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The Effect of Control Measures on COVID-19 Transmission and Work Resumption: International Evidence

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THE EFFECT OF CONTROL MEASURES ON COVID-19 TRANSMISSION AND WORK RESUMPTION: INTERNATIONAL EVIDENCE

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Abstract

Many countries have taken non-pharmaceutical interventions (NPIs) to contain the spread of the coronavirus (COVID-19) and push the recovery of national economies. This paper investigates the effect of these control measures by comparing five selected countries, China, Italy, Germany, the United Kingdom, and the United States. There is evidence that the degree of early intervention and efficacy of control measures are essential to contain the pandemic. China stands out because its early and strictly enforced interventions are effective to contain the virus spread. Furthermore, we quantify the causal effect of different control measures on COVID-19 transmission and work resumption in China. Surprisingly, digital contact tracing and delegating clear responsibility to the local community appear to be the two most effective policy measures for disease containment and work resumption. Public information campaigns and social distancing also help to flatten the peak significantly. Moreover, material logistics that prevent medical supply shortages provide an additional conditioning factor for disease containment and work resumption. Fiscal policy, however, is less effective at the early to middle stage of the pandemic.

The novel coronavirus (COVID-19) pandemic poses a common threat to humanity. As of May 13, 2020, the World Health Organization (WHO) had reported confirmed cases in 215 countries and territories around the world with more than 4,369,000 infected, resulting in more than 297,000 deaths[1]. Of those affected, China, Italy, Germany, the United Kingdom, and the United States are some of the most severely impacted by COVID-19 (see Supplementary Figure 1).

Around the world, key control measures—i.e. non-pharmaceutical interventions (NPIs)—have been adopted to reduce the transmission of COVID-19. More than 120 countries have already enforced lockdown policies with different levels of strictness[2]. The growing COVID-19 literature[3-5] shows that both lockdown and other NPIs help reduce transmission, thereby delaying the timing and reducing the size of COVID-19 peaks. However, very little research to date explores the following question:

Q1: Is the timing and efficacy of control measures on virus spread different across different countries?

In most countries, a wide range of NPIs have been utilized, including contact tracing, social distancing, school closures, restrictions in human mobility, and quarantining suspected cases, among others. Several countries, such as Italy, Germany, Spain, the UK, and parts of the US are only now beginning to gradually ease restrictions after the lockdown policies. As these countries, and others, attempt to return to normalcy, another key question arises:

Q2: What are the effects of control measures on pandemic containment and work resumption?

Our research differs from prior work by exploring the effects of control measures on the spread of COVID-19 and providing the following international evidence. First, we quantify the effect of different NPIs on the COVID-19 spread in China, Italy, Germany, the United Kingdom, and the United States. We then simulate the predicted transmission of COVID-19 in the coming one month using scenario analysis, under the enforcement of current NPIs. Second, within China, we use a difference-in-difference (DID) estimator to compare changes in daily new cases within severely affected areas (treated cities) using different control measures to changes within control cities. Unlike a generalized linear regressions model[4], the DID estimator helps us identify a clear causal effect of control measures on the spread of COVID-19 in China. Third, we construct a daily city-level strictness index of Chinese control measures using textual analysis of an enforcement corpus, based on hand-collected official documents from local governments, to reveal the specific effects of control measures on disease containment, rather than a national wide aggregate measure, such as lockdown[6, 7] or social distancing[4, 8].

Taken together, this urgent research highlights the crucial role of early intervention on COVID-19 containment. More specifically, this work indicates information provision through digital contact tracing and clear, unambiguous delegation of risk management responsibilities to the local community are two of the most effective policy measures for early stages of an outbreak and work resumption.

Results

Comparing the control measures on COVID-19 transmission in five selected countries

In China, mass quarantine, public gathering bans, and school closures, together with a total city lockdown, were implemented to reduce COVID-19's reproduction rate in the population and thereby reduce transmission of the virus in late January and February 2020[4, 7]. Italy and other European countries have mostly followed these measures during the outbreak since March 2020. The United States began following similar control measures in late March 2020, with a different transmission outcome[9].

We first estimate the effects of several NPIs on the COVID-19 spread in the five countries by a generalized linear regressions model (see Methods). Fig. 1 presents the estimated effects of the NPIs, including contact tracing, public information campaigns, testing policy, gathering bans, school closure, and stay-at-home order (or lockdown), on virus spread by countries. Except for the enforcement of stay-at-home order, all other control measures significantly reduced the daily new confirmed cases in China. The enforcement of stay-at-home order in Germany also reduce the daily confirmed cases, flattening the peak significantly. The interventions enforced in China and Germany are effective to contain the virus spread. Surprisingly, the enforcement of large gathering bans and school closure increase the daily new confirmed cases in Italy. A possible reason is that the local community transmission and family cluster transmission may be increased when people have nowhere to go[10]. However, those effective control methods enforced in China and Germany did not reduce the confirmed cases in the United Kingdom and the United States.

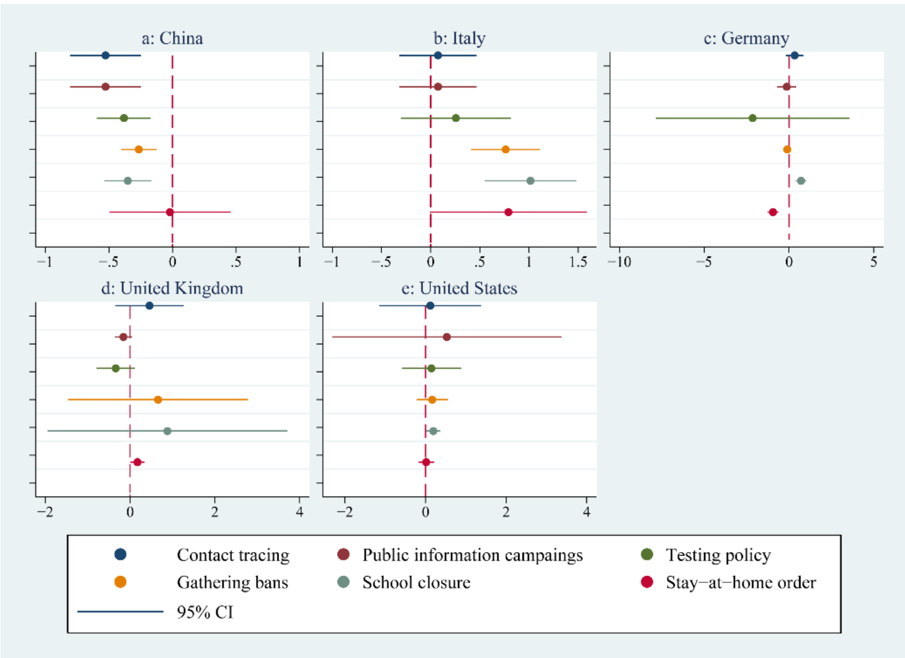

Figure 1 The effect of several NPIs on COVID-19 transmission in five counties: China, Italy, Germany,

the United Kingdom and the United States. The full estimation results are provided in Supplementary Table 5.

We then calculate the daily dynamic of basic reproduction ratio R_0 using the SEIR model (see Methods), to compare the effectiveness of stay-at-home order (lockdown) and other control measures on COVID-19 infections. Key parameters used in the calculation were obtained from published research[3, 11]. These results show that R_0 in China peaked at 2.30 [95% CI: 2.02 to 2.57], 13 days after the lockdown of Wuhan city on January 23, 2020, and then steadily decreased to 1.24 (95% CI: 0.97 to 1.50) on May 13, 2020 (Fig. 2a), 112 days after the lockdown of Wuhan city. Having reached the peak of R_0 (3.07, 95%CI: 2.69 to 3.44) on March 1, 2020, Italy enforced progressive measures of lockdown on March 9, which dramatically reduced the R_0 to 1.92 (95% CI: 1.65 to 2.19) in 64 days after the lockdown (Fig. 2b). A similar decreasing trend of transmission dynamics is observed in Germany (Fig. 2c). In contrast, both the United Kingdom[12] and the Untied States[13, 14] did not have widespread stay-at-home orders until the end of March, when the R_0 reached 2.42 (95% CI: 2.14 to 2.70) and 2.423 (95% CI: 2.15 to 2.71) respectively (Fig. 2d and 2e).

One comparison is the degree of early intervention measured by R_0 at the date of lockdown. The estimated values of R_0 were 2.00 (95% CI: 1.65 to 2.36), 2.96 (95% CI: 2.60 to 3.31), 2.56 (95% CI: 2.20 to 2.91), 2.42 (95% CI: 2.06 to 2.77), and 2.42 (95% CI: 2.07 to 2.77) for China, Italy, Germany, the United Kingdom and the United States, respectively. Another comparison is the efficacy of the lockdown polices across countries. In 50 days after the lockdown, R_0 significantly decreased to 1.79 (95% CI:1.44 to 2.14) in China, 1.80 (95% CI: 1.45 to 2.15) in Germany and 1.99 (95% CI: 1.64 to 2.35) in the United Kingdom. By contrast, R_0 only decreased to 2.09 (95% CI: 1.74 to 2.44) in Italy and 2.06 (95% CI: 1.71 to 2.41) in the United States. The comparisons show that China have enforced earlier and more effective intervention than other countries.

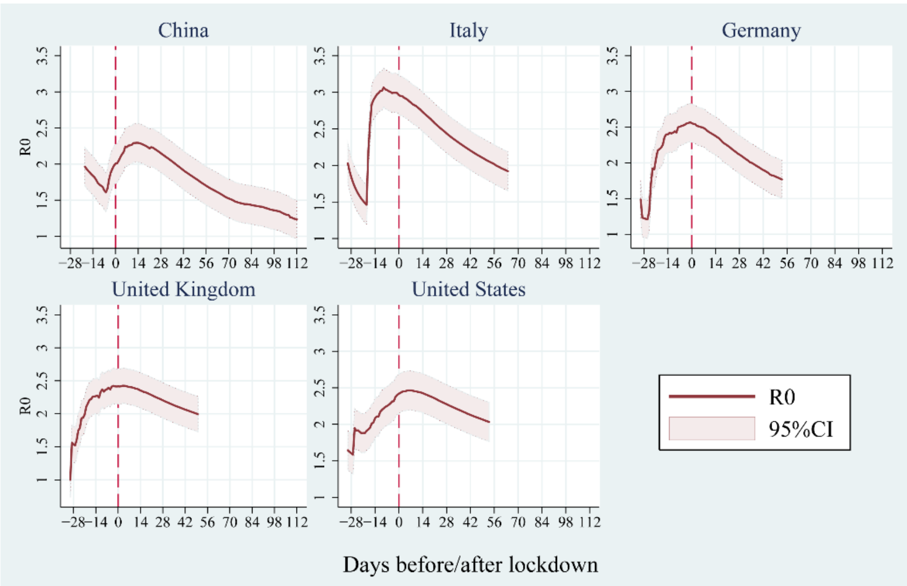

Figure 2: The basic reproduction ratio (R0) in five selected countries. (a) China; (b) Italy; (c) Germany; (d) United Kingdom; (e) United States. The red lines are the estimated R0 by the SEIR model (see Methods) with 95% confidence intervals. The red dash-lines indicate the date of stay-at-home order (lockdown).

We use an auto-regressive (AR) model where the optimal number (q) of lags is found using LASSO—a machine learning linear technique (see Methods)[15], to simulate the confirmed cases in the coming one month, under the enforcement of current NPIs. The simulation in Fig. 3 shows that, Germany and Italy will peak on May 31 and June 11, 2020 (Fig. 3b and 3c), respectively. The trends of daily new confirmed cases in the United Kingdom and the United States, gently move downwards in the coming one month (Fig. 3d and 3e).

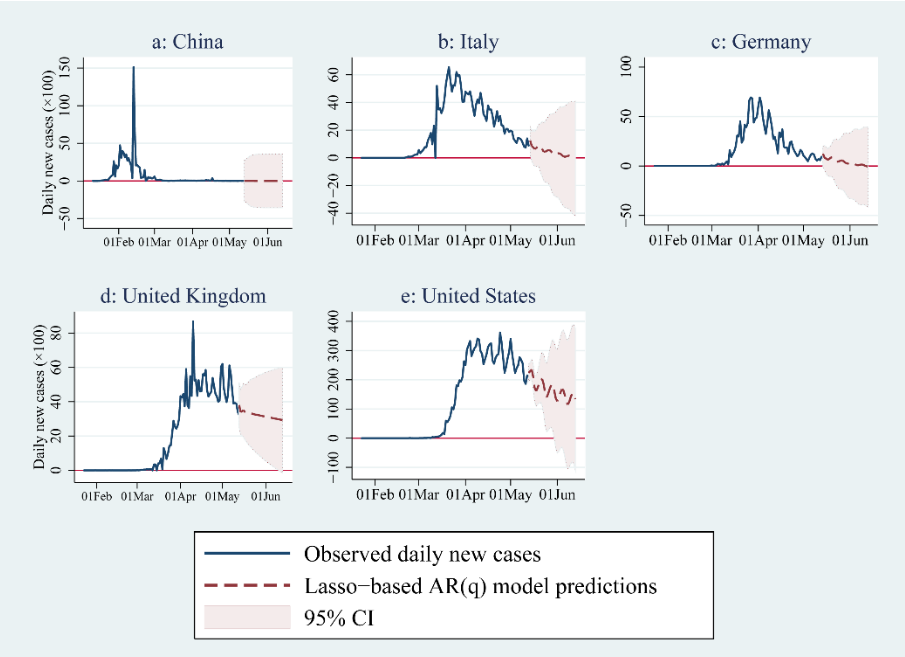

Figure 3 The prediction of daily new confirmed cases in five selected countries. (a) China; (b) Italy; (c) Germany; (d) United Kingdom; (e) United States. The navy lines are the daily confirmed cases from January 20 to May13, 2020, at the time of writing; the red dash-lines are the simulated daily new cases by the LASSO-based AR(q) model with 95% confidence intervals from May 13 to June 13, 2020.

Alongside the deep distress felt by many countries that are still experiencing a peak in new infections cases, there has also been a growing realization of the importance of early, preventative interventions during strict lockdown[16]. Moreover, the estimated effects by the generalized linear regressions model may bias due to potential endogeneity. The economy in China slowly started to recover and schools gradually reopened. It provides us a good laboratory to estimate the causal effect of the control measures on daily new cases and work resumption by a DID framework. The effectiveness of other control measures on virus spread is valuable information for countries looking to reopen their economies amid the ongoing pandemic.

Quantifying control measures on the COVID-19 outbreak in China

The outbreak began in the city of Wuhan, a major transportation hub of China, in late 2019, and spread quickly to all regions of China during the travel rush for the 2020 Chinese Lunar New Year. Migration from Wuhan city before January 23, 2020 is a clear catalyst[3, 7, 17]. Big data on travelers' movement across cities by China's search engine giant Baidu showed that 5 million people flowed out of Wuhan[18], and about half of them traveled to other cities in Hubei province (Fig. 4a). Jia *et al* [17] show that the correlation of population inflow from Wuhan with other cities' daily new cases is larger than 0.9 in the two weeks after the lockdown of Wuhan. Supplementary Table 6 shows that population inflow from Wuhan before the lockdown is significantly correlated with daily new cases in destination cities.

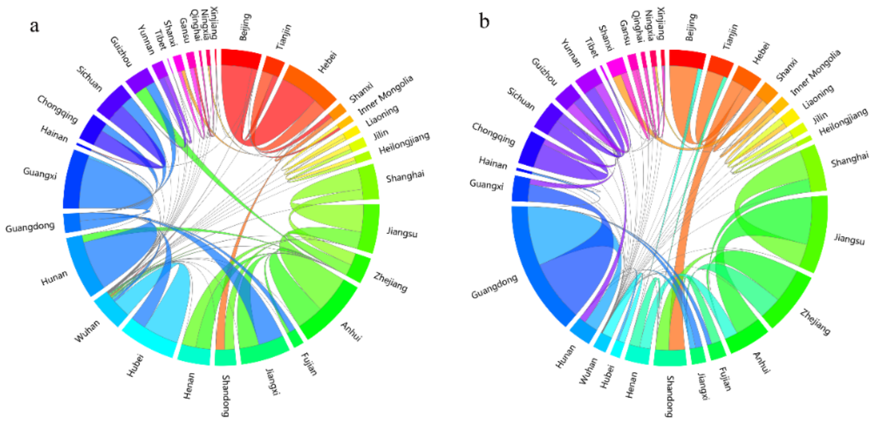

Figure 4: The population flow in China, (a) The population flow from January 01 to January 23 2020; (b) The population flow from February 08 to March 27, 2020. The larger the arc, the larger volume of population flow during the sample period. Data on inter-city population flow was accessed from Baidu Migration data (http://qianxi.baidu.com/).

This correlation allows us to use a DID estimator to quantify the containment effects of a series of specific control measures on the spread of COVID-19 (see Methods). We define the top 50% of cities with population outflow from Wuhan from January 1 to January 23 2020 as the treated cities (N = 164), the other cities as the control cities (N = 187). Different from Fang *et al* [6], we define a daily strictness index of control measures using textual analysis on a corpus of control measures derived from official city government documents (see Supplementary Table 1). At the early stages of the outbreak, the Chinese government focused on public information campaigns and health care provision before paying more attention to social distancing and material logistics. When China started to resume work on February 10, 2020, the government steadily introduced fiscal measures designed to stimulate economic recovery (see Supplementary Figure 2). Detailed econometric models and methodology for constructing the strictness index of control measures can be found in the Methods section.

Table 1 the effect of control measures on COVID-19 spread and work resumption in China

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: the dependent variable is daily new cases							
Treat cities	-0.227	-0.236	-0.275	-0.168	-0.238	-0.196	-0.246
	(0.398)	(0.398)	(0.398)	(0.398)	(0.397)	(0.395)	(0.397)
× Public information campaigns$_{t-14}$	-0.039^{***}						
	(0.007)						
× Social distancing$_{t-14}$		-0.039^{***}					
		(0.006)					
× Contact tracing$_{t-14}$			-0.087^{***}				
			(0.014)				
× Health care$_{t-14}$				-0.012^{***}			
				(0.004)			
× Material logistics$_{t-14}$					-0.043^{***}		
					(0.007)		
× Fiscal measures$_{t-14}$						-0.018^{***}	
						(0.003)	
× Clear responsibility$_{t-14}$							-0.054^{***}
							(0.008)
Control variables	Y	Y	Y	Y	Y	Y	Y
City and week fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	24394	24394	24394	24394	24394	24394	24394
Adjusted R^2	0.630	0.630	0.630	0.630	0.630	0.630	0.630
Panel B: the dependent variable is daily work resumption rate							
Treat cities	-0.091	-0.084	-0.106	-0.092	-0.089	-0.092	-0.074
	(0.273)	(0.272)	(0.273)	(0.274)	(0.276)	(0.274)	(0.273)
× Public information campaigns$_{t-14}$	0.010^{***}						
	(0.003)						
× Social distancing$_{t-14}$		0.012^{***}					
		(0.002)					
× Contact tracing$_{t-14}$			0.024^{***}				
			(0.006)				
× Health care$_{t-14}$				0.002			
				(0.002)			
× Material logistics$_{t-14}$					0.009^{***}		
					(0.002)		
× Fiscal measures$_{t-14}$						0.005^{***}	
						(0.001)	
× Clear responsibility$_{t-14}$							0.009^{***}
							(0.003)
Control variables	Y	Y	Y	Y	Y	Y	Y
City and week fixed effects	Y	Y	Y	Y	Y	Y	Y
Observations	17869	17869	17869	17869	17869	17869	17869
Adjusted R^2	0.900	0.901	0.900	0.900	0.901	0.900	0.900

Note: the definition of variables presented in Table 1 are provided in Supplementary Table 2. To save space, we provided the full information of the estimation by Eq.(10) in Supplementary Table 7 and 8. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Panel A of Table 1 shows the results of control measures on cities' daily new cases. Each control measure is lagged two weeks according to Fang *et al*[6]. The interaction term between *Treat* and a specific control measure (e.g. *Contact Tracing)* measures the effect of the control measure on a cities' daily new cases. We also graph the treatment effect of control measures on the spread of COVID-19 in Fig. 5a for easy visualization. Contact tracing is most effective in containing the spread of the virus. The 1% increase in the strictness of contact tracing reduces infections by 8.33% ($=\exp(-0.087)-1$). Contact tracing was widely used to control the epidemic in China. This process typically utilizes a mobile phone app with a plug-in from WeChat and Alipay—two online platform giants. The app allows a central database to collect data on user movement and identify his/her risk status through an artificial intelligence algorithm. When the viral spread is too fast to be controlled using manual contacting tracing, algorithm based, digital contact tracing is used to effectively control the epidemic[19].

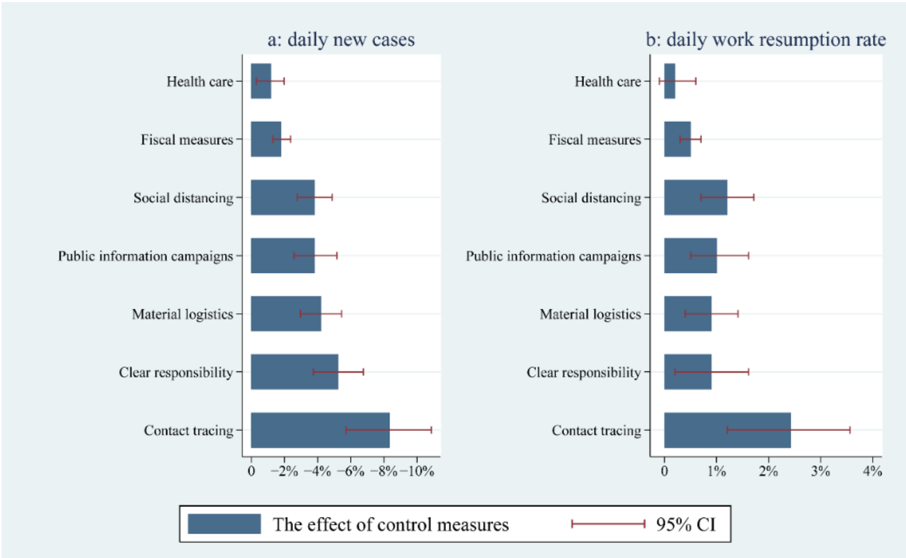

Figure 5: The effect of control measures on COVID-19 spread (a) and work resumption (b). the height of each bar indicates the quantified effects of each measure on the percentage change of interested variables (COVID-19 spread and work resumption) with 95% confidence intervals.

At the early stages of the epidemic, the Chinese government enforced a grid-mode management system, thereby delegating clear responsibilities to local communities. Through "early detection and early isolation" as well as full community assessments, the government left "no one unchecked." The enforcement of these control measures conveyed a sense of urgency and reinforced the viral risk to the public. Although local temperature checks, disinfection, and resident registration significantly restricted human mobility, these measures also removed uncertainty around the source and location of confirmed cases—a task which is often extremely difficult to pinpoint during a pandemic. Government officials and grassroot organizers were also held accountable for their actions, and in certain cases demoted for inaction. Those measures significantly suppressed infections by 5.26% .

Material logistics that prevented medical supply shortages and secured daily necessities also helped flatten the curve. The 1% increase in the strictness of material logistics suppressed the spread of the virus by 4.21% ($=\exp(-0.043)-1$). Public information campaigns and social distancing yielded a similar containment effect on the epidemic. A 1% increase in the strictness of public information campaigns and social distancing reduced infections by $3.82\%\ (= \exp(-0.0.39) - 1)$.

Finally, regarding financial/fiscal support measures, medical costs borne by the government reduced the infection rate by 1.78%. Health care measures, including setting up fever clinics, isolating and rescuing confirmed cases, monitoring body temperatures, and testing nucleic acid were also important. We found that those health care measures reduced the daily new cases by 1.19% ($=\exp(-0.012)-1$). Although mass institutional isolation (Chinese mode) could have indeed contained the COVID-19 outbreak[9], without other measures, mass institutional isolation, screening, and medical treatment alone would have likely created a shortage in medical supplies and caused the healthcare system to overload[20].

The effect of control measures on work resumption in China

Enterprises in China have gradually resumed work since February 10, 2020 and population flows increased after the end of the Chinese Lunar New Year holiday (February 8, 2020). The largest destination provinces were Guangdong, Jiangsu, Zhejiang and Shanghai province/municipality (Fig. 4b). Control measures thus remain important to work resumption amid a possible second wave of infections. We measure the daily work resumption rate using big data of real-time intra-city commuting traffic volume from Baidu Inc. and then re-estimate the DID model to explore the effect of control measures on work resumption in China. Detailed methodology for the variable definitions can be found in the Methods section.

Panel B of Table 1 presents the estimated results of control measures on work resumption, and Fig. 5b shows the treatment effect of a control measure on cities' daily new cases based on the estimated coefficients in Panel B of Table 1. Again, population-wide contact tracing contributes to the largest effect on work resumption, encouraging work resumption by 2.4%. Social distancing measures are much more important than other control measures on work resumption because close contact tends to be unavoidable. A certain range of social distancing is thus essential to work resumption. Overall, a 1% increase in the strictness of social distancing encouraged work resumption by 1.2%. Other control measures, including clear responsibility, material logistics, and public information campaigns, also encouraged work resumption of approximately 0.9% - 1.0%. It is surprising that fiscal measures, including special-purpose loans, tax deduction, factor price deduction, and so on, contribute less to work resumption (only 0.5%) while the strictness of health care does not directly help at all.

We further separate the full sample into two periods.: the first is from January 20 to March 10, and the second is March 11 to 28, 2020. These two periods helped identify the dynamic effects of control measures on the spread of COVID-19 and work resumption (see Supplementary Table 9 and 10). We find the enforcement of control measures significantly reduces the spread of COVID-19 and encourages work resumption at the early stage of outbreak (January 20 to March 10). From March 11 to 28, the average daily new confirmed cases were less than 36 cases each day. This assured the public health system had enough capacity to manage and treat new viral cases. The strict enforcement of control measures, such as restrictions on human mobility, social distancing, etc., however, still hindered economic activity and work resumption overall.

Discussion

As the COVID-19 pandemic spread, many countries enforced a broad range of control measures to contain and mitigate its impacts. Several counties, such as Italy, Germany, the UK, and parts of the US are now looking to ease their lockdowns and reopen their economies. Our results demonstrate that the degree of early intervention and efficacy of control measures are essential to contain the pandemic. China stands out from the five selected countries because its early and strictly enforced interventions are effective to contain the virus spread.

Furthermore, digital contact tracing has the largest effect and is beneficial for both containing the spread of COVID-19 and encouraging work resumption. The results extend findings of Ferretti *et al*[19] and Bi *ea al*[21] by highlighting the quantitative effect of digital contact tracing. Beyond China, South Korea has also contained COVID-19 through scaled testing and a mobile phone app for both contact tracing and recommended quarantine[19]. Moreover, unlike mass quarantines such as lockdowns, digital contact tracing can contain the epidemic's spread while limiting harm to the economy. This offers a careful balance between pandemic control and work resumption. Long-term human mobility restriction is also not a feasible measure for many countries. The experiences in China, therefore, can help inform strategies in other countries looking to resume work amid the COVID-19 pandemic.

Beyond digital contact tracing, delegating clear responsibility to local communities, public information campaigns, and social distancing also help. Social organizations at the grassroots level of Chinese society were mobilized to tackle the challenge of human mobility. Grid-mode management systems provided early detection and early isolation mechanisms and allowed the government, the community, and individuals to have more accurate information about the source and location of confirmed cases, thereby reducing uncertainty. The government also instituted several guidelines to educate people on the use of face masks outdoors, washing hand, and disinfection when needed. These measures significantly reduce the probability of infection.

Social distancing is also widely used in many countries to flatten the peak of confirmed cases. China restricted human mobility in many cities,[6] postponed the reopening of schools after China's Lunar New Year, banned mass gatherings, and quarantined close contracts as well as suspected cases as early as January 26, 2020. Our work shows that the enforcement of social distancing is effective at these early stages of an outbreak as well as work resumption, findings which are consistent with Fang *et al* [6], Abouk and Heydari[22].

Additionally, many countries have implemented fiscal measures to stimulate the economy in the post-pandemic period. Our work, however, suggests that fiscal measures are less clear on both epidemic containment and work resumption. It suggests the enforcement of control measures to reduce the probability of onward transmission is more important than fiscal measures to save the economy at the early to middle stages of a pandemic. But it should be noted that material logistics and supply chains which avoid shortages of medical supplies remain important for both infection containment and work resumption.

Finally, Prem et al[23] were concerned about the rebound of the epidemic when China eased the physical distancing measures in March. They modeled that the pandemic may resurge three months later in June if China relaxed the physical distancing measures in March. China eased the lockdown policy of Hubei province on April 8, 2020, but enforced the wide use of apps in public to evaluate the risk of individuals to others based on past contacts in a given time period. Despite the easing of restrictions on human mobility, China has achieved sustained epidemic containment: averaging more than 32 new imported cases from overseas each day between April 9 and April 24, 2020, but only 6 new cases from local community transmission in the same period. Our work suggests that, a combination of other control measures such as digital contact tracing and delegating clear responsibility to local communities helped prevent the rebound of the epidemic and enabled a gradual process of work resumption, even as a large range of human mobility increased.

For international community, this paper highlights the crucial role of early intervention on COVID-19's containment. Information provision through digital contact tracing and the delegation of clear, unambiguous workflow to local communities made a major impact. Chinese leadership learned hard lessons from the initial outbreak in Wuhan about the importance of greater emphasis on conveying specific, unambiguous and tangible risk management, holding local officials accountable, and delegating clear responsibility to local community stakeholders. Consequently, these actions ultimately reduced epistemological and aleatory uncertainty relating to the source, location, and transmission mechanism of the disease.

Methods

Data description

The global COVID-19 data is collected from the World Health Organization (WHO) Situation Report. We consider a time series of each country's daily infections from January 20 to May 13, 2020 at the time of writing. The Chinese data on daily cases was collected from the National Health Commission of China (NHSC), spanning from December 1, 2019 to May 13, 2020. The data on global coronavirus government response is from Blavatnik School of Government, University of Oxford[2].

We also constructed a panel dataset of daily observations from January 8 to March 28, 2020 at the

Chinese city level to quantify the effects of control measures on COVID-19 spread and work resumption. COVID-19 cases refer to the laboratory-confirmed cases reported by the provincial NHS in China. Work resumption is measured by the real-time intra-city commuting data from Baidu Inc.. It equals the commuting traffic volume within the city during the workday related to that in the first week of January 2020. We also measure the real-time human mobility data across cities from Baidu's migration index (http://qianxi.baidu.com/).

In China's top-down political system, the governments use official documents to mandate policy action. Those official documents strengthen policy enforcement and transmission to lower-level governments[24]. We thus construct a daily strength measure for policy enforcement of control measures based on the official documents released by the prefecture-level cities. We hand-collected the daily official documents on the control measures for COVID-19 from the governments' website from January 8 to March 28, 2020 when China shifted its control measures on imported cases from overseas. Based on the frequency of pre-defined keywords in the official documents (see Supplementary Table 1), we calculated a strictness index of control measures in seven dimensions using textual analysis: contact tracing, public information campaigns, social distancing, health care, material logistics, fiscal measures, and delegating clear responsibility to local community:

$$m_{it}^{d} = \left(\sum_{u=0}^{t} \sum_{w=1}^{20} c_{iu,w}^{d}\right) / \sum_{u=0}^{t} C_{iu} \tag{1}$$

where m is the strictness of the dth control measures for city i at date t; c is the word counts of pre-defined keywords w for the dth control measures (see Supplementary Table 1) and C is the total word counts of the announcements posted by city i. The control variables include the number of days since the first confirmed case, a dummy of level 1 public health emergence response, and the latitude and longitude of the city center.

Supplementary Table 2 provides detailed variable definitions used in our work and summary statistics are given in Supplementary Table 4. Overall, the sample period is from January 8, 2020 to March 28, 2020. As China started to reopen on February 8, 2020, the end of Chinese Lunar New Year holiday, we analyzed the impact of control measures on work resumption from February 10, 2020 (the first workday after the holiday) to March 28, 2020.

Epidemic modeling

For the five selected countries, we followed the susceptible-exposed-infectious-recovered (SEIR) model to calculate the basic reproduction number R_0[11]. The model is:

$$\frac{dS(t)}{dt} = -\frac{S(t)}{P}\left(\frac{R_0}{D_I} I(t) + z(t)\right) + L_{I,W} + L_{C,W}(t) - \left(\frac{L_{W,I}}{P} + \frac{L_{W,C}(t)}{P}\right) S(t) \tag{2}$$

$$\frac{dE}{dt} = \frac{S(t)}{P}\left(\frac{R_0}{D_I}I(t) + z(t)\right) - \frac{E(t)}{D_E} - \left(\frac{L_{W,I}}{P} + \frac{L_{W,C}(t)}{P}\right)E(t) \quad (3)$$

$$\frac{dI(t)}{dt} = \frac{E(t)}{D_E} - \frac{I(t)}{D_I} - \left(\frac{L_{W,I}}{P} + \frac{L_{W,C}(t)}{P}\right)I(t) \quad (4)$$

where *S(t)*, *E(t)*, *I(t)* and *R(t)* are the number of susceptible, latent, infections and removed individuals at time *t*; *P* is the population size, $P = S(t) + E(t) + I(t) + R(t)$; D_E and D_I are the mean latent and infection period; *z(t)* is the zoonotic force of infection equal to 86 cases per day in the baseline scenario before the seafood market closed on 1 January 2020, and equals to 0 thereafter[11].

The basic reproduction number R_0 then is calculated by the following equation:

$$R_0 = \left(1 + \frac{\lambda}{\gamma_1}\right)\left(1 + \frac{\lambda}{\gamma_2}\right) = 1 + \lambda T_g + \rho(1-\rho)\left(\lambda T_g\right)^2 \quad (5)$$

where $\lambda = lnY(t)/t$ is the exponential growth rate of COVID-19 confirmed cases. Latent period $T_E = 1/\gamma_1$ equals to 4.5 days, and infection period $T_I = 1/\gamma_2$ equals to 4 days following the literature[11, 25]. Then the generation time T_g is equal to $T_g = T_E + T_I = 8.5$, and $\rho = T_E/T_g$.

The larger in R_0, the higher the transmission rate of COVID-19. We compare the R_0 to estimate the effect of those NPIs among the five selective countries.

A generalized linear regression model to estimate the effect of control measures in five countries

In order to identify the relationship between the control measures and daily new confirmed cases, we use the following generally linear regression model:

$$Y_{ct} = a_0 + a_1 Y_{ct-14} + a_2 NPI_{ct-14}^{d} + \lambda X_c + \kappa_w + \varrho_c + \varepsilon_{ct} \quad (6)$$

where *Y* denote the daily new COVID-19 cases in country *c* on date *t*, Y_{ct-7} and Y_{ct-14} are the lagged daily new COVID-19 cases by 14 days. *NPI* is a variable indicating the enforcement intensity of a specific control measures *d*, including contact tracing, public information campaigns, testing policy, large gathering bans, school closure, and stay-at-home order. *X* is a vector of control variables, including the days since the first confirmed cases, the latitude and longitude of the country *c*. *k* is the week dummy and ϱ is the country fixed effect. ε_{ct} is the error term.

The summary statistics use in the estimations are given in Supplementary Table 3.

LASSO-based auto-regressive (AR) model

COVID-19 spread is human-to-human transmission, which means the confirmed cases is self-dependent. Combing insights from Adda[26], Cerulli[10] and Qiu *et al*[8], we construct an auto-regressive (AR) model, rather than other predicted models (e.g. time trend model[27]), to predict daily new COVID-19 cases in each country:

$$Y_{ct} = \alpha_0 + \alpha_1 Y_{ct-1} + \alpha_2 Y_{ct-2} + \cdots + a_q Y_{ct-q} + \varepsilon_{ct} \tag{7}$$

where Y denote the daily new COVID-19 cases in country c on date t, a_s are parameters, q is the number of auto-regressive lags, and ε_{it} is an error term with zero mean and finite variance.

A typical problem in auto-regressive models stems from determining the optimal lag structure, where the term "optimal" refers to the number of lags of Y that maximizes the out-of-sample prediction accuracy of the model. It is a typical machine learning problem, as the number of lags can be found by minimizing the test-error associated to the out-of-sample prediction performance of the model. We thus use the *least absolute shrinkage and selection operator* (LASSO) technique[15].

The LASSO is a penalizing regression approach that selects the optimal number of lags by minimizing a constrained (penalized) version of the classical least-squares objective function. Given a λ, the LASSO penalization parameter, one can find a perfect mapping between the degree of penalization and the lags that remain active in the model. The solution is obtained by minimizing the following equation:

$$\frac{1}{2N}\left(Y_t - \sum_{k=1}^{q} \alpha_k{}' Y_{t-k}\right)' \left(Y_t - \sum_{k=1}^{q} \alpha_k{}' Y_{t-k}\right) + \lambda \sum_{k=1}^{q} |\alpha_k| \tag{8}$$

where N is the number of observations in the sample; the first term, $\left(Y_t - \sum_{k=1}^{q} \alpha_k{}' Y_{t-k}\right)' \left(Y_t - \sum_{k=1}^{q} \alpha_k{}' Y_{t-k}\right)$, is the in-sample prediction error; the second term, $\lambda \sum_{k=1}^{q} |\alpha_k|$, is a penalty that increases in value the more complex the model is. It is this term that causes LASSO to select or omit variables.

We use LASSO to select the optimal lagged terms q in Eq.(7) for each country, and then use the auto-regressive model AR(q) to simulate daily new confirmed cases with and without the strictest control measure, lockdown.

The economic model to identify the causal effect of control measures on COVID-19 spread

We first explore the relationship between population inflow from Wuhan city and the daily new cases in other cities, excluding Wuhan:

$$lnY_{it} = \beta_0 + \beta_1 Inflow_{it-7} + \beta_2 Inflow_{it-14} + \beta_3 F_{it} + \beta_4 L1_{it} + \beta_5 Lat_i + \beta_6 Lng_i + \kappa_w + \varphi_i + \varepsilon_{it} \tag{9}$$

where Y_{it} is the daily new cases in city i on date t; *Inflow* is the index of population inflow from *Wuhan* to the destination city i. Considering that the population from Wuhan may be in the latent period without any symptoms, we include the population inflow from Wuhan lagged by 7 days and 14 days[28, 29]. F is the days from the date when the first case was reported to the local date t; $L1$ is a dummy variable of first-level public health emergency response. *Lat* and *Lng* is the latitude and longitude of the city i, to control the natural conditions, such as temperature, precipitation, wind speed and so on. We also include the week dummy κ to control the time trends. φ_i is the city-fixed effect, and ε_{it} is the error term.

Results in Supplementary Table 4 show that city i's daily new cases are positively correlated with population inflow from Wuhan 14 days ago, which is consistent with Fang *et al.'s*[6] estimation. All other things equal, the more population inflow from the source city, the higher rate of virus transmission with secondary infection[3]. That is, population inflow from Wuhan before the lockdown is an "exogenous shock" to the destination city i. It provides us a good natural laboratory to identify the causal effects of control measures in the affected cities. In particular, we employ a difference-in-difference (DID) estimation to quantify the effects of control measures on virus transmission. We define the treated cities as the top 50% of cities with largest cumulative population inflow from Wuhan before the lockdown on January 23, 2020. The rest of the cities are control cities. Both the treated and control cities exclude cities in Hubei province for two reasons. First, about half of the population outflow from Wuhan moved to other cities in Hubei province (Fig. 4a). This made the infections in Hubei province boom, and the healthcare systems in Hubei province were overwhelmed. It was impossible to take sufficient laboratory tests, resulting in under-reported confirmed cases in Hubei at the early stage of the COVID-19 outbreak. Second, other cities in Hubei province were strictly locked down on January 26, 2020. People were not allowed to walk outside, and the public transportation system was shut down. The strictest control measures in Hubei province are not comparable to those in other cities outside Hubei.

Supplementary Figure 3 compares the differences between treated and control cities. Obviously, the treated cities received much more population inflow from Wuhan before the lockdown (Supplementary Figure 1a); the daily new confirmed cases sharply increased after the lockdown of Wuhan on January 23 2020, indicating a wide spread of the virus in those treated cities (Supplementary Figure 3b). The work resumption rate in the control cities, on average, is better than that of treated cities after the reopening on February 10, 2020 (Supplementary Figure 3c). The strength of policy enforcement on control measures (measured by the word counts of the official documents) in the treated cities is also generally higher than that of the control cities (Supplementary Figure 3d).

The DID specification can be described as follows:

$$lnY_{it} = \beta_0 + \beta_1 Treat_i \times m_{it-14}^d + \beta_2 Treat_i + \theta M_{it-14} + \vartheta X_{it} + \kappa_w + \varphi_i + \varepsilon_{it} \tag{10}$$

where m_{it}^d is the dth dimension of control measures enforced by city i on date t. It is calculated by textual analysis as described in Eq.(1). M is a 1×7 metric of the control measures enforced by city i on date t. X is a set of control variables as described in Eq. (9). We control for the week-specific fixed effect κ_w to eliminate the time-specific impact. City-specific fixed effect φ_i is included to absorb the city-specific heterogeneities. The estimated coefficient β_1 captures the effect of control measures m_{it}^d on virus spread.

Test of parallel trend assumption

A requirement for unbiased DID estimation results is satisfying the parallel trend assumption. This means that the treated cities and the controlled cities should have the same trends of virus spread before the enforcement of the control measures. If the parallel trend assumption is true, the impact of control measures should only work after their enforcement. To test for parallel trends, we use the event-study method:

$$lnY_{it} = \beta_0 + \sum_{j=-14}^{j=28} \beta_j IMPLEMENT_{it-j}^{d} + \theta M_{it-14} + \vartheta X_{it} + \kappa_w + \varphi_i + \varepsilon_{it} \quad (11)$$

where $IMPLEMENT_{it-j}^{d}$ is a dummy variable: when city i implemented the dth control measures ($m_{t-j}^{d} > 0$) on date $t-j$, it takes 1, 0 otherwise. If β_{-14} to β_{-1} are statistically insignificant, then evidence suggests that the parallel trend hypothesis is fullfilled[30]. However, it is reasonable to expect that β_1 to β_7 may not be statistically significant because the latent period may last up to 14 days[29].

The results of the parallel trend tests are reported in Supplementary Figure 4 and Supplementary Figure 5. They show that the coefficients for the dummy variables representing 14 days before the enforcement of control measures are not statistically significant at the 10% level. That is, the parallel tread assumption holds.

Acknowledgements

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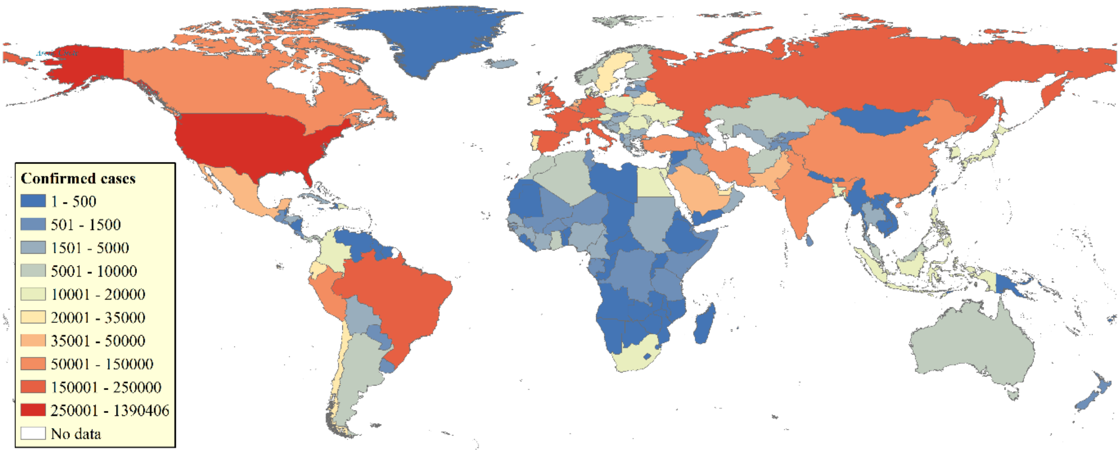
Supplementary Information

The effect of control measures on COVID-19 transmission and work resumption: International Evidence

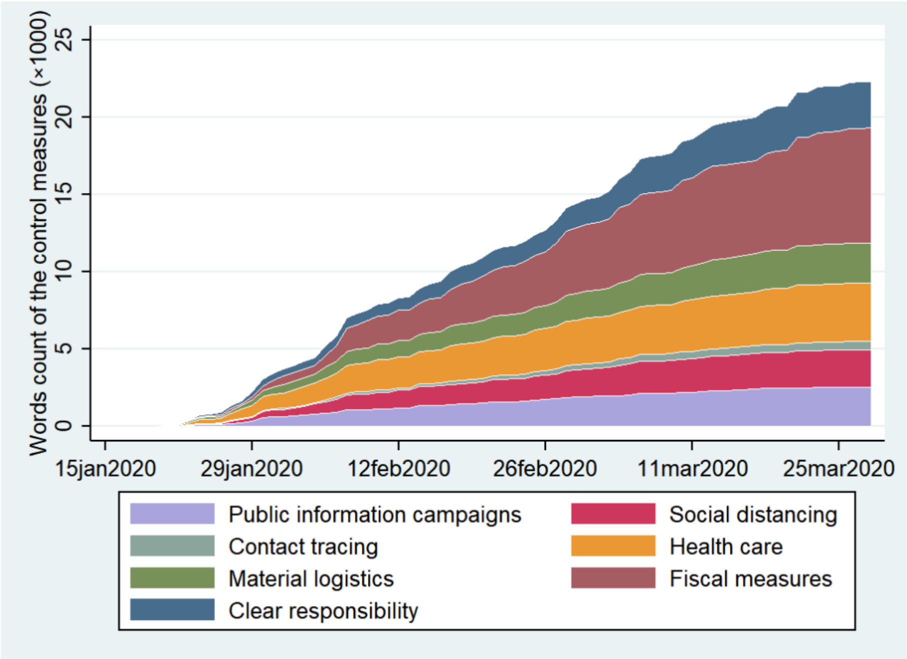
Meng et al.

Contents

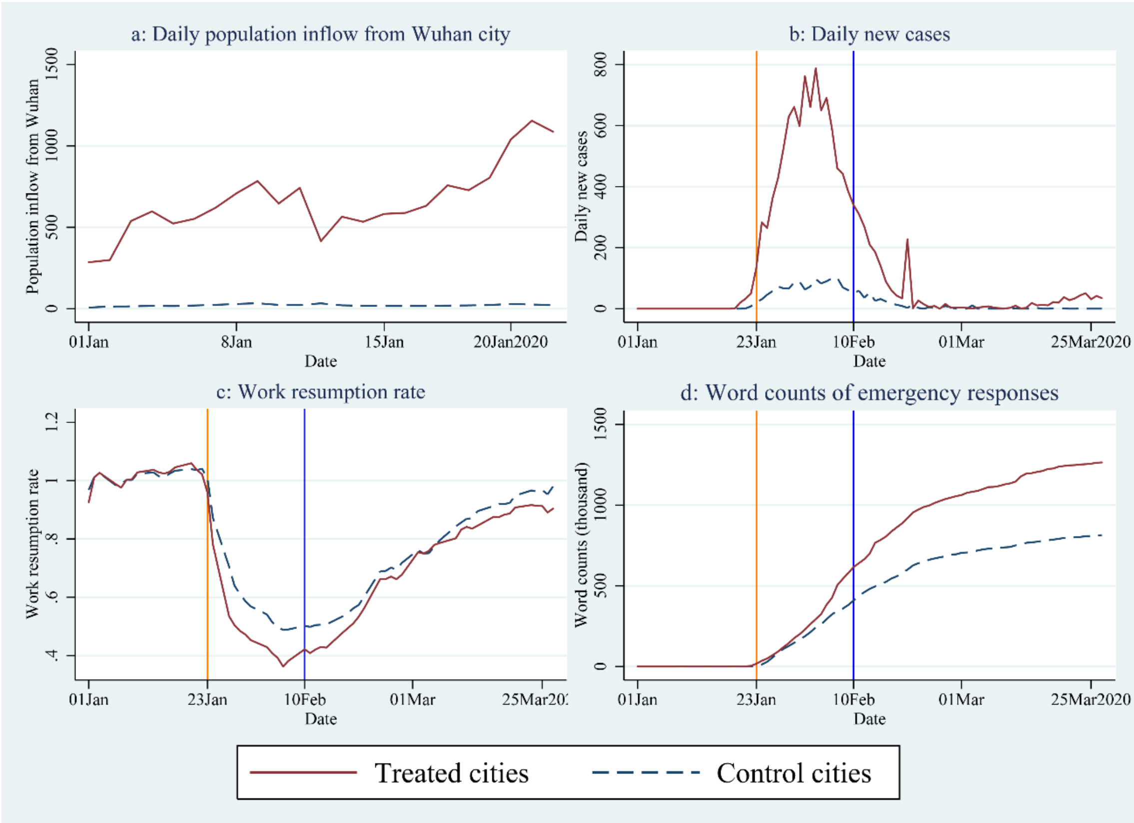


Supplementary Figure 1 Cumulative confirmed COVID-19 cases globally (as of May 13, 2020).

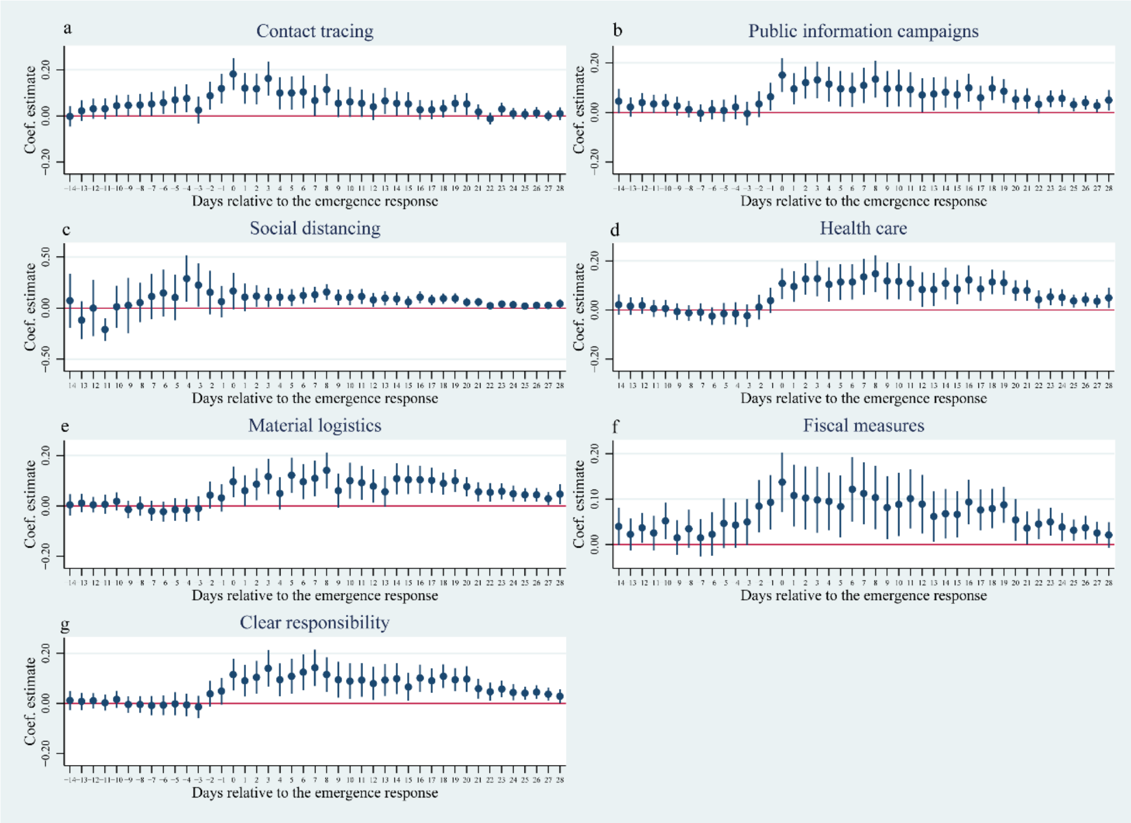
Note: the confirmed cases by countries is accessed from the World Health Organization (WHO)[1].



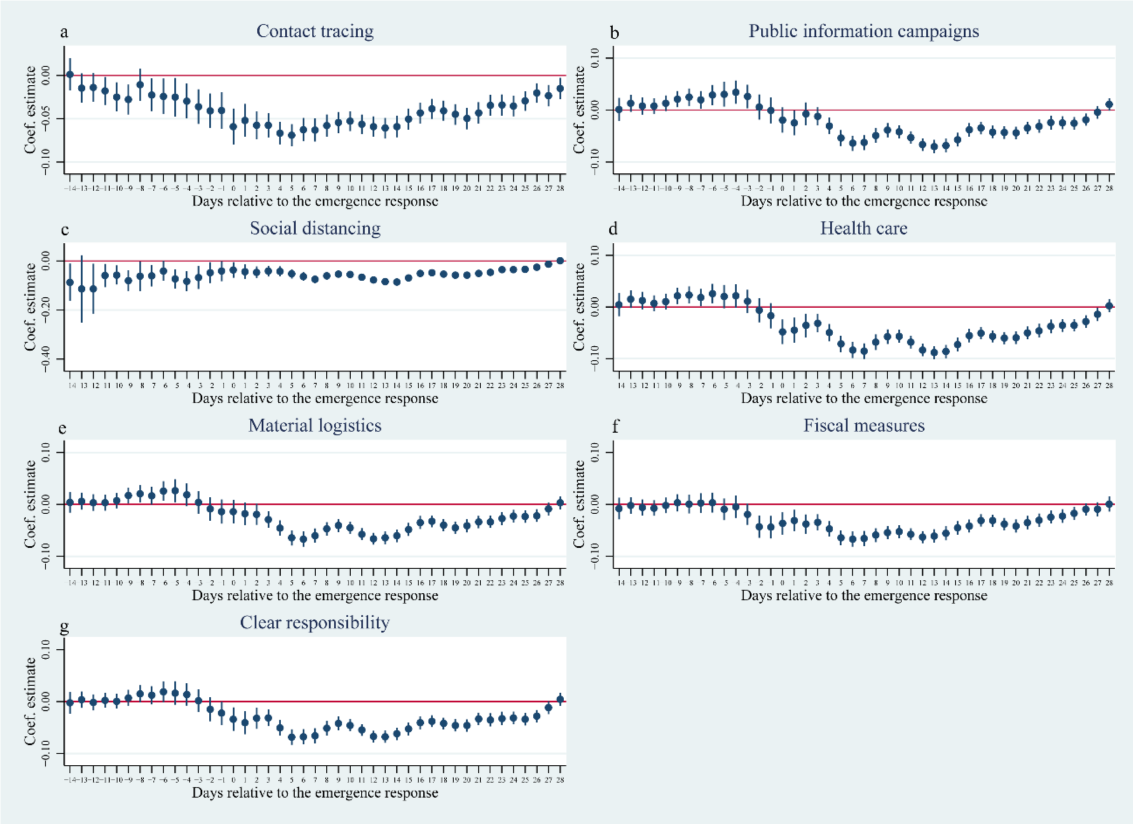
Supplementary Figure 2 Words count of control measures during the COVID-19 outbreak.



Supplementary Figure 3: The differences in daily changes of interested variables. (a) population flow; (b) new confirmed cases (c) work resumption rate; (d) work counts of emergency response in both treated cities (red line) and control cities (navy dash). The orange line indicates the date of lockdown in Wuhan; the blue line indicates the first workday after the Chienses Lunar New Year holiday.



Supplementary Figure 4: Parallel trend of new confirmed cases. The coefficients are estimated by Eq.(11). It illustrates the difference in daily new confirmed cases before and after the implementation of the *d*th control measures to test the pre-treatment parallel trend assumption. (a) contact tracing; (b) public information campaigns; (c) social distancing; (d) health care; (e) material logistics; (f) fiscal measures; (g) clear responsibility. The dots indicate coefficient estimation and the vertical lines indicate 95% confidence interval. The horizontal red lines are the reference line of y = 0.



Supplementary Figure 5: Parallel trend of work resumption rate. The coefficients are estimated by Eq.(11). It illustrates the difference in work resumption rate before and after the implementation of the *d*th control measures to test the pre-treatment parallel trend assumption. (a) contact tracing; (b) public information campaigns; (c) social distancing; (d) health care; (e) material logistics; (f) fiscal measures; (g) clear responsibility. The dots indicate coefficient estimation and the vertical lines indicate 95% confidence interval. The horizontal red lines are the reference line of y = 0.

Supplementary Table 1: Corpus of control measures on COVID-19 at the city level

Index	Control measures	Corpus
M1	Contact tracing	Internet; big data; artificial intelligence; health code; app; Scanning code; tracing 5G; information technology (IT); platform; online; report; network; technology; distance; digitalization; non-contact; information system; recognition; inform and report; broadband; cyber security; QR code; online processing; paperless; intelligence
M2	Public information campaigns	Preventative control; prevention and protection; disinfection; lead and conduct; propaganda; health; ventilation; percent; precaution; transmission; clean; consciousness; washing hands; raise the alarm; propaganda and education; prevention and protection measure; public health; science popularization; spray alcohol; media
M3	Social distancing	Face mask; quarantine; monitoring and measurement; university and college; reduction; public gathering; postpone; teaching; suspension; preventative control measures; school; governing and control; point to point; going out; stay at home; close; dense gathering; restriction; extension; temporary injunction
M4	Health care	Training; medical staffs; infection; patience; medical treatment; suspected cases; detection; medical; preventative treatment; medical and health (authority); medical agency; rescue; medicine; temperature; symptom; hospital; confirmed cases; hospital admission; high temperature; close contact; epidemics; fever clinics; test
M5	Material logistics	Material/resources; transportation; emergency supply; quality; supply; flow; logistic; market supervision; green channel; protection equipment; circulation; cargo; highway; quarantine; goods; passenger; farming; PPE(personal protection equipment); necessities; disinfectant; emergency transport; transport carrier; road; basket (of food)
M6	Fiscal measures	Enterprise; production; work and production resumption; taxation; employment; human resource; work resumption; interest repayment; rural (migrant) worker; loan; SME; agriculture; industry; VAT; exemption; returning to work; subsidy; financing; payment; price; purchase; finance; MSE; fiscal; financial institutions; credit
M7	Clear responsibility	Community; help and support; disease prevention; monitoring and control; supervision; urban and rural; national health commission; poverty alleviation; department of civil affairs; management agency; public health authority; coordination; responsibility; affected area; rural resident; public service; social service; spread prevention; filtration; visit and inspection; grid-mode management; left-behind; resident; close scrutiny; probe and exclusion

Supplementary Table 2: Variable definition

Variable	Definition	Freq.
Dependent variable:		
New case	The logarithmic value of daily new confirmed cases	Daily
Work resumption rate	Commuting traffic volume within the city during the workday related to that in the first week of January 2020	Daily
Independent variable:		
Treat	A dummy variable that equal to 1 if the city is the top 50% cities of largest population inflow from Wuhan, 0 otherwise. the city received a population inflow from Wuhan	
Contact tracing (M1)	The word frequency of pre-defined M3 corpuses in the emergency management announcements	Daily
Public information campaigns (M2)	The word frequency of pre-defined M1 corpuses in the emergency management announcements	Daily
Social distancing (M3)	The word frequency of pre-defined M2 corpuses in the emergency management announcements	Daily
Health care (M4)	The word frequency of pre-defined M4 corpuses in the emergency management announcements	Daily
Material logistics (M5)	The word frequency of pre-defined M5 corpuses in the emergency management announcements	Daily
Fiscal measures (M6)	The word frequency of pre-defined M6 corpuses in the emergency management announcements	Daily
Clear responsibility (M7)	The word frequency of pre-defined M7 corpuses in the emergency management announcements	Daily
Population inflow from Wuhan	The volume of population inflow from Wuhan, measured by Baidu migration index.	Daily
Population inflow	The volume of population inflow from other cities, excluding Wuhan, measured by Baidu migration index	Daily
Weighted population inflow	0.3 × Population inflow + 0.7 Population inflow from Wuhan	Daily
First_day	The days since the local government reported the first confirmed case	Daily
L1 response	A dummy variable that is equal to 1 if the province implemented Level-1 public health emergency response	Daily
Latitude	The Latitude (degree) of the city center	
Longitude	The Longitude (degree) of the city center	
Week	The week dummy	

Supplementary Table 3 Summary statistics: five selective countries

Variable	N	Mean	S.D.	P1	P50	P99
New cases	611	3436	7381	0	200	32491
Contact tracing	612	1.292	0.802	0	2	2
Public information campaigns	612	1.557	0.808	0	2	2
Testing policy	612	1.374	0.964	0	1	3
Gathering bans	612	2.324	1.94	0	4	4
School closure	612	1.879	1.441	0	3	3
Stay-at-home order	612	1.248	1.13	0	1	3
First days	612	60.09	39.38	0	58	158
lat	612	41.95	9.816	29.18	43	55.38
lng	612	17.88	72.62	-95.71	9	120.1
week	581	11.58	4.902	2	12	20

Supplementary Table 4: Summary statistics: data at the city level of China

Variable	N	Mean	S.D.	P1	P50	P99
New case	30145	0.101	0.403	0	0	2.197
Work resumption rate	21453	0.777	0.254	0.195	0.844	1.246
Treat	351	0.473	0.500	0	0	1
Public information campaigns	30537	0.898	0.697	0	0.947	2.53
Social distancing	30537	0.99	0.779	0	1.073	2.958
Contact tracing	30537	0.384	0.334	0	0.399	1.216
Health care	30537	1.262	1.152	0	1.288	4.617
Material logistics	30537	0.953	0.749	0	1.078	2.864
Fiscal measures	30537	2.172	1.787	0	2.308	5.617
Clear responsibility	30537	0.75	0.549	0	0.891	1.872
First_day	30537	19.96	21.12	0	13	64
L1 response	30537	0.417	0.493	0	0	1
Latitude	30537	32.77	7.502	18.64	32.69	48
Longitude	30537	110.8	10.57	79.08	112.6	130.4
Week	30537	7	3.604	1	7	13

Supplementary Table 5 The effects of NPIs on the COVID-19 spread in five selective countries

	(1) Contact tracing	(2) Public information campaigns	(3) Testing policy	(4) Gathering bans	(5) School closure	(6) Stay-at-home order
Panel A: China						
NPIs	-0.527***	-0.527***	-0.382***	-0.263***	-0.351***	-0.020
	(0.140)	(0.140)	(0.107)	(0.070)	(0.094)	(0.240)
Daily new cases$_{t-14}$	0.717	0.717	0.772	0.717	0.717	0.707
	(0.485)	(0.485)	(0.488)	(0.485)	(0.485)	(0.488)
First days	0.052	0.052	0.060	0.052	0.052	0.053
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.063)
Observations	119	119	119	119	119	119
Adjusted R^2	0.855	0.855	0.855	0.855	0.855	0.853
Panel B: Italy						
NPIs	0.073	0.073	0.256	0.761***	1.015***	0.790*
	(0.198)	(0.198)	(0.282)	(0.176)	(0.235)	(0.402)
Daily new cases$_{t-14}$	0.326	0.326	0.285	0.278	0.278	0.203
	(0.255)	(0.255)	(0.272)	(0.255)	(0.255)	(0.268)
First days	0.097**	0.097**	0.096**	0.079**	0.079**	0.096***
	(0.040)	(0.040)	(0.040)	(0.036)	(0.036)	(0.036)
Observations	112	112	112	112	112	112
Adjusted R^2	0.927	0.927	0.927	0.934	0.934	0.931
Panel C: Germany						
NPIs	0.331	-0.146	-2.141	-0.116	0.694***	-0.945***
	(0.265)	(0.286)	(2.870)	(0.119)	(0.163)	(0.160)
Daily new cases$_{t-14}$	0.919***	0.874***	0.876***	0.944***	0.808***	0.985***
	(0.151)	(0.145)	(0.144)	(0.147)	(0.138)	(0.141)
First days	0.027	0.027	0.026	0.024	0.010	0.030
	(0.027)	(0.026)	(0.026)	(0.026)	(0.021)	(0.026)
Observations	112	112	112	112	112	112
Adjusted R^2	0.977	0.977	0.978	0.977	0.983	0.978
Panel D: United Kingdom						
NPIs	0.458	-0.152	-0.339	0.659	0.878	0.174**
	(0.406)	(0.101)	(0.226)	(1.067)	(1.423)	(0.085)
Daily new cases$_{t-14}$	0.351	0.143	0.142	0.151	0.151	0.147
	(0.392)	(0.512)	(0.512)	(0.510)	(0.510)	(0.513)
First days	0.030	0.044	0.045	0.041	0.041	0.042
	(0.032)	(0.033)	(0.033)	(0.032)	(0.032)	(0.032)
Observations	112	112	112	112	112	112
Adjusted R^2	0.956	0.954	0.954	0.955	0.955	0.954
Panel E: Untied States						
NPIs	0.115	0.531	0.149	0.167	0.194**	0.017
	(0.634)	(1.432)	(0.369)	(0.194)	(0.088)	(0.095)
Daily new cases$_{t-14}$	0.757***	0.759***	0.719***	0.646***	0.677***	0.755***
	(0.163)	(0.161)	(0.196)	(0.168)	(0.175)	(0.162)
First days	0.007	0.007	0.005	0.009	0.006	0.007
	(0.029)	(0.029)	(0.026)	(0.028)	(0.029)	(0.029)
Observations	112	112	112	112	112	112
Adjusted R^2	0.989	0.989	0.989	0.989	0.989	0.989

Note: the results are estimated by Eq.(6). The dependent variable is the logarithmic value daily new confirmed cases. The control variables in each regression include the days since the first reported cases in the specific country, the latitude and longitude of the country, and the constant term. Standard errors in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Supplementary Table 6: The correlation of population inflow from Wuhan on COVID-19 infection

This table provides results estimated by Eq. (9).

	Cities excluding Wuhan		Cities excluding Hubei province	
	(1)	(2)	(3)	(4)
Dependent variable: new case				
Population inflow from Wuhan_{t-7}	0.608^{*}	-9.415^{***}	1.162	-63.006^{***}
	(0.345)	(0.815)	(1.092)	(3.653)
Population inflow from Wuhan_{t-14}		12.638^{***}		74.990^{***}
		(0.892)		(3.940)
First_day	-0.003^{***}	-0.004^{***}	-0.003^{***}	-0.003^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
L1 response	-0.152^{***}	-0.119^{***}	-0.005	0.019^{**}
	(0.012)	(0.012)	(0.008)	(0.008)
Latitude	-0.003	-0.002	-0.003	0.000
	(0.006)	(0.006)	(0.006)	(0.005)
Longitude	0.038^{***}	0.040^{***}	0.036^{***}	0.026^{***}
	(0.003)	(0.003)	(0.004)	(0.004)
week=3	-0.003	0.000	-0.003	0.000
	(0.009)	(.)	(0.006)	(.)
week=4	0.208^{***}	0.163^{***}	0.121^{***}	-0.012
	(0.011)	(0.012)	(0.007)	(0.010)
week=5	0.718^{***}	0.666^{***}	0.448^{***}	0.321^{***}
	(0.020)	(0.020)	(0.016)	(0.016)
week=6	0.764^{***}	0.645^{***}	0.477^{***}	0.250^{***}
	(0.022)	(0.020)	(0.016)	(0.017)
week=7	0.518^{***}	0.517^{***}	0.243^{***}	0.203^{***}
	(0.020)	(0.021)	(0.012)	(0.014)
week=8	0.309^{***}	0.316^{***}	0.095^{***}	0.056^{***}
	(0.015)	(0.016)	(0.010)	(0.011)
week=9	0.186^{***}	0.217^{***}	0.091^{***}	0.062^{***}
	(0.010)	(0.011)	(0.007)	(0.008)
week=10	0.160^{***}	0.206^{***}	0.105^{***}	0.082^{***}
	(0.010)	(0.010)	(0.007)	(0.008)
week=11	0.164^{***}	0.220^{***}	0.122^{***}	0.101^{***}
	(0.010)	(0.011)	(0.007)	(0.008)
week=12	0.187^{***}	0.252^{***}	0.150^{***}	0.130^{***}
	(0.011)	(0.011)	(0.008)	(0.009)
week=13	0.207^{***}	0.280^{***}	0.172^{***}	0.154^{***}
	(0.012)	(0.013)	(0.009)	(0.010)
Constant	-3.131^{***}	-3.353^{***}	-2.911^{***}	-2.196^{***}
	(0.330)	(0.324)	(0.313)	(0.301)
City fixed effect	Y	Y	Y	Y
Observations	30032	27463	28741	26284
Adjusted R^2	0.368	0.460	0.317	0.425

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

Supplementary Table 7: The effect of control measures on daily new COVID-19 cases.

This table provides the full results estimated by Eq.(10).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat cities	-0.227	-0.236	-0.275	-0.168	-0.238	-0.196	-0.246
	(0.398)	(0.398)	(0.398)	(0.398)	(0.397)	(0.395)	(0.397)
×Public information campaigns$_{t-14}$	-0.039***						
	(0.007)						
×Social distancing$_{t-14}$		-0.039***					
		(0.006)					
× Contact tracing$_{t-14}$			-0.087***				
			(0.014)				
×Health care$_{t-14}$				-0.012***			
				(0.004)			
×Material logistics$_{t-14}$					-0.043***		
					(0.007)		
×Fiscal measures$_{t-14}$						-0.018***	
						(0.003)	
× Clear responsibility$_{t-14}$							-0.054***
							(0.008)
Public information campaigns$_{t-14}$	0.021**	0.002	0.001	0.007	-0.002	0.001	0.001
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Social distancing$_{t-14}$	0.009	0.032***	0.008	0.000	0.011	0.010	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Contact tracing$_{t-14}$	0.029	0.029	0.074***	0.028	0.029	0.038*	0.035*
	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)
Health care$_{t-14}$	-0.000	-0.001	0.000	0.007*	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Material logistics$_{t-14}$	-0.012	-0.010	-0.012	-0.010	0.011	-0.011	-0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)
Fiscal measures$_{t-14}$	0.001	0.001	0.000	-0.002	-0.000	0.009**	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Clear responsibility$_{t-14}$	-0.014	-0.017	-0.015	-0.009	-0.015	-0.024	0.006
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.016)
Average work resumption rate$_{t-7}$	0.926***	0.924***	0.925***	0.934***	0.922***	0.921***	0.924***
	(0.027)	(0.027)	(0.027)	(0.026)	(0.027)	(0.027)	(0.027)
Average work resumption rate$_{t-14}$	-0.135***	-0.134***	-0.137***	-0.146***	-0.134***	-0.143***	-0.137***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
First_day	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L1 response	0.060***	0.060***	0.061***	0.058***	0.061***	0.062***	0.061***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Latitude	0.012	0.012	0.011	0.010	0.012	0.012	0.012
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Longitude	0.013	0.013	0.014	0.011	0.013	0.013	0.014
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)
Week dummy	Y	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y	Y
Observations	24394	24394	24394	24394	24394	24394	24394
Adjusted R^2	0.630	0.630	0.630	0.630	0.630	0.630	0.630

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

Supplementary Table 8: The effect of control measures on work resumption rate

This table provides the full results estimated by Eq.(10).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable: work resumption rate							
Treat cities	-0.091	-0.084	-0.106	-0.092	-0.089	-0.092	-0.074
	(0.273)	(0.272)	(0.273)	(0.274)	(0.276)	(0.274)	(0.273)
×Public information campaigns$_{t-14}$	0.010***						
	(0.003)						
×Social distancing$_{t-14}$		0.012***					
		(0.002)					
×Contact tracing$_{t-14}$			0.024***				
			(0.006)				
×Health care$_{t-14}$				0.002			
				(0.002)			
×Material logistics$_{t-14}$					0.009***		
					(0.002)		
×Fiscal measures$_{t-14}$						0.005***	
						(0.001)	
×Clear responsibility$_{t-14}$							0.009***
							(0.003)
Public information campaigns$_{t-14}$	0.042***	0.047***	0.046***	0.048***	0.048***	0.047***	0.047***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Social distancing$_{t-14}$	-0.050***	-0.057***	-0.048***	-0.050***	-0.051***	-0.049***	-0.050***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Contact tracing$_{t-14}$	-0.010***	-0.010***	-0.032***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)
Health care$_{t-14}$	-0.031***	-0.032***	-0.032***	-0.011***	-0.031***	-0.032***	-0.031***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.003)	(0.003)	(0.003)
Material logistics$_{t-14}$	0.020***	0.020***	0.021***	0.021***	-0.036***	0.021***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Fiscal measures$_{t-14}$	0.050***	0.051***	0.049***	0.050***	0.053***	0.018***	0.050***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	0.002	(0.006)
Clear responsibility$_{t-14}$	-0.019***	-0.019***	-0.019***	-0.019***	-0.022***	-0.020***	0.046***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Average work resumption rate$_{t-7}$	1.057***	1.055***	1.058***	1.057***	1.054***	1.056***	1.056***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Average work resumption rate$_{t-14}$	-0.642***	-0.640***	-0.647***	-0.644***	-0.641***	-0.645***	-0.642***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
First_day	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L1 response	-0.049***	-0.049***	-0.049***	-0.049***	-0.050***	-0.049***	-0.049***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Latitude	0.013	0.013	0.014	0.013	0.013	0.013	0.013
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Longitude	0.000	-0.000	0.001	0.000	0.000	0.000	-0.000
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Week dummy	Y	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y	Y
Observations	17869	17869	17869	17869	17869	17869	17869
Adjusted R^2	0.900	0.901	0.900	0.900	0.901	0.900	0.900

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

Supplementary Table 9: The effect of control measures on COVID-19 spread: different sample periods

The government stressed that control measures should be taken based on different conditions of each region to combat the epidemic and encourage work resumption on February 18, 2020. Gansu province is the first to ease the first-level public health emergence response (*L1 response)* on February 21, 2020. Till March 10, 24 provinces have eased the first-level public health emergence, excluding Beijing, Tianjin, Hebei , Shanghai, Jiangxi and Henan. We divided the sample into two periods: January 20 to March 10, and March 11 to 28, 2020, to identify the dynamic effects of control measures on the COVID-19 spread. Combining the results in Panel A and Panel B, it is clear that the control measures are effective at the early stage of the outbreak.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: sample period from January 20 to March 10, 2020							
Treat cities	-1.220	-1.238	-1.306	-1.065	-1.218	-1.099	-1.262
	(1.702)	(1.703)	(1.706)	(1.705)	(1.697)	(1.686)	(1.697)
×Public information campaigns$_{t-14}$	-0.058***						
	(0.010)						
×Social distancing$_{t-14}$		-0.059***					
		(0.009)					
×Contact tracing$_{t-14}$			-0.119***				
			(0.021)				
×Health care$_{t-14}$				-0.016***			
				(0.005)			
×Material logistics$_{t-14}$					-0.059***		
					(0.009)		
×Fiscal measures$_{t-14}$						-0.030***	
						(0.004)	
×Clear responsibility$_{t-14}$							-0.084***
							(0.012)
Control variables	Y	Y	Y	Y	Y	Y	Y
Week fixed effect	Y	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y	Y
Observations	17420	17420	17420	17420	17420	17420	17420
Adjusted R^2	0.618	0.618	0.618	0.617	0.618	0.619	0.618
Panel B: sample period from March 11 2020 to March 28, 2020							
Treat cities	-0.804	-0.987	-0.715	-1.068	-1.043	-1.128	-0.840
	(0.590)	(0.630)	(0.557)	(0.659)	(0.645)	(0.697)	(0.685)
×Public information campaigns$_{t-14}$	0.107						
	(0.073)						
×Social distancing$_{t-14}$		0.048					
		(0.040)					
×Contact tracing$_{t-14}$			0.105				
			(0.068)				
×Health care$_{t-14}$				0.037			
				(0.036)			
×Material logistics$_{t-14}$					0.029		
					(0.025)		
×Fiscal measures$_{t-14}$						-0.025	
						(0.084)	
×Clear responsibility$_{t-14}$							0.081**
							(0.036)
Control variables	Y	Y	Y	Y	Y	Y	Y
Week fixed effect	Y	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y	Y
Observations	5927	5927	5927	5927	5927	5927	5927

Adjusted R^2	0.819	0.819	0.819	0.819	0.819	0.819	0.819

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

Supplementary Table 10: The effect of control measures on work resumption: different sample periods

We divided the sample into two periods: January 20 to March 10, and March 11 to 28, 2020, to identify the dynamic effects of control measures on the work resumption. It shows that control measures do encourage work resumption amid the virus outbreak. When the epidemic decreases to a certain range of infections who are isolated by the public health department, the effects of other control measures are less clear to work resumption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: sample period from January 20 to March 10 2020							
Treat cities	-0.071	-0.068	-0.056	-0.087	-0.072	-0.072	-0.062
	(0.263)	(0.261)	(0.264)	(0.262)	(0.264)	(0.265)	(0.265)
×Public information campaigns$_{t-14}$	0.018***						
	(0.004)						
×Social distancing$_{t-14}$		0.017***					
		(0.004)					
×Contact tracing$_{t-14}$			0.031***				
			(0.008)				
×Health care$_{t-14}$				0.005**			
				(0.002)			
×Material logistics$_{t-14}$					0.015***		
					(0.003)		
×Fiscal measures$_{t-14}$						0.010***	
						(0.001)	
×Clear responsibility$_{t-14}$							0.024***
							(0.005)
Control variables	Y	Y	Y	Y	Y	Y	Y
Week fixed effect	Y	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y	Y
Observations	12428	12428	12428	12428	12428	12428	12428
Adjusted R^2	0.881	0.881	0.881	0.880	0.881	0.881	0.881
Panel B: sample period from March 11 2020 to March 28 2020							
Treat cities	-0.689**	-0.699**	-0.705**	-0.679**	-0.693**	-0.741**	-0.729**
	(0.308)	(0.308)	(0.309)	(0.308)	(0.308)	(0.311)	(0.308)
×Public information campaigns$_{t-14}$	0.019						
	(0.021)						
×Social distancing$_{t-14}$		-0.012					
		(0.018)					
×Contact tracing$_{t-14}$			-0.009				
			(0.028)				
×Health care$_{t-14}$				-0.031*			
				(0.017)			
×Material logistics$_{t-14}$					0.018		
					(0.021)		
×Fiscal measures$_{t-14}$						0.016	
						(0.014)	
×Clear responsibility$_{t-14}$							-0.058**
							(0.027)
Control variables	Y	Y	Y	Y	Y	Y	Y
Week fixed effect	Y	Y	Y	Y	Y	Y	Y
City fixed effect	Y	Y	Y	Y	Y	Y	Y
Observations	4366	4366	4366	4366	4366	4366	4366
Adjusted R^2	0.921	0.921	0.921	0.921	0.921	0.921	0.921

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

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