The dependent variables are logarithmic daily new cases in city \(i\) on date \(t\). Treatment cities are defined as cities where the residual from the regression of NPI stringency on the number of cumulative confirmed cases and population inflow from Wuhan by January 23 is positive. Columns (1)–(3) use the full sample (Panel A in Fig. 2), and Columns (4)–(5) restrict treatment and control cities with adjacent boundaries (Panel B in Fig. 2). The specifications include city-specific time trends as days since the first confirmed case and its square term. Cumulative confirmed cases in seven days leading up to the current date \(t\) are included to control the loading of local public health systems. Finally, weather controls include the daily average temperature, relative humidity, and wind speed, which are seven days leading up to the current date \(t\). Regressions in Columns (3, 6) include city fixed effects and week fixed effects. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.

Table 4
The extended baseline results from January 3 to May 3, 2020.

|                | Full sample | Adjacent cities sample |
|----------------|-------------|------------------------|
|                | (1)         | (2)        | (3)         | (4)         | (5)        | (6)         | (7)         |
| Dependent variable: logarithmic daily new cases |             |             |             |             |             |             |             |
| Treatment      | -0.034***   | -0.049***   | 1.428***    | -0.030***   | -0.043***   | 1.452***    | 1.418***    |
|                | (0.005)     | (0.006)     | (0.101)     | (0.005)     | (0.007)    | (0.010)     | (0.098)     |
| Treatment × (0-6 days after NPIs) | -0.185***   | -0.162***   | -0.078**    | -0.087**    | -0.067      | 0.017       | 0.081**     |
|                | (0.036)     | (0.036)     | (0.032)     | (0.042)     | (0.042)    | (0.037)    | (0.039)     |
| Treatment × (7-13 days after NPIs) | 0.150***    | 0.192***    | 0.036       | 0.152**     | 0.185***    | 0.046       | 0.173***    |
|                | (0.055)     | (0.054)     | (0.049)     | (0.066)     | (0.064)    | (0.058)    | (0.062)     |
| Treatment × (14-20 days after NPIs) | 0.169***    | 0.148***    | 0.095*      | 0.120*      | 0.095      | 0.061      | 0.071       |
|                | (0.056)     | (0.052)     | (0.050)     | (0.068)     | (0.063)    | (0.060)    | (0.065)     |
| Treatment × (21+ days after NPIs) | -0.097***   | -0.124***   | -0.043      | -0.147***   | -0.172***   | -0.096**    | -0.260***   |
|                | (0.036)     | (0.034)     | (0.033)     | (0.044)     | (0.041)    | (0.039)    | (0.043)     |
| City           | No Hubei    | No Hubei    | No Hubei    | No Hubei    | No Hubei   | No Hubei   | No Wuhan    |
| Observations   | 30,378      | 29,133      | 29,133      | 22,570      | 21,645     | 21,645     | 22,698      |
| R-squared      | 0.299       | 0.344       | 0.468       | 0.295       | 0.345      | 0.474      | 0.468       |
| Time Trends    | No          | Yes         | Yes         | No          | Yes        | Yes        | Yes         |
| Weather Controls | No        | Yes         | Yes         | No          | Yes        | Yes        | Yes         |
| City FE        | No          | No          | Yes         | No          | No         | Yes        | Yes         |
| Week FE        | No          | No          | Yes         | No          | No         | Yes        | Yes         |

Note: Estimates are obtained using a weighted DID regression analysis. The sample period is from January 3 to March 3, 2020. We add cities in Hubei but exclude Wuhan in Column (7). The dependent variables are logarithmic daily new cases in city \(i\) on date \(t\). Treatment cities are defined as cities where the residual from the regression of NPI stringency on the number of cumulative confirmed cases and population inflow from Wuhan by January 23 is positive. Columns (1)–(3) use the full sample (Panel A in Fig. 2), and Columns (4)–(5) restrict treatment and control cities with adjacent boundaries (Panel B in Fig. 2). The specifications include city-specific time trends as days since the first confirmed case and its square term. Cumulative confirmed cases in 7 days leading up to the current date \(t\) are included to control the loading of local public health systems. Finally, weather controls include the daily average temperature, relative humidity, and wind speed, which are seven days leading up to the current date \(t\). Regressions in Columns (3, 6) include city fixed effects and week fixed effects. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.
Focusing on the adjacent sample in Column (6), we find that the containment effect is slightly smaller when we use the extended sample. From January 3 to May 3, the enforcement of NPIs significantly reduced the number of newly confirmed COVID-19 cases by 9.6% at 21 + days post-NPIs enforcement.

To date, we have argued for the exclusion of cities in Hubei Province due to the extremely large numbers of COVID-19 infections and confirmed cases in those cities. In Column (7), we add cities in Hubei Province but exclude Wuhan from our sample. Results show that the COVID-19 cases significantly increase from 0 to 13 days after NPI enforcement, but the containment effects on COVID-19 cases are much larger at 21 + days after the NPI enforcement. A 26% decrease in the number of COVID-19 cases is observed, an effect that is significantly different from zero at the 1% level. The results are reasonable because cities in Hubei Province reported large numbers of COVID-19 cases and the harshest NPIs.

To verify the accuracy of NPIs measured by dictionary-based frequency analysis, we propose three alternative measures of NPI stringency at the city level, and the results are reported in Table 5. Columns (1, 4) simply measure NPI stringency based on the official documents issued by city governments, Columns (2, 5) include the prespecified terms of easing NPIs when calculating the NPI stringency (see Eq. A.1 in Appendix A.1); and Columns (3, 6) use the TF-IDF scores as the measurement of NPI stringency. Focusing on the results estimated for the adjacent city sample, the containment effects on COVID-19 cases remain, statistically significant at the 5% level, regardless of the measures of NPI stringency we used (Columns (4)–(6) in Table 5).

The daily new confirmed cases of infectious diseases with a relatively high R0, such as COVID-19, are significantly related to the new confirmed cases in the past, which may also be affected by the implementation of NPIs. We replace cumulated confirmed cases in 7 days leading up to the current date $t$ with the daily new confirmed cases in date $t-1$ in Eq. (3) to address this potential endogeneity. The estimated results obtained using both the full sample and the adjacent cities sample are reported in Columns (1, 3) of Table 6, respectively. Replacing the cumulative confirmed cases in 7 days leading up to the current date $t$ by the daily new confirmed cases on date $t-1$ in Eq. (3), we find that overall, the implementation of NPIs curbs the spread of COVID-19. Focusing on the results in Column (3) of Table 6, the containment effects of NPIs become much smaller than the baseline estimates in Column (6) of Table 5. This result is reasonable, as the daily number of confirmed cases of infectious diseases is generally driven by the number of confirmed cases in the past. However, even after controlling for the daily number of new confirmed cases on date $t-1$, the implementation of NPIs significantly curbed the spread of COVID-19.

However, adding time-varying controls $X_t$ in Eq. (3) creates a within-timing-group comparison, which may bias the DID estimates (see the weight of the “within” component in Appendix Table B.2). Inspired by Goodman-Bacon (2021), we simply include city-by-week fixed effects in the estimates, excluding the time-varying $X_t$ in Eq. (3). Focusing on the sample of adjacent cities, the results in Column (4) of Table 6 show that adjusting the city-week specific trends changes the curbing effects of NPIs implemented after 21 + days to 7.4%, which is statistically significant at the 5% level, but is slightly smaller than the estimates obtained with time-varying controls in Table 3. In Column (2) of Table 6, the containment effects of NPIs implemented after 21 + days remain negative but are not different from zero.

Overall, we conclude that the estimated effects of NPIs on the COVID-19 cases are robust when we address the potential measurement error and endogeneity concerns in the estimates.

### 4.4 Which NPIs are the most effective in curbing COVID-19?

The Chinese government implemented a bundle of NPIs to control the spread of COVID-19, such as city lockdowns and first-level responses to the major public health emergency. More specifically, we are interested in what types of NPIs are the most effective in containing the spread of COVID-19: public information provision, contact tracing, or social distancing.

To account for the confounding effects of policies implemented simultaneously, we employ a stacked DID estimation, which has been described in Section 3.2. The results are shown in Table 7. First, regardless of the types of NPIs implemented, they work effectively to curb the spread of COVID-19 after the implementation of certain NPIs. Second, focusing on the NPIs without the easing terms (Columns 1–3), contact tracing is the most effective in containing COVID-19 spread among the three types of NPIs, followed by public information provision. Within 6 days of more stringent contact tracing, the number of daily new cases significantly decreased by 35.8%. However, the effects of contact tracing become less effective over time.

The containment effects of the three NPIs change if we consider the easing of NPIs over time (Columns 4–6 in Table 7). Contact tracing is still the most effective control measure to curb the spread of COVID-19. Importantly, the more stringent the contact tracing implemented in 0–6 days in city $i$, the greater the number of new COVID-19 cases are confirmed (Column 5 in Table 7). However, the number of daily new confirmed cases decreased sharply 7 days after the stricter contact tracing was implemented. The containment effects of contact tracing remain and exhibit a slight decrease, even after 21 days of implementation. The effects of social distancing are generally more significant than those of public information provision when we consider the stringency of NPIs with easing terms over time. The effects of social distancing are persistent after 21 days of implementation.

Ferretti et al. (2020) suggest that contact tracing and public information provision exert less harmful effects on the economy than strict social distancing. Together with the results in Table 7, these findings suggest that contact tracing and public information provision provide a careful balance between pandemic control and reopening the economy. Long-term restrictions on human mobility are also not a feasible measure for many countries. Our results provide new insights for countries to reopen the economy amid the COVID-19 crisis.
Table 5
The effects of NPIs on COVID-19 spread: Different measures of NPIs.

|                  | Full sample | Adjacent cities sample |
|------------------|-------------|------------------------|
|                  | City's NPIs | Easing NPIs | TF-IDF | City's NPIs | Easing NPIs | TF-IDF |
|                  | (1)         | (2)         | (3)    | (4)         | (5)         | (6)    |
| Treatment        |             |             |        |             |             |        |
|                  | 1.544***    | 1.544***    | 1.536*** | 1.674***    | 1.674***    | 1.670*** |
|                  | (0.127)     | (0.127)     | (0.126) | (0.126)     | (0.126)     | (0.126) |
| Treatment × (0–6 days after NPIs) | −0.040       | −0.038       | 0.059   | 0.066*       | 0.069*       | 0.080*  |
|                  | (0.033)     | (0.033)     | (0.038) | (0.038)     | (0.038)     | (0.046) |
| Treatment × (7–13 days after NPIs) | 0.011        | 0.010        | 0.018   | −0.033       | −0.033       | 0.006   |
|                  | (0.046)     | (0.046)     | (0.047) | (0.054)     | (0.054)     | (0.058) |
| Treatment × (14–20 days after NPIs) | 0.060        | 0.057        | 0.001   | 0.045        | 0.041        | −0.021  |
|                  | (0.043)     | (0.043)     | (0.038) | (0.051)     | (0.051)     | (0.046) |
| Treatment × (21+ days after NPIs) | −0.029       | −0.027       | −0.079*** | −0.066**     | −0.064**     | −0.066** |
|                  | (0.027)     | (0.027)     | (0.025) | (0.033)     | (0.032)     | (0.030) |

Note: Columns (1, 4) simply measure the NPI stringency based on the official documents issued by city governments, Columns (2, 5) include the prespecified terms of easing NPIs when calculating the NPI stringency (see Eq. A.1 in Appendix A); and Columns (3, 6) use the TF-IDF scores as the measurement of NPI stringency. Estimates are obtained using a weighted DID regression analysis. The sample period is from January 3 to March 28, 2020. The dependent variables are logarithmic daily new cases in city \( i \) on date \( t \). Treatment cities are defined as cities where the residual from the regression of NPI stringency on the number of cumulative confirmed cases and population inflow from Wuhan by January 23 is positive. We include city-specific temporal trends as days since the first confirmed case and its square term, cumulative confirmed cases in 7 days leading up to the current date \( t \), and weather controls such as the daily average temperature, relative humidity, and wind speed for the seven days leading up to the current date \( t \) in each regression analysis. City fixed effects and week fixed effects are included in the regressions. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level, and *** significant at 1% level.

Table 6
The effects of NPIs on COVID-19 spread: Alternative controls.

|                  | Full sample | Adjacent cities sample |
|------------------|-------------|------------------------|
|                  | (1)         | (2)         | (3)    | (4)         |
| Treatment        | 0.702***    | 1.467***    | 0.733*** | 1.428***    |
|                  | (0.096)     | (0.118)     | (0.097) | (0.117)     |
| Treatment × (0–6 days after NPIs) | −0.033       | −0.094***    | 0.0251  | 0.004       |
|                  | (0.032)     | (0.033)     | (0.038) | (0.038)     |
| Treatment × (7–13 days after NPIs) | 0.044        | 0.057        | 0.026   | 0.055       |
|                  | (0.046)     | (0.050)     | (0.054) | (0.058)     |
| Treatment × (14–20 days after NPIs) | 0.0348       | 0.091*       | 0.021   | 0.054       |
|                  | (0.043)     | (0.0493)    | (0.050) | (0.058)     |
| Treatment × (21+ days after NPIs) | −0.036       | −0.021       | −0.057* | −0.074**    |
|                  | (0.028)     | (0.032)     | (0.032) | (0.037)     |
| Observations     | 21,414      | 21,414      | 15,910  | 15,910      |
| R-squared        | 0.581       | 0.467       | 0.589   | 0.472       |
| Adding control: log\( Y_{it-1} \) | Yes         | No          | Yes     | No          |
| Time Trends      | Yes         | No          | Yes     | No          |
| Weather Controls | Yes         | No          | Yes     | No          |
| City FE          | Yes         | No          | Yes     | No          |
| Week FE          | Yes         | No          | Yes     | No          |
| City-by-Week FE  | No          | Yes         | No      | Yes         |

Note: Columns (1, 3) simply replace the cumulative confirmed cases in the 7 days leading up to the current date \( t \) by the number of daily new confirmed cases on date \( t-1 \) in Eq. (3); Columns (2, 4) alternatively drop the time-varying controls in Eq. (3), and control for the city – week specific trends by city-by-week fixed effects. Estimates are obtained using a weighted DID regression analysis. The sample period is from January 3 to March 28, 2020. The dependent variables are the logarithmic number of daily new cases in city \( i \) on date \( t \). Treatment cities are defined as cities where the residual from the regression of NPI stringency on the number of cumulative confirmed cases and population inflow from Wuhan by January 23 is positive. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level, and *** significant at 1% level.
Given the significant containment effects of NPIs implemented in China, we are concerned about the political determinants of NPI stringency, which ultimately affects the spread of COVID-19. The Literature has reported a political difference in attitudes toward the containment effects of NPIs implemented in China, with upper-level leaders generally showing a more stringent approach due to their role in national decision-making. This political influence is reflected in the way city leaders formulate NPIs, with upper-level leaders potentially setting the tone for more stringent measures.

Given the significant containment effects of NPIs implemented in China, we are concerned about the political determinants of NPI stringency, which ultimately affects the spread of COVID-19. The Literature has reported a political difference in attitudes toward the containment effects of NPIs implemented in China, with upper-level leaders generally showing a more stringent approach due to their role in national decision-making. This political influence is reflected in the way city leaders formulate NPIs, with upper-level leaders potentially setting the tone for more stringent measures.

5. Political determinants of NPI stringency

Given the significant containment effects of NPIs implemented in China, we are concerned about the political determinants of NPI stringency, which ultimately affects the spread of COVID-19. The Literature has reported a political difference in attitudes toward the containment effects of NPIs implemented in China, with upper-level leaders generally showing a more stringent approach due to their role in national decision-making. This political influence is reflected in the way city leaders formulate NPIs, with upper-level leaders potentially setting the tone for more stringent measures.

We employ a spatial autoregression (SAR) model to explore the role of top-down political connections in the formulation of NPIs by city officials, as well as the potential spillover effects:

\[ NPI_{it} = \sum_{k=1}^{K} w_{ik} NPI_{ik} + \rho \text{Connect}_{i} + \mu X_{it} + \epsilon_{it} \]  

(5)

where \( w \) is a spatial weight, which equals one if cities \( i \) and \( k \) share a boundary, and zero otherwise. \( \text{Connect} \) is an indicator that equals one if city \( i \)’s leaders have a political connection to the upper-level leaders (including provincial governors and party secretaries). We excluded observations in four municipalities, Beijing, Tianjin, Shanghai, and Chongqing, which are under the direct administration of the central government.

Following Kahn (2021) and Jia et al. (2015), we measure the connection between city leaders and provincial leaders by determining 1) whether they were born in the same province, 2) whether they graduated from the same university, 3) whether they formerly worked in the same city at the same time, and 4) whether they formerly worked in the Communist Youth League (CYL). The \( \text{Connect} \) indicator is constructed from the curriculum vitae of Chinese politicians posted on People.cn.\(^{18}\) One may be concerned about the potential endogeneity of \( \text{Connect} \) in Eq. (5) due to the nonrandom assignments of city leaders. COVID-19 is a pandemic, and the outbreak began at the beginning of January 2020, without a prediction. All city leaders assumed office before the outbreak, and no turnover occurred during the sample period (except for city leaders in Hubei Province). The nonrandom assignments of city leaders

\(^{18}\) The website is http://ldzl.people.com.cn/dfzlk/front/firstPage.htm
thus have little effect on the stringency of NPIs. Other confounding factors, such as promotion potential, may encourage city leaders to implement harsher NPIs to contain the spread of COVID-19 or looser NPIs to facilitate economic recovery. We include several promotion-related factors, including a dummy of age <55 years old, education, and terms of office, in the regression to address the bias due to omitted variables. Moreover, officers’ professionalism, such as holding a degree in medical science or public health, or having experience in handling the SARS outbreak, may also affect the stringency of the NPIs (Li, 2022). We thus include two dummy variables, Med and SARS, in the regressions. Med equals one if the officer has a degree in the field of medicine or public health or has worked in hospitals, centers of disease control, or public health departments. SARS is assigned a value of one if the officer had worked in Guangdong Province or Beijing municipality in 2003 when the SARS outbreak occurred.

The results in Panel A of Table 8 present the regression of mayors’ connections on NPI stringencies. Column (1) shows that all others are equal, and the mayor’s connection with provincial leaders significantly increases the overall NPI stringency in the city. In particular, Columns (2) to (4) show that mayors’ political connections help them form harsher NPIs related to public information provision, contact tracing, and social distancing. Among the results presented in Table 7, the results imply that the political connections of mayors to upper-level politicians reduce the information asymmetry. The mayors with political connections know the primary goal of the upper-level politicians, which is to control the COVID-19 spread during the outbreak period. Thus, the NPIs implemented in those cities are generally harsher NPIs. Moreover, the results in Columns (2)–(4) show that, the effects of mayors’ connections on contact tracing are much weaker than the effects on the other two NPIs. This finding may imply that provincial politicians pay less attention to contact tracing, which is the most effective method to contain the spread of COVID-19. Other characteristics of a mayor, including age <55 years old, terms of office, education, medical background (Med), and SARS experiences, have less effect on the stringency of NPIs.

Panel B of Table 8 shows the direct effects and spillover effects of political connections of mayors on the stringency of NPIs in neighboring cities. Unsurprisingly, the NPI stringency shows a significant spatial dependence on each other. The mayors with connections implemented harsher NPIs in their cities. The actions of mayors with connections also serve as an informal channel to signal to their neighboring cities as “that is the way that the provincial politicians want to deal with COVID-19.” This signal helps the neighboring cities implement more rigid NPIs known as spillover effects of Connect. Overall, the direct effect of Connect is more significant than the spillover effects on the NPI stringency. The mayor’s connection induces the city to implement more rigid NPIs of 0.347. It also prompts neighboring cities to implement tougher NPIs with an average value of 0.236.

Panel A of Table 9 shows the effects of the connections of the city’s party secretary on the NPI stringency. Overall, the political

Table 8
The political determinants of NPIs: Mayor’s connections.

|                       | Overall NPIs | Public information provision | Contact tracing | Social distancing |
|-----------------------|--------------|------------------------------|-----------------|-------------------|
| (1)                   |              | (2)                          | (3)             | (4)               |
| Connection            | 0.328***     | 0.108***                     | 0.059*          | 0.196***          |
| (0.102)               | (0.041)      | (0.033)                      | (0.059)         |                   |
| Age <55               | −0.045       | −0.056                       | 0.010           | −0.001            |
| (0.108)               | (0.044)      | (0.035)                      | (0.063)         |                   |
| Term of office        | 0.028        | 0.006                        | 0.016           | 0.008             |
| (0.034)               | (0.014)      | (0.011)                      | (0.020)         |                   |
| Education             | 0.089        | 0.020                        | −0.013          | 0.091**           |
| (0.076)               | (0.031)      | (0.024)                      | (0.044)         |                   |
| Med                   | −0.477       | −0.143                       | −0.149          | −0.182            |
| (0.317)               | (0.129)      | (0.102)                      | (0.185)         |                   |
| SARS                  | 0.096        | 0.005                        | −0.021          | 0.123             |
| (0.375)               | (0.153)      | (0.120)                      | (0.219)         |                   |
| Time trends           | Yes          | Yes                          | Yes             | Yes               |
| Weather controls      | Yes          | Yes                          | Yes             | Yes               |
| City controls         | Yes          | Yes                          | Yes             | Yes               |

Panel B: Spatial effects of NPIs

| Spatial dependence    | 0.432***     | 0.184***                     | 0.269***        | 0.421***          |
| (0.007)               | (0.009)      | (0.008)                      | (0.007)         |                   |
| Direct effect of Connect on NPIs | 0.347*** | 0.111***                     | 0.061*          | 0.206***          |
| (0.109)               | (0.043)      | (0.034)                      | (0.063)         |                   |
| Spillover effect of Connection on NPIs | 0.236*** | 0.024**                      | 0.021*          | 0.134***          |
| (0.075)               | (0.009)      | (0.012)                      | (0.042)         |                   |
| N                     | 25.122       | 25.122                       | 25.122          | 25.122            |
| R²                    | 0.311        | 0.207                        | 0.182           | 0.248             |

Note: Estimates are obtained using an SAR regression with Eq. (5). The sample period is from January 3 to May 3, 2020. All prefecture cities, excluding cities in Hubei Province, are included in the sample (Panel A in Fig. 2). The dependent variables are the stringency of NPIs in city i on date t. The specifications include an indicator of the mayor’s age <55 years old, mayor’s education, terms of office, mayor’s medical background, SARS experience, the number of one-day lagged daily new confirmed cases, city-specific time trends as days since the first confirmed cases, and its square term. City-specific characteristics, including GDP per capita and population size, are included in the regression. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.
connections of the city’s party secretary to the provincial politicians exert a significant marginal effect on the city’s NPI stringency. Among the three types of NPIs, the connections of the city’s party secretary only significantly increase the severity of contact tracing at a 10% level. The spillover effects of the party secretary’s connections on the stringency of contact tracing in neighboring cities are also marginally significant. However, the effects of the party secretary’s connections on the other two NPIs, namely public information provision and social distancing, are statistically insignificant.

Party secretaries are the head of the provincial branch of the Communist Party, and are responsible for party affairs and the personnel appointment and removal of city officials. In comparison, mayors are the heads of city governments who are responsible for policy formulation and implementation (Xu, 2011), including NPIs. We argue that the differences in responsibilities between the party secretary and mayor account for the significant effect of the mayor’s connections to the provincial politicians on the NPI stringency in each city.

6. Cost of COVID-19 containment

Next, we perform a cost analysis of these NPIs. China has enforced various restrictions on human mobility and postponed the opening of schools, which exerts considerable effects on economic growth and the human capital associated with children. We account for the short-term losses in the economy and loss of children’s human capital, which has a long-term effect.

We first compare the mean differences in the gross domestic product (GDP) growth rate among the adjacent treatment and control cities. The mean economic growth in the fourth quarter of 2019 is not statistically different from zero between the two groups (Row 1 of Table 10). Row 2 shows a significant decrease in the economic growth rate by 4.69% and 5.19% in both groups during the first quarter of 2020. The differences between groups are statistically insignificant. Rows 3 and 4 show that the economy steadily recovered in China. The overall decrease in economic growth is approximately 13.04% and 15.27% in adjacent treatment and control cities in the first three quarters of 2020, respectively, compared to the fourth quarter of 2019. The results are consistent with the range reported in the literature. Adda (2016) estimates the cost of public transportation shutdown, with values ranging from €8 to €19 per capita per week. Ke and Hsiao (2022) documented an economic impact of approximately 37% of the counterfactuals in the lockdown quarter. But the economy quickly recovered after the government lifted the lockdown in early April 2020.

However, the cost of NPIs is high for children who suffer from a loss of human capital due to school closure. We hand-collected the number of days primary schools were closed in each city during the COVID-19 pandemic in China and compared their mean differences

| Table 9 | The political determinants of NPIs: party secretary’s connections. |
|---------|---------------------------------------------------------------|
|         | Overall NPIs | Public information provision | Contact tracing | Social distancing |
|         | (1)          | (2)                         | (3)              | (4)               |
| Panel A: Dependent variable, the stringency of NPIs | | | | |
| Connection | 0.189* | 0.056 | 0.078* | 0.068 |
| (0.103) | (0.042) | (0.042) | (0.061) |
| Age <55 | –0.099 | –0.070 | –0.011 | –0.017 |
| (0.118) | (0.048) | (0.037) | (0.070) |
| Term of office | –0.020 | –0.007 | 0.013 | –0.021 |
| (0.030) | (0.012) | (0.010) | (0.018) |
| Education | 0.119 | 0.038 | 0.029 | 0.059 |
| (0.073) | (0.030) | (0.023) | (0.043) |
| Med | 0.220 | –0.072 | 0.251* | 0.130 |
| (0.443) | (0.180) | (0.139) | (0.260) |
| SARS | –0.034 | –0.057 | –0.116 | 0.127 |
| (0.404) | (0.164) | (0.127) | (0.237) |
| Time trends | Yes | Yes | Yes | Yes |
| Weather controls | Yes | Yes | Yes | Yes |
| City controls | Yes | Yes | Yes | Yes |

Panel B: Spatial effects of NPIs

| Spatial dependence | 0.433*** | 0.184*** | 0.269*** | 0.421*** |
| (0.007) | (0.009) | (0.008) | (0.007) |
| Direct effect of Connection on NPIs | 0.202* | 0.058 | 0.008* | 0.073 |
| (0.111) | (0.043) | (0.044) | (0.065) |
| Spillover effect of Connection on NPIs | 0.137** | 0.012 | 0.028* | 0.048 |
| (0.076) | (0.009) | (0.017) | (0.042) |
| N | 25,122 | 25,122 | 25,122 | 25,122 |
| R² | 0.296 | 0.200 | 0.188 | 0.231 |

Note: Estimates are obtained using a SAR regression by Eq. (5). The sample period is from January 3 to May 3, 2020. All prefecture cities, excluding cities in Hubei Province, are included in the sample (Panel A in Fig. 2). The dependent variables are the stringency of NPIs in city \( i \) on date \( t \). The specifications include an indicator of the party secretary’s age <55 years old, the party secretary’s education and terms of office, the party secretary’s medical background, SARS experience, one-day lagged daily new confirmed cases, city-specific time trends as days since the first confirmed case and its square term. City-specific characteristics, including GDP per capita and population size, are included in the regression. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level and *** significant at the 1% level.
between the adjacent treatment and control cities. The last row of Table 10 shows that the number of days of school closures in adjacent treatment cities is significantly higher than that in adjacent control cities by 4.58 days until the end of July.\textsuperscript{19} Because almost all of the schools started online teaching & learning in mid-February, we assume the outcome of online learning is 50\% of the traditional face-to-face method, based on the estimates from Ariana (2016) and Bloom (2015), and a return to the schooling of 5\% per year (Adda, 2016; Heckman & Li, 2004). We compute the loss of life cycle earning (37 years) as approximately 2153 yuan per child (net present value with an annual discount rate of 7\%).\textsuperscript{20} Our estimate is consistent with that reported by Adda (2016). He estimates that a child who experiences a flu-like illness loses three days of schooling, which reduces the net present value of their life cycle earning by 850 yuan per child.\textsuperscript{21}

### 7. Conclusions

We use a border discontinuous DID framework to provide new evidence for the effect of NPIs on the spread of COVID-19 and estimate the cost of those NPIs. The enforcement of NPIs significantly reduced the spread of COVID-19 in China by 10.8\% by March 2020. The results are robust when we use alternative measures of NPIs and other specifications. Among the three alternative NPIs, contact tracing is the most effective NPI for COVID-19 containment. We also find that a political connection of mayors to the provincial leaders significantly increases the stringency of NPIs in the city. The more rigid NPIs implemented by cities with political connections also serve as a signal to their neighboring cities, urging them to implement stricter NPIs in some manner. We argue that the political connections of mayors reduce information asymmetry with provincial leaders, which helps them form NPIs more effectively.

Using the estimates from the related literature, we calculate the short-term loss in the economy and loss of children's human capital due to COVID-19 containment, which exerts long-term effects. A reduction in the economic growth rate occurs in both the treatment and control cities. However, we also observe that the economy steadily recovered in the second and third quarters of 2020. The net present value for the loss of life cycle earnings is approximately 2153 yuan per child due to the additional school closure of 4.58 days in adjacent treatment cities. This loss exerts a long-term effect that policy-makers should consider carefully.

Overall, our analysis provides novel findings on the effectiveness and costs of alternative NPI policies in battling the current COVID-19 outbreak. They also provide helpful guidelines for future pandemic containment.

### Acknowledgment

Yinggang Zhou gratefully acknowledges financial support from the National Natural Science Foundation of China (71871195, and 71988101), the Chinese National Social Science Foundation (19ZDA060), and the Humanities and Social Sciences grant of the Chinese Ministry of Education (18YJA790121). Lina Meng acknowledges the financial support from the National Natural Science Foundation of China (72173109).

### Appendix A. Data details

#### A.1. Measuring the stringency of NPIs by textual analysis

The three NPIs we initially tracked included two NPIs related to the response of the public health system and one NPI related to

\textsuperscript{19} The schools, by law, are not allowed to make up the lost instruction time when reopened.

\textsuperscript{20} The additional days of school closure in treatment cities is 4.58 days. This reduces the students' human capital by approximately 1.25\% during the epidemic period. Following the literature, we assume a return to school of 5\% per year, and the outcome of online learning is 50\% of the traditional face-to-face mode. Moreover, the loss of income per year is 30.733 thousand yuan with an annual growth rate of 8.9\% in 2019 in China. The loss of earning per child due to additional school closure in treatment cities in year \(T\) is: \(\text{Loss}_T = 30733 \times (1 + 8.9\%)^{T-2019-1} \times 5\% \times 1.25\% \times 50\%.\) We assume the annual discount rate is 7\% in China. The net present value of loss of life cycle earning (37 years) per child is: \(\text{Loss}_{\text{npv}}^T = \sum_{t=1}^{37} \frac{\text{Loss}_T}{(1+7\%)^t}.\)

\textsuperscript{21} We converted Adda (2016)'s estimation of €100 per child into Chinese Yuan by the exchange rate of 8.50 CNY/€.
pandemic containment, as described below:

(1) **Public information provision**: This NPI is one of the key measures enforced by the public health system at the beginning of the pandemic in China. These measures include guidelines issued by the government to educate individuals on, for example, using face masks outdoors, washing hands, disinfecting when necessary, and emergency declarations, as well as daily numbers of confirmed cases, recovered cases, and deaths disclosed to the public through official media channels. This NPI is the earliest form and may have reduced the inflections through information and precaution channels rather than strict social distancing, such as a lockdown. In addition, official evidence-based information disclosure may relieve the fear caused by the dissemination of fake information on social media (Pulido, Villarejo-Carballido, Redondo-Sama, & Gómez, 2020).

(2) **Contact tracing**: The public health department first enforced manual contact tracing in the early stage of the COVID-19 outbreak. Guan et al. (2020) assessed manual contact tracing reports in Guangdong Province and confirmed that COVID-19 is an infectious disease with human-to-human transmission. On February 11, 2020, the second day after the reopening of China, Hangzhou city in Zhejiang Province first introduced a digital contact tracing measure. This process typically uses a mobile phone app with a plug-in from WeChat and Alipay—two online platform giants—to collect data on user movement and identify their risk status through an artificial intelligence algorithm. When the viral spread is too fast to be controlled using manual contact tracing, algorithm-based, digital contact tracing is used to effectively control the epidemic (Ferretti et al., 2020). Since mid-February, the digital contact tracing measure has been widely used in cities across China.

(3) **Social distancing**: Social distancing measures aim to contain disease spread by reducing contact in public. Wuhan enforced the most rigid social distancing policy—lockdown—on January 23, 2020. Several days after the lockdown of Wuhan, all cities in Hubei Province were locked down. Subsequently, various social distancing measures were imposed on cities outside Hubei Province, including school closures, bans of large gatherings, reducing public transport, and quarantining of close contacts and suspected cases (Fang et al., 2020). These measures have also been widely used in many countries to flatten the peak of confirmed cases (Allcott et al., 2020).

The corpora of NPI enforcement and the easing of restrictions are defined by the word frequency analysis of the official documents issued by the central government. Notably, only the official documents titled “novel coronavirus”, “epidemic control” or “work and production resumption” are included. Related terms with top word frequencies in the central-government-issued documents are classified into the four categories listed in Table A.1.

| NPIs                  | Corpus                                      |
|-----------------------|---------------------------------------------|
| Public information provision | information, propaganda, announcement, internet, proactive, communication, disclosure, propaganda and education, bulletin, popularization, guideline |
| Contact tracing        | supervision, monitoring, precisely, test, investigate, suspected/suspected cases, contact tracing, closed contacts, trace, inspect, grided |
| Social distancing      | face mask, quarantine, public gathering, postpone, suspend, closed, canceled, stay-at-home, restrictions, avoided, extended, point-to-point, |
| Easing NPIs            | work and production resumption, production resumption, work resumption, class resumption, resume, relief |

Fig. A.1 shows the number of cities that enforced NPIs to contain COVID-19 over time. Fig. A.2 compares the stringency of NPIs calculated using the measures we proposed and those measured using the Oxford COVID-19 Government Response Tracker (OxCGRT).
Fig. A.1. Number of cities that enforced NPIs over time.
Note: We consider that cities started to implement NPIs only if the stringency of NPIs was greater than zero. The red line indicates the date of the Wuhan lockdown.

Fig. A.2. Comparison of the stringency of the NPIs we calculated and those measured by OxCGRT.
Note: This Figure compares the trends of NPIs calculated using different measures. The red line is the stringency of NPIs calculated from the textual analysis we proposed. The dark blue line is the stringency index reported by the OxCGRT. The light blue line is the government response index reported by the OxCGRT.

Data source: authors’ calculation and OxCGRT data from https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

In the robustness analysis, we replace the stringency of NPIs calculated using Eq. (1) by alternative measures: 1) the word frequency of prespecified terms in the official documents imposed by city i’s government g, namely, $NPI^g_{it}$ as city i’s stringency of $NPI^g_{it}$; 2) including the prespecified terms measuring the easing of NPIs; and 3) the TF-IDF (term frequency – inverse document frequency) score.
to measure city i’s stringency of NPI\textsuperscript{d\textprime}.

Similar to Huang and Luk (2020), NPIs with easing restrictions are calculated as:

\[
NPI_{i}^{d\textprime} = 0.5f(\hat{e}_d) + 0.5f(\hat{e}_p) = 0.5 \times \frac{\sum_{j=t_0}^{t_1} w_{d,T+j}^d - w_{p,T+j}^p}{\sum_{j=t_0}^{t_1} \text{counts}_{p,T+j}} - 0.5 \times \frac{\sum_{j=t_0}^{t_1} w_{d,T+j}^p - w_{p,T+j}^p}{\sum_{j=t_0}^{t_1} \text{counts}_{p,T+j}}
\]  

(A.1)

where \(f(c_d, e)\) is the d\textsuperscript{th} word frequency of prespecified terms with the easing restrictions, and \(w_e\) is the word counts of prespecified terms for the easing NPIs (the 4th row in Table A.1) in the official documents. The definitions of the other variables are the same as in Eq. (1).

The TF-IDF score is the product of term frequency (TF) by inverse document frequency (IDF) of the prespecified terms:

\[
TF_{id} = NPI_{i}^{d\textprime} = f(c^d)
\]  

(A.2)

\[
IDF_{id} = \log \left( \frac{n_i}{m_d} + 1 \right) \text{, where } m_d = \sum_{j=0}^{t_1} 1_{[\text{counts}_{d,T+j}>0]}
\]  

(A.3)

\[
TFIDF_{id} = TF_{id} \times IDF_{id}
\]  

(A.4)

where \(n_i\) is the total number of COVID-19-related official documents in city i, and \(m_d\) is the number of COVID-19-related documents containing the d\textsuperscript{th} prespecified term. Using this way, the city that imposes loose NPIs will have low TF-IDF scores because \(TF_{id}\) will be low. Moreover, a city that imposes similar NPIs over time will have low TF-IDF scores because \(IDF_{id}\) will be low (Gentzkow et al., 2019).

Table A.2 provides the summary statistics of the three alternative measures of NPIs.

### Table A.2
Summary statistics of NPIs by calculated using other measures.

|                          | Count | Mean | SD  | P1   | P50  | P99   |
|--------------------------|-------|------|-----|------|------|-------|
| Panel A: NPIs calculated by city policy documents only |       |      |     |      |      |       |
| Stringency of NPIs       | 19,436| 2.17 | 1.74| 0.00 | 2.32 | 6.85  |
| Public information provision | 19,436| 0.64 | 0.54| 0.00 | 0.69 | 2.22  |
| Contact tracing          | 19,436| 0.45 | 0.48| 0.00 | 0.41 | 2.01  |
| Social distancing        | 19,436| 1.07 | 0.99| 0.00 | 1.01 | 4.23  |
| Panel B: NPIs with easing policies |       |      |     |      |      |       |
| Stringency of NPIs       | 19,436| 1.48 | 1.14| 0.00 | 1.50 | 4.55  |
| Public information provision | 19,436| 0.22 | 0.37| -0.50| 0.10 | 1.44  |
| Contact tracing          | 19,436| 0.02 | 0.33| -0.67| 0.00 | 1.13  |
| Social distancing        | 19,436| 0.41 | 0.58| -0.49| 0.25 | 2.39  |
| Panel C: NPIs calculated by TF-IDF |       |      |     |      |      |       |
| Stringency of NPIs       | 19,436| 0.10 | 0.15| 0.00 | 0.07 | 0.68  |
| Public information provision | 19,436| 0.11 | 0.11| 0.00 | 0.10 | 0.53  |
| Contact tracing          | 19,436| 0.18 | 0.17| 0.00 | 0.18 | 0.76  |
| Social distancing        | 19,436| 0.15 | 0.15| 0.00 | 0.13 | 0.72  |

**Note:** Panel A provides the summary statistics calculated using the official documents issued by the city’s government \(g\), namely, \(NPI_{i}^{d\textprime,g}\). Panel B summarizes the statistics of NPIs calculated using Eq. A.1, and Panel C summarizes the statistics of TF-IDF scores, as alternative measures of NPIs across the cities.

### A.2. Confirmed COVID-19 confirmed cases
Fig. A.3. National daily number of confirmed cases.
Note: Panel A shows the overall daily number of new confirmed cases in China from January 3 to August 2, 2020. Panel B divides the overall daily number of new confirmed cases into domestic cases and imported cases. The sample period is from February 21 to August 2. All data are collected from the provincial health commission in China.

A.3. Real-time population flow among cities

Fig. A.4. The population flow among provinces in China.
Note: Panel A shows the population flow from January 01 to January 20, 2020. Panel B shows the population flow from February 08 to March 28, 2020. The larger the arc, the larger the volume of population flow during the sample period. Data on inter-city population flow was accessed from Baidu Migration data (http://qianxi.baidu.com/).

A.4. Political connections to the provincial leaders

We accessed the curriculum vitae of Chinese politicians from the website of People.cn (the website is http://ldzl.people.com.cn/dfzlk/front/firstPage.htm). A city leader is identified as having a political connection if he or she and his or her upper-level leaders (including provincial governors and party secretary) were either 1) born in the same province (birth-place connection), 2) graduated from the same university/college (alumni connection), 3) formerly worked in the same city at the same time (worked-place connection), or 4) formerly worked in the CYL (tuannpai connection) (Jia et al., 2015). We summarize the Connect indicator and city leaders' demographic characteristics in Appendix Table A.3.
Table A.3
Summary statistics of Connect.

| Variable                  | N  | Mean | S.D. | P1  | P50 | P99 |
|---------------------------|----|------|------|-----|-----|-----|
| **Panel A: mayor**        |    |      |      |     |     |     |
| Connect                   | 318| 0.534| 0.499| 0   | 1   | 1   |
| Age < 55                  | 318| 0.553| 0.498| 0   | 1   | 1   |
| Education                 | 318| 2.050| 0.663| 0   | 2   | 3   |
| Terms of office           | 318| 3.400| 1.620| 1   | 3   | 8   |
| Med                       | 318| 0.025| 0.157| 0   | 0   | 1   |
| SARS                      | 318| 0.019| 0.136| 0   | 0   | 1   |
| **Panel B: City’s party secretary** |    |      |      |     |     |     |
| Connect                   | 318| 0.613| 0.488| 0   | 1   | 1   |
| Age < 55                  | 318| 0.254| 0.436| 1   | 0   | 0   |
| Education                 | 318| 1.994| 0.710| 0   | 2   | 3   |
| Terms of office           | 318| 3.490| 1.759| 1   | 3   | 8   |
| Med                       | 318| 0.013| 0.112| 0   | 0   | 1   |

Appendix B. Additional results

B.1. The baseline estimates obtained without a propensity score reweighted regression analysis

We regress Eq. (3) without a propensity score reweighting to gauge bias due to unbalanced exposure to Wuhan inflows and other characteristics. Exposure to Wuhan inflows significantly increases the number of COVID-19 cases. The results in Columns (3, 6) show that relaxing the assumption that both treatment and control cities have similar exposure to Wuhan inflows, and NPIs are only effective for one week after implementation.

Table B.1
The baseline estimates obtained without propensity score reweighting.

| Dependent variable: logarithmic daily new cases | Full sample | Adjacent cities sample |
|------------------------------------------------|-------------|------------------------|
| Treatment                                      | (1)         | (2)        | (3)         | (4)         | (5)        | (6)         |
| -0.027*** | 1.405*** | 1.737*** | -0.032*** | -0.048*** | 1.847*** |
| (0.003)   | (0.117)  | (0.126)  | (0.005)   | (0.007)   | (0.126)   |
| Treatment × (0-6 days after NPIs)               | (0.030)     | (0.028)    | (0.027)    | (0.037)    | (0.036)   | (0.032)   |
| -0.192*** | -0.127***| -0.088***| -0.193*** | -0.153*** | -0.082*** |
| (0.047)   | (0.043)  | (0.040)  | (0.058)   | (0.054)   | (0.049)   |
| Treatment × (7-13 days after NPIs)              | (0.047)     | (0.043)    | (0.041)    | (0.059)    | (0.054)   | (0.050)   |
| 0.157***  | 0.072*   | 0.049    | 0.148**   | 0.205***   | 0.033     |
| (0.031)   | (0.027)  | (0.027)  | (0.039)   | (0.035)   | (0.033)   |
| Treatment × (14-20 days after NPIs)             | (0.031)     | (0.027)    | (0.027)    | (0.039)    | (0.035)   | (0.033)   |
| 0.135***  | 0.068    | 0.056    | 0.128**   | 0.100*     | 0.054     |
| (0.031)   | (0.027)  | (0.027)  | (0.039)   | (0.035)   | (0.033)   |
| Treatment × (21+ days after NPIs)               | (0.031)     | (0.027)    | (0.027)    | (0.039)    | (0.035)   | (0.033)   |
| -0.066** | 0.003    | -0.014   | -0.047    | -0.086**   | -0.008    |
| (0.031)   | (0.027)  | (0.027)  | (0.039)   | (0.035)   | (0.033)   |
| Time trends                                     | No          | Yes       | Yes       | No         | Yes       | Yes       |
| City FE                                        | No          | No        | Yes       | No         | Yes       | Yes       |
| Week FE                                        | No          | No        | Yes       | No         | Yes       | Yes       |
| N                                               | 27,606      | 27,606    | 19,671    | 19,436     | 17,854    | 17,854    |

Note: Estimates are obtained using a DID regression analysis. The sample period is from January 3 to March 28, 2020. The dependent variables are logarithmic daily number of new cases in city i on date t. Treatment cities are defined as cities where the residual from the regression of NPI intensity on the number of cumulative confirmed cases and population inflow from Wuhan by January 23 is positive. Columns (1)–(3) use the full sample (Panel A in Fig. 2), and Columns (4)–(5) restrict treatment and control cities with adjacent boundaries (Panel B in Fig. 2). City-specific time trends are days since the first confirmed case and its square term. Cumulative confirmed cases in the seven days leading up to the current date t are included to control the loading of local public health systems. Finally, weather controls include the daily average temperature, relative humidity, and wind speed for the seven days leading up to the current date t. The regressions in Columns (3, 6) include city fixed effects and week fixed effects. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level.
B.2. Robustness analysis: Estimations addressing the time-varying treatment effects

| Table B.2 | Difference-in-Differences weights (Bacon Decomp.) |
|-----------|--------------------------------------------------|
| Type of DD comparison | Beta | Weight |
| Timing groups | 0.047 | 0.022 |
| Never VS timing groups | –0.023 | 0.959 |
| Within | –1.191 | 0.019 |

Note: This table shows results from the bacondecomp Stata command. It shows the weights placed on the various 2 × 2 DD estimates from the estimations using Eq. (3). The bias comes from the results in the first row and represents only 2.2% of the weight.

| Table B.3 | Robustness analysis: Results from fuzzy DID estimators. |
|-----------|--------------------------------------------------|
| Dependent variable: logarithmic daily new COVID-19 cases | January 3 – March 28 | January 3 – May 3 |
| DIDM | –0.0011** | –0.0013*** |
| (0.00046) | (0.00041) |
| Control variables | Yes | Yes |
| N | 14,615 | 22,310 |

Note: This table reports the estimate obtained using fuzzy DID to address the potential heterogeneous treatment effects across cities and over time. All the regression equations use the treatment and control cities with adjacent boundaries (Panel B in Fig. 2). We scaled up the stringency of NPIs by ten times and retained the integer to maintain the sensibility of the treatment variables (21 days lagged stringency of NPIs). The treatment variables should adopt a binary or a finite number of ordered values. City-specific time trends are the number of days since the first confirmed case and its square term. Cumulative confirmed cases in the seven days leading up to the current date are included to control the loading of local public health systems. Finally, weather controls include the daily average temperature, relative humidity, and wind speed for the seven days leading up to the current date t. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level.

B.3. Robustness analysis: Estimates obtained using different definitions for treatment and control cities

We redefine the treatment cities as cities where the residual from the regression of NPIs stringency on the cumulated population inflow by January 23 is positive. The remaining cities are defined as the control cities. Similarly, the adjacent treatment-control cities are defined based on the adjacent borders between the treatment and control cities. Using these definitions, the estimates obtained with Eq. (3) are shown in Table B.4.

| Table B.4 | Robustness analysis: different definitions for treatment cities. |
|-----------|--------------------------------------------------|
| Dependent variable: logarithmic daily new cases | Full sample | Adjacent cities sample |
| Treatment | –0.024*** | –0.028*** | 1.613*** | –0.030*** | –0.037*** | 1.710*** |
| (0.003) | (0.005) | (0.124) | (0.005) | (0.006) | (0.123) |
| Treatment × (0–6 days after NPIs) | –0.165*** | –0.147*** | –0.067** | –0.161*** | –0.131*** | –0.045 |
| (0.031) | (0.030) | (0.028) | (0.040) | (0.039) | (0.036) |
| Treatment × (7–13 days after NPIs) | 0.208*** | 0.245*** | 0.112*** | 0.220*** | 0.263*** | 0.115** |
| (0.047) | (0.045) | (0.042) | (0.062) | (0.059) | (0.055) |
| Treatment × (14–20 days after NPIs) | 0.103*** | 0.065 | 0.016 | 0.091 | 0.049 | 0.007 |
| (0.048) | (0.043) | (0.043) | (0.063) | (0.057) | (0.056) |
| Treatment × (21+ days after NPIs) | –0.108*** | –0.142*** | –0.034*** | –0.107*** | –0.144*** | –0.051*** |
| (0.031) | (0.028) | (0.002) | (0.041) | (0.037) | (0.004) |
| Observations | 27,606 | 26,001 | 26,001 | 17,372 | 16,362 | 16,362 |
| R-squared | 0.239 | 0.307 | 0.447 | 0.258 | 0.328 | 0.465 |
| Time Trends | No | Yes | Yes | No | Yes | Yes |
| Weather Controls | No | Yes | Yes | No | Yes | Yes |
| City FE | No | No | Yes | No | No | Yes |
| Week FE | No | No | Yes | No | No | Yes |
Note: Estimates are obtained using a weighted DID regression analysis. The sample period is from January 3 to May 3, 2020. The dependent variables are logarithmic daily number of new cases in city \( i \) on date \( t \). Treatment cities are defined as cities where the residual from the regression of NPI stringency on the cumulative population inflow from Wuhan by January 23 is positive. Columns (1)–(3) use the full sample (Panel A in Fig. 2), and Columns (4)–(5) restrict treatment and control cities with adjacent boundaries (Panel B in Fig. 2). The specifications include city-specific time trends as the number of days since the first confirmed cases and square terms. Cumulative confirmed cases in seven days leading up to the current date \( t \) are included to control the loading of local public health systems. Finally, weather controls include the daily average temperature, relative humidity, and wind speed for the seven days leading up to the current date \( t \). The results of regression analyses shown in Columns (3, 6) include city fixed effects and week fixed effects. Robust standard errors are reported in parentheses. * Significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level.

B.4. Robustness analysis: Time series analysis using the NPIs constructed by OxCGRT

We employ a time series analysis using the stringency index and government response index produced by OxCGRT. The results in Table B.5 show that the policy responses implemented by the Chinese government in the previous 14 and 28 days significantly reduced the daily number of new confirmed cases in China, consistent with our baseline findings shown in Table 3.

Table B.5
Robustness analysis: Time series analysis.

| Explained variable: logarithmic daily new cases | (1) | (2) |
|-----------------------------------------------|-----|-----|
| Stringency index \( t-7 \)                   | 0.017** |     |
|                                               | (0.007) |     |
| Stringency index \( t-14 \)                  | -0.008 |     |
|                                               | (0.005) |     |
| Stringency index \( t-21 \)                  | 0.018  |     |
|                                               | (0.012) |     |
| Stringency index \( t-28 \)                  | -0.023*** |     |
|                                               | (0.006) |     |
| Government response index \( t-7 \)           | 0.021* |     |
|                                               | (0.012) |     |
| Government response index \( t-14 \)          | -0.014** |     |
|                                               | (0.007) |     |
| Government response index \( t-21 \)          | 0.027  |     |
|                                               | (0.018) |     |
| Government response index \( t-28 \)          | -0.033*** |     |
|                                               | (0.007) |     |
| Daily new cases \( t-7 \)                     | -0.063 | -0.051 |
|                                               | (0.077) | (0.077) |
| Control variable                              | Yes  | Yes |
| Week FE                                       | Yes  | Yes |
| \( N \)                                       | 181  | 181 |
| adj. \( R^2 \)                                 | 0.918 | 0.918 |

Note: This table shows the results from the time series analysis. The stringency index and government response index are accessed from the Oxford COVID-19 Government Response Tracker (OxCGRT, https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker#data). The specifications include the daily average temperature, relative humidity, and wind speed for the seven days leading up to the current date \( t \). We also include the week fixed effects in the estimates. Robust standard errors are reported in parentheses; * \( p < 0.1 \), ** \( p < 0.05 \), and *** \( p < 0.01 \).

References

Adda, J. (2016). Economic activity and the spread of viral diseases: Evidence from high frequency data. The Quarterly Journal of Economics, 131(2), 891–941.
Alexander, D., & Karger, E. (2021). Do stay-at-home orders cause people to stay at home? Effects of stay-at-home orders on consumer behavior. The Review of Economics and Statistics. https://doi.org/10.1162/rest_a_01108, 10.1162/rest_a_01108
Allcott, H., Boxell, L., Conway, J., Ferguson, B., Gentzkow, M., & Goldman, B. (2020). Economic and health impacts of social distancing policies during the coronavirus pandemic. Available at SSRN 3610422 https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3610422.
Ambrus, A., Field, E., & Gonzalez, R. (2020). Loss in the time of cholera: Long-run impact of a disease epidemic on the urban landscape. American Economic Review, 110(2), 475–525.
Ariana, A., Amin, M., Pakneshan, S., Dolan-Evans, E., & Lam, A. K. (2016). Integration of traditional and E-learning methods to improve learning outcomes for dental students in histopathology. Journal of Dental Education, 80(9), 1140–1148.
Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), 1593–1636.
Bertrand, M., Dutlo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? The Quarterly Journal of Economics, 119(1), 249–275.
Bloom, N., Liang, J., Roberts, J., & Ying, Z. J. (2015). Does working from home work? Evidence from a Chinese experiment. The Quarterly Journal of Economics, 130(1), 165–218.
