Using social media data to assess the impact of COVID-19 on mental health in China

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Abstract

The outbreak and rapid spread of COVID-19 not only caused an adverse impact on physical health but also brought about mental health problems among the public. To assess the causal impact of COVID-19 on psychological changes in China, we constructed a city-level panel data set based on the expressed sentiment in the contents of 13 million geotagged tweets on Sina Weibo, the Chinese largest microblog platform. Applying a difference-in-differences approach, we found a significant deterioration in mental health status after the occurrence of COVID-19. We also observed that this psychological effect faded out over time during our study period and was more pronounced among women, teenagers and older adults. The mental health impact was more likely to be observed in cities with low levels of initial mental health status, economic development, medical resources, and social security. Our findings may contribute to the understanding and control of COVID-19's mental health impact.

Introduction

The epidemic of coronavirus disease 2019 (COVID-19) has become a severe public health crisis[1]. In addition to the adverse impact on physical health, the outbreak and rapid spread of COVID-19 have also brought about mental health problems among the public, such as anxiety and depression[2-4]. To capture the psychological problems during the COVID-19 epidemic, online questionnaires and surveys are widely used in ongoing studies[5-9]. Researchers detect the symptoms of mental illness and identify risk factors by asking participants to answer well-designed questions and report their characteristics. The challenge of these traditional methods is that it is difficult to monitor the mental health condition in real time and understand its dynamic changes[10,11]. The large-scale and real-time data generated by the widespread use of social media provide an approach to overcome these problems. By applying Natural Language Processing (NLP), the expressed sentiment of tweets posted on the online social media platforms could be extracted from the text[12,13]. This is an effective indicator to reflect psychological response and has been increasingly used for measuring the mental health status[14-16].

In this study, we investigated how the COVID-19 epidemic affected mental health across China's cities using social media data from Sina Weibo, the largest microblog platform in China. The data included around 13 million geotagged tweets in mainland China between January 1, 2020 and March 1, 2020 from active Weibo users (see details in the 'Data' section of the Methods). For each tweet, we conducted the sentiment analysis to extract the expressed sentiment using the open-source NLP technique from Baidu[17]. Then we measured the daily mental health status for a city by calculating the median sentiment value based on tweets in that city on each day[18], which ranges from 0 to 1 with 0 indicating a strongly negative emotion and 1 indicating a strongly positive emotion. To quantify the causal effect of COVID-19 epidemic on mental health, we employed a difference-in-differences[19-21] (DiD) approach.

The details about empirical models and variables were provided in the 'Models' section of the Methods. The treatment group was defined as cities that have reported the first COVID-19 case. Following the definition, our analyses included 324 treated cities and 35 control cities, as described in Figs. 1 and 2. Specifically, the COVID-19 was first detected in Wuhan city in December 2019, but the pathogen was unknown and the severity was underestimated at first[22-24]. Therefore, the situation in Wuhan is different from other cities in treatment group and we excluded it from our data. We controlled daily air pollution and weather conditions since these factors could also affect the expressed sentiment on Weibo tweets[18]. The summary statistics of different variables are reported in Supplementary Table 1.

Our study has the following strengths and contributions. First, the scale of our data is large, which are collected based on a 20-million-level active user pool in Sina Weibo[25]. All geotagged tweets posted by these active users during our study period were selected and used to construct a national panel data set, covering 359 cities in China. Second, the DiD approach helps us to infer the causal relationship between COVID-19 epidemic and mental health. For example, since the occurrence of COVID-19 in China almost coincided with the Chinese Spring Festival (January 25, 2020), it is hard to distinguish the effect of the national holiday from the impact of COVID-19 epidemic just by before-after comparison[24,26]. In our DiD strategy, cities without COVID-19 cases can serve as the counterfactual and various confounding factors can be controlled in the model. So, we could plausibly identify the causal impact of COVID-19. Third, our comprehensive dataset allows us to examine whether COVID-19 disproportionately affects the mental health among different segments of the population, categorized by gender and age, and investigate whether the psychological effect varies across different types of city. Relying on these strengths, our findings may assist the policymakers to understand the impact of COVID-19 on mental health in detail using social media data and provide useful implications for the

psychological interventions especially when the second wave of the epidemic occurs.

Results

The impact of COVID-19 epidemic on mental health. We estimated the relative change in mental health status between the treated and control cities by equation (1). The results reported in Table 1 indicate that the occurrence of COVID-19 had a significantly negative impact on mental health. After reporting the first COVID-19 case, the mental health status measured by the median sentiment value of Weibo tweets in treated cities declined by 0.0097 relative to cities without COVID-19 cases when controlling air pollution, weather conditions and a set of fixed effects (in column (2)). This finding is consistent with our expectation which expects that both the coronavirus itself and subsequent transmission control measures such as lockdown could aggravate the mental health status[27,28].

We conducted some additional analyses to validate the robustness of our main finding. We first excluded cities in Hubei province, the worst-hit region in China during the epidemic. Similar results suggest that the psychological effect of COVID-19 is not only driven by these cities (Supplementary Table 2). We conducted further robustness check by replacing the dependent variable with the mean value (instead of the median value) of the expressed sentiment on Weibo tweets. The finding is still consistent (Supplementary Table 3). After the occurrence of COVID-19, our Weibo data may contain more tweets from those people who are more sensitive to COVID-19 since they participate more on social media during the epidemic, which may affect our results. To address this issue, we conducted a tweet-level analysis and controlled user fixed effects. The dependent variable is the expressed sentiment of each tweet, and the independent variable is a binary variable, which is equal to 1 when the tweet was posted after the city reported the first COVID-19 case, and 0 otherwise. We still observed similar results when

controlling the user fixed effects (Supplementary Table 4).

Although our results are consistent across various robustness checks, it is still possible that the decrease in the mental health status may be driven by some unobserved differences between the treatment and control groups. If this were true, the psychological effect of COVID-19 would be statistically significant with any ordering of COVID-19 occurrence in treatment cities. Thus, we carried out a random implementation model to determine how likely it was that a random occurrence of COVID-19 would yield an aggregate effect size comparable to our true estimates[29-31]. First, we randomly assigned COVID-19's pseudo-presence to our treated cities, and then estimated the effect of the random occurrence of COVID-19 using equation (1) to get the coefficient for the pseudo-treated (denoted as β_{pseudo}). This procedure was repeated 1,000 times and then we calculated the mean and standard deviation of β_{pseudo}. The Z-score was used to examine the difference between our original estimate β (reported in Table 1) and the mean of β_{pseudo}. In addition, we also replicated the whole procedure on all cities (instead of only the treatment group). The results show that the mean of β_{pseudo} is close to 0 and significantly different from the true estimate β (Supplementary Table 4). Therefore, our original estimation is not spurious, and the causal claim is strengthened as well.

Test for pre-treatment parallel trends. To test whether the parallel trends assumption in our DiD model is violated, we adopted an event study approach and fitted a relative time model (see equation (2) in Methods)[21,29,30]. This model could measure the difference in mental health status between treated and control cities in each period relative to the difference one week before the treatment. The estimated coefficients and their 95% confidence intervals are plotted in Fig. 3. We find that the estimated coefficients are not significantly different from 0 before the occurrence of COVID-19, suggesting that there is no systematic difference in trends between treated and control cities before the treatment. This

implies parallel trends assumption of our DiD model would be reasonable in the absence of the COVID-19 epidemic.

In addition to the test for pre-treatment parallel trends, this relative time model could also examine whether the impact of COVID-19 epidemic on mental health status among the public changes over time. We expect that the estimated coefficients are negative and statistically significant at first after the occurrence of the epidemic, and then become not significantly different from 0 in subsequent periods because the psychological effect is likely to fade out when the epidemic tends to be stable during our study period. All results shown in Fig. 3 are consistent with our expectation except for the estimated coefficient in one week after the occurrence of COVID-19 epidemic. The unexpected result is probably due to the temporary "pulling together" or "honeymoon period" phenomenon[32-34]. That is, to fight with COVID-19, social connectedness, community cohesion and mutual support are enhanced, mitigating the negative psychological impact of the epidemic. More future studies are needed to explore the underlying mechanisms. Besides, we also obtained similar results when using the mean sentiment value as the dependent variable in equation (2) (Supplementary Figure 1).

Heterogeneity across different subpopulations and cities. To investigate the heterogeneous effects of COVID-19 epidemic on mental health, we conducted two types of heterogeneity analyses. In the first analysis, we examine whether different subpopulations are disproportionately affected by the occurrence of COVID-19. To do so, we divided the tweets data into subgroups according to the self-reported gender and age information of the Weibo users. Then we calculated the daily city-level mental health status for each subgroup by the same method mentioned before and estimated equation (1) separately. The disproportionate effects on mental health among different gender and age groups are shown in Fig. 4. We find that women are more susceptible to the psychological impact of COVID-19. After the occurrence of

this epidemic, the negative effect on mental health is more pronounced among teenagers (younger than 18 years old) and older adults (older than 45 years old). Collectively, these results imply that, by and large, the adverse psychological outcomes caused by COVID-19 are more likely to be observed among the vulnerable groups.

In the second heterogeneity analysis, we investigate whether the psychological effect of COVID-19 varies across different types of cities. We first collected socio-economic statistics reported in the 2019 China City Statistical Yearbook[35] for the cities in our data, such as regional GDP and the number of hospitals (see 'Data' in Methods). For the initial mental health status, we measured it by using the median sentiment value of tweets posted in each city during the first week of our study period. Then our data were partitioned into High and Low based on the median value for each factor. For example, if the regional GDP in a city is lower than the median GDP, it falls into a low GDP group, otherwise a high GDP group. The psychological effect was estimated separately using equation (1) based on data in each subgroup. We expect that the deterioration of mental health after COVID-19's occurrence is more likely to be observed in cities with low levels of economic development, medical resources, and social security, since these areas own poor financial, material and human support in the fight against this epidemic and the provision of mental health service. Our conjecture is confirmed in Fig. 5a-c: the negative effect is more notable in the low group. In Fig. 5d, we find that cities with poor initial mental health status are more susceptible to the psychological impact of COVID-19, so more related measures should be taken in these areas after the occurrence of epidemic.

Discussion

In addition to the physical harm, the outbreak and rapid spread of COVID-19 has caused some additional

effects, such as the improvement in air quality[21] and the changes in mental health[28]. To fully understand the influence of this unprecedented event, we need to quantify these additional effects and this paper is an essential component. Our findings in this study could contribute to answering three research questions related to COVID-19's mental health impact.

First, does COVID-19 has a causal effect on the psychological changes reflected on social media in China? Applying a DiD approach on a comprehensive panel data set, our analyses reveal a deterioration in mental health status caused by the occurrence of COVID-19 among users on Sina Weibo, the Chinese equivalent of Twitter. This finding is robust in a set of robustness checks. However, the mental health measure is derived from the people who post tweets on social media. Although this group contains a large number of people, we acknowledge that it is not randomly drawn from the full population. Little children and people who are very old are less likely to use Sina Weibo[18,36], and these individuals in fact may be more vulnerable to the COVID-19's psychological effect[37,38]. Therefore, our results may underestimate the overall adverse effect of COVID-19 epidemic on the mental health status of a representative sample of the full population.

This finding also provides new evidence that the expressed sentiment by Chinese social media users could provide a real-time spatiotemporal indicator of how the public's psychological status changes during the epidemic. Because of the embarrassing attitude, poor recognition of mental illness, low perceived need for treatment, and the limited knowledge of available services, a large number of people with mental health problems have not been detected in China[39]. Under these circumstances, it is an effective approach for the governments and policymakers to monitor the psychological response in real time on the social media and then provide timely mental health services. For example, the social media platform could easily evaluate a user's mental health status by sentiment analysis and take the initiative

to recommend information about mental health knowledge and services through recommender systems when this user suffers psychological problems.

Second, does the psychological impact of COVID-19 fade out as the epidemic tends to be stable over time? The results of our relative time model show that the effect of COVID-19 on mental health is likely to fade out during our study period. But our results do not allow us to draw any conclusion that the psychological effect will disappear in the long term although the epidemic in China has been almost controlled. The end of this COVID-19 epidemic could not mean the disappearance of its effect on mental health among the public. The socio-economic effects caused by COVID-19, like economic recession and social inequalities, are also harmful to our mental health status in the post-epidemic era, which might last for a long period of time[40]. Besides, a group of people may have difficulties in adjusting back to normal life when the epidemic is over, such as the students[41]. For example, during the COVID-19, students have to adapt themselves to online study. However, if the schools are reopened, they have to readjust to the traditional classes. The frequent shifts in lifestyle could bring about further psychological problems. The assessment of these subsequent impacts on mental health may be complex and need further rigorous analysis.

Third, does the effect of COVID-19 on mental health vary across different population groups and cities? Our first heterogeneity analysis shows that the psychological effect is more pronounced among women, teenagers (younger than 18 years old) and older adults (older than 45 years old). Thus, we should pay more attention to these vulnerable people when providing mental health services. Nevertheless, we are unable to capture the heterogeneous effects on little children and people who are very old, due to the limitation of the age distribution of Weibo users[18,36]. Traditional questionnaires and surveys may be better methods to investigate the psychological impact on these population groups. The results of the second

heterogeneity analysis imply that COVID-19's mental health impact is more likely to be observed in cities with low levels of initial mental health status, economic development, medical resources, and social security. So, people with poor mental health status before COVID-19 and those living in underdeveloped areas that lack financial, material and human support could suffer more serious mental health problems. This finding may help the government to grasp the point in decision making. For example, when allocating public resources and providing mental health support, giving priority to these areas at high risk may make the inputs produce more benefits. Additionally, the heterogeneity analysis also reminds us of the important role of the economic state, medical resources, and social security in mitigating the negative psychological effect.

We conclude this paper by pointing out several directions for future research. First, we only focus on the text of tweets. However, some tweets contain other types of valuable data, such as pictures and videos, which provide rich information[42]. More further studies are needed to extract sentiment from them and take advantage of these data to measure the psychological response more accurately. Besides, bad mental health status could lead to subsequent severe consequences, like suicide behaviour[43]. This suggests the need to collect related data to quantify the causal impact of COVID-19 on these adverse outcomes. In addition, the outbreak of COVID-19 simultaneously brought about infodemic[44]. The rapid spread of misinformation through social media platforms may also affect mental health, and assessing this phenomenon is a meaningful task[45]. We believe that our findings in this study, together with future research, will assist the understanding of COVID-19's mental health impact and yield useful insights on how to make effective psychological interventions in this kind of sudden public health event.

Methods

Data. *Social media data*. Sina Weibo (https://www.weibo.com/), the Chinese equivalent of Twitter, is the largest microblog platform in China. Large-scale data access is difficult for Weibo because of the limitation of its application programming interface (API)[46]. Our Weibo data were obtained based on a pool of 20 million active users[25], which was selected from over 250 million Weibo users generated by snowball sampling. We collected all geotagged tweets of these active users between January 1, 2020 and March 1, 2020. Geotagged tweets mean that the users share their location information based on the exact latitude and longitude when they post these tweets. Then, 13 million geotagged tweets in mainland China during our study period were selected, including the gender and age information of their users.

Using these data, we conducted our sentiment analysis by applying the SKEP model[17] from Baidu Senta (an open-source python library) published in 2020, which integrated sentiment knowledge into pre-trained models and achieved new state-of-the-art results on most of the test datasets. For each tweet, the sentiment analysis could return two probabilities representing the intensity of the positive and negative emotions based on the text, and the sum of these two probabilities is 1. In this study, we used the positive probability as a measurement of the user's mental health status at the time when the tweet was posted. The daily mental health status for a city is measured by calculating the median positive probability for that city on each day[18]. This city-level mental health status ranges from 0 to 1 with 0 indicating a strongly negative emotion and 1 indicating a strongly positive emotion. We also calculated the mean value of the positive probabilities and used it to measure city-level mental health status in our robustness check.

COVID-19 epidemic data. In this paper, the treatment group was defined as cities that have reported the first COVID-19 case. We collected the date of the first confirmed case in each city from the official

238 websites of local health commissions. COVID-19 was first detected in Wuhan city in December 2019,
239 but the pathogen was unknown at first and human-to-human transmission was not verified. So, the
240 situation in Wuhan is different from other cities in the treatment group and we excluded Wuhan from our
241 data. Finally, our data included 324 treated cities and 35 control cities. The geographical distribution of
242 these 359 cities and the cumulative number of treated cities by March 1, 2020 are presented in Figs. 1
243 and 2.

244 *Air pollution and weather data*. Since air pollution and weather conditions could affect the expressed
245 sentiment on social media[18], these confounders should be controlled in our analyses. In China, the air
246 quality index (AQI) is a composite measure of air pollution, constructed by the concentrations of $PM_{2.5}$,
247 PM_{10}, SO_2, CO, O_3 and NO_2[47]. A lower AQI means better air quality. We collected daily city-level AQI
248 data from the Ministry of Ecology and Environment in China (https://datacenter.mee.gov.cn/). City-level
249 weather data including daily mean temperature, wind speed, rainfall and cloud, were obtained from an
250 online platform called Huiju Data (http://hz.zc12369.com/), which collects data from China
251 Meteorological Administration (CMA).

252 *Socio-economic data*. To explore the heterogeneity across cities, we collected the cities' socio-economic
253 status from the 2019 China City Statistical Yearbook[35]. These data contain city-level statistics reflecting
254 economic development, medical resources, and social security level.

255 *Summary statistics*. The summary statistics of different variables between January 1, 2020 and March 1,
256 2020 are reported in Supplementary Table 1. The average city-level mental health status was 0.6397,
257 with a standard deviation of 0.0684. We observed a decline in the mental health status of treated cities
258 after reporting COVID-19 cases.

259 **Models.** We used a difference-in-differences (DiD) model to identify the impact of COVID-19 epidemic

on mental health in China. This model could estimate the relative change in mental health status between the treated and control cities, specified as follows:

$$Y_{it} = \alpha + \beta \cdot \mathrm{COVID\_19}_{it} + \gamma \cdot \mathrm{X}_{it} + \mu_i + \pi_i + \varepsilon_{it} \quad (1)$$

where Y_{it} represents the mental health status in city i on date t measured by the social media data. $\mathrm{COVID\_19}_{it}$ denotes whether the COVID-19 epidemic has occurred in city i on date t, and takes the value 1 if the city has reported the first COVID-19 case and 0 otherwise. X_{it} are the control variables, including AQI, mean temperature, mean temperature squared, rainfall, wind speed and cloud. μ_i indicate city fixed effects, which are a set of city-specific dummy variables. By introducing the city fixed effects, we can control for time-invariant confounders specific to each city, such as geographical conditions and short-term economic level. π_i indicate the date fixed effects, which are a set of dummy variables accounting for shocks that are common to all cities on a given day, such as the Chinese Spring Festival Spring and nationwide policies. In this specification, both location and time fixed effects are included in the regression, so the coefficient β estimates the difference in mental health status between the treatment cities and the control cities before and after the occurrence of the COVID-19 epidemic. We expected β to be negative, as both the coronavirus itself and counter-COVID-19 measures such as lockdown could harm the mental health[27,28].

The underlying assumption for the DiD estimator is that treatment and control cities would have parallel trends in mental health status in the absence of the COVID-19 event. Even if the results show that mental health status declines in treated city after the occurrence of COVID-19, the results may not be driven by the epidemic, but by systematic differences in treatment and control cities. For example, if treatment cities have a decreasing trend in mental health status and the control cities not, this could also drive the results. Although we cannot observe what would happen to mental health in the treated cities if

the COVID-19 epidemic did not occur, we can still examine the parallel trends in mental health for both groups before the COVID-19 epidemic and investigate whether the two groups are comparable. To achieve this goal, we adopted an event study approach using the following relative time model[29,30,48]:

$$Y_{it} = \alpha + \sum_{m=k,m\neq-1}^{M} \beta^k \cdot \mathrm{COVID\_19}_{it,k} + \gamma \cdot \mathrm{X}_{it} + \mu_i + \pi_i + \varepsilon_{it} \quad (2)$$

where $\mathrm{COVID\_19}_{it,k}$ are a set of dummy variables, which indicate the treatment status at different periods (weeks). Here, 7 days (one week) are put into one bin (bin $m \in M$), so the high volatility of the daily mental health level could not affect the trend test[21]. We omit the dummy for $m = -1$ (one week before the event), so the coefficient β^k measures the difference in mental health status between the treatment and control cities in period k relative to the difference one week before the treatment. This specification could not only test the parallel trend assumption, but also examine whether the impact of COVID-19 epidemic fades out over time. If the pre-treatment trends are parallel, the coefficient β^k would be not significantly different from zero when $k \leq -2$. The psychological effect of COVID-19 would fade out over time during our study period if we observe that β^k is negative at first and then becomes not significantly different from zero in subsequent periods when $k \geq 0$. In all analyses, the standard errors were clustered at the city level.

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Author Contributions

Y.Z. and J.X. conceptualized the study and implemented the initial research plan. Y.Z. and A.C. contributed to the data collection and cleaning. Y.Z. carried out the statistical analysis and performed the figure production, which was refined by J.X. and Y.Y. for the final version. Y.Z. prepared the original draft of the manuscript and J.X. revised it. All authors reviewed the manuscript and approved the final version for publication.

Competing Interests statement

The authors declare no competing interests.

Figures

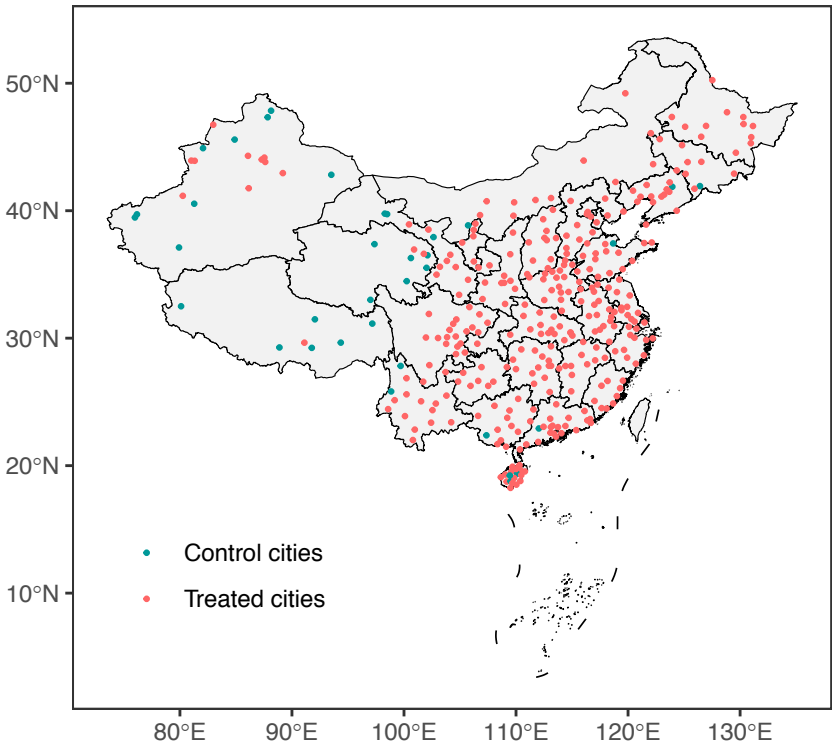


Fig. 1 | The geographical distribution of 359 cities. As of March 1, 2020, 324 cities (Wuhan was excluded) have reported COVID-19 cases and the rest is the control group, including 35 cities.

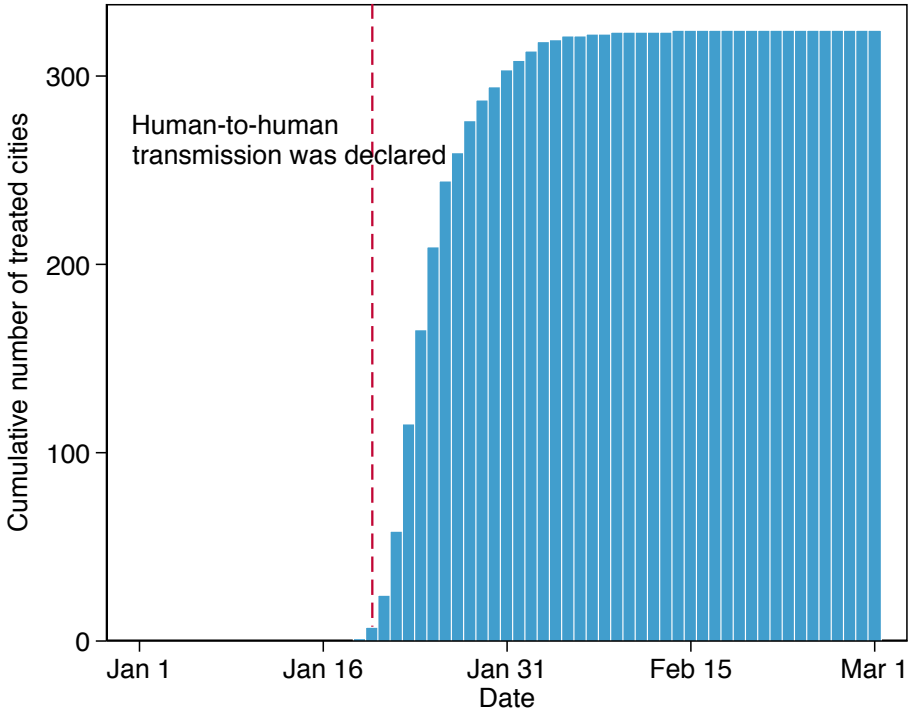


Fig. 2 | The time trend of the cumulative number of treated cities. The cumulative number of cities that have reported COVID-19 cases from January 1, 2020 to March 1, 2020 are shown. Human-to-human transmission was declared on January 20, 2020.

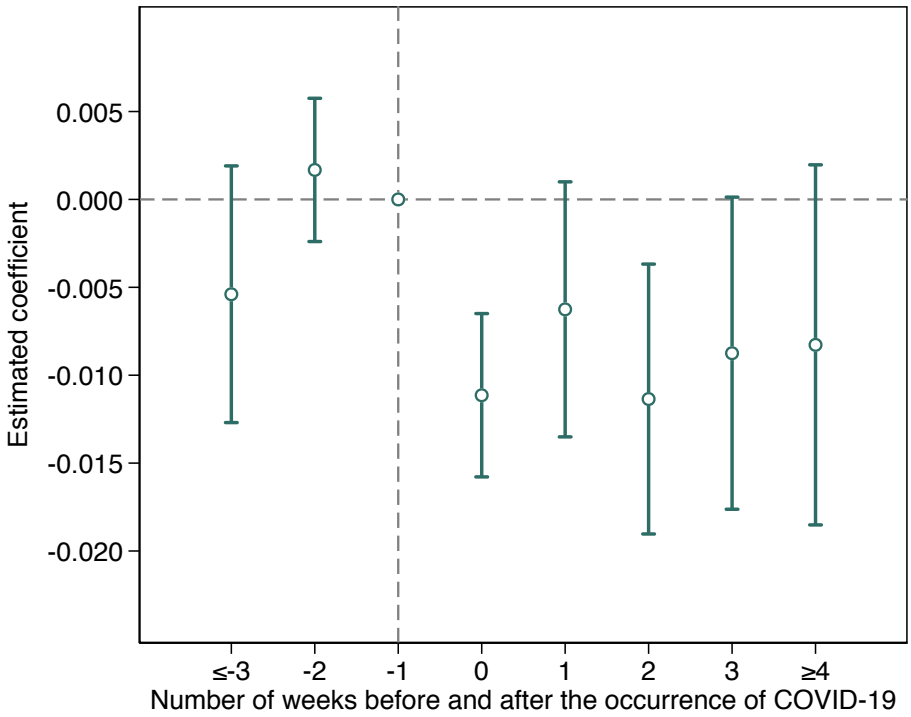


Fig. 3 | The effect of COVID-19 on mental health over time. The estimated coefficients from equation (2) and their 95% confidence intervals (error bars) are shown. The dummy variable indicating one week before the occurrence of COVID-19 is omitted from the regression (see Methods). Thus, the difference in mental health status between treated and control cities one week before the treatment is set to be zero and serves as the reference point. The estimation signifies the difference in mental health status in each period relative to the difference one week before the treatment.

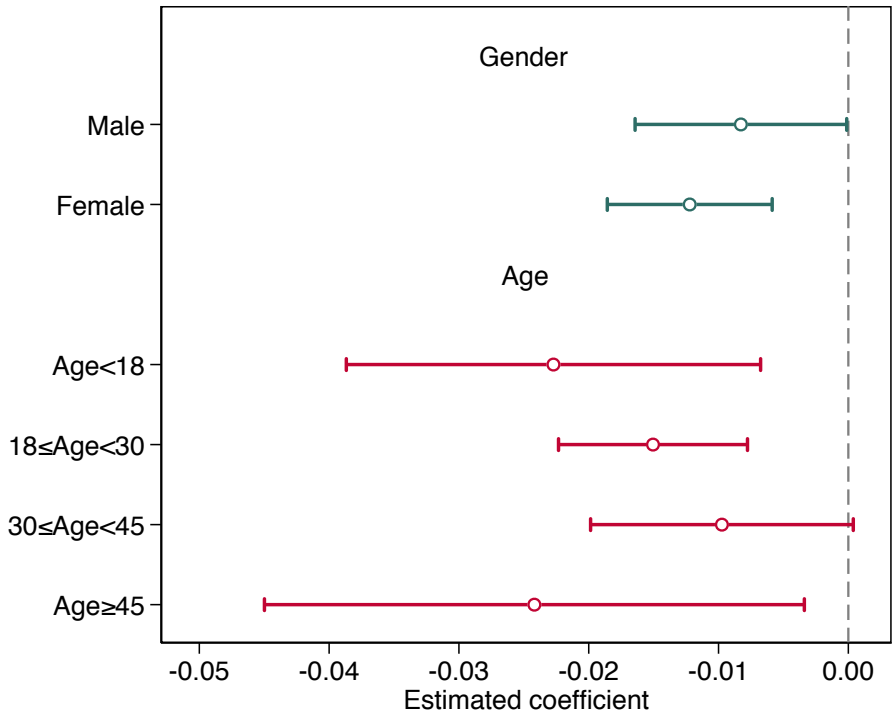


Fig. 4 | The heterogeneous effects of COVID-19 on mental health across different subpopulations. Each row means a separate regression using equation (1) on the corresponding subsample. We use the gender and age information of Weibo users to separate our data. The estimated effects of COVID-19 and their 95% confidence intervals (error bars) are plotted.

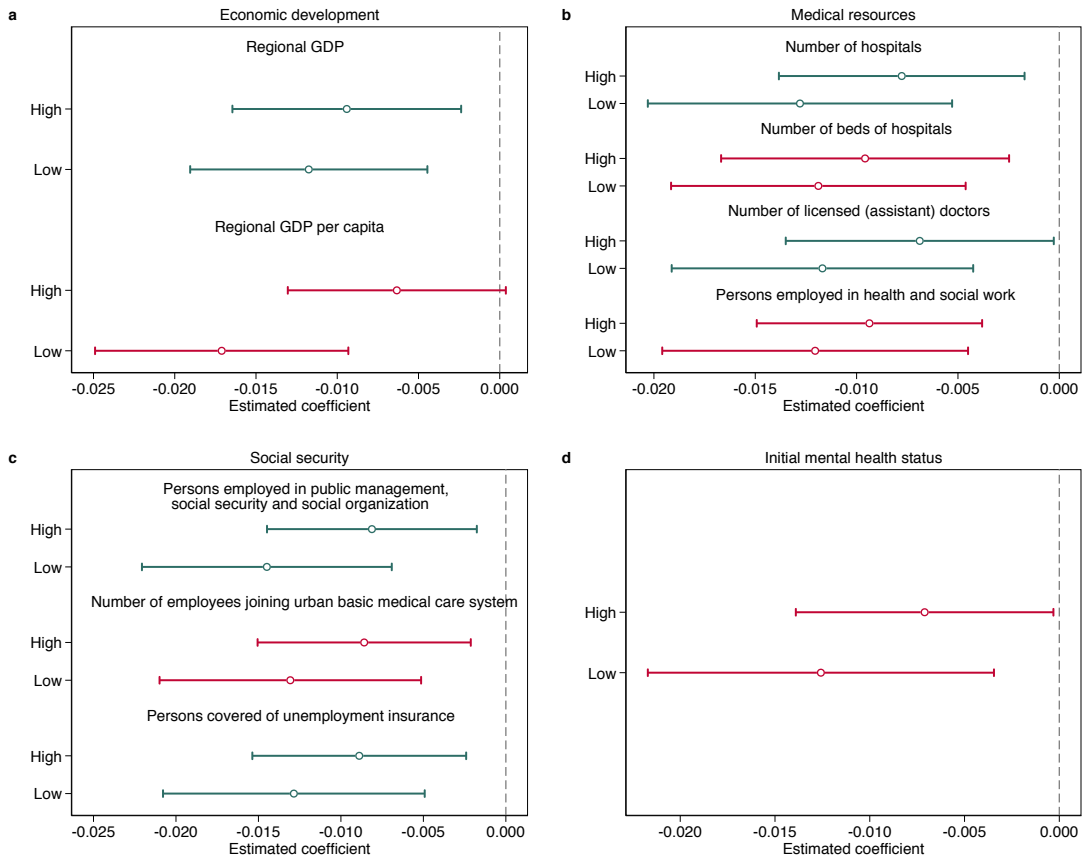


Fig. 5 | The heterogeneous effects of COVID-19 on mental health across cities. These heterogeneity analyses are divided into four categories: economic development (**a**), medical resources (**b**), social security (**c**) and initial mental health status (**d**). Data are partitioned into High and Low based on the median value for each factor. Each row means a separate regression using equation (1) on the corresponding subsample. The estimated effects of COVID-19 and their 95% confidence intervals (error bars) are plotted.

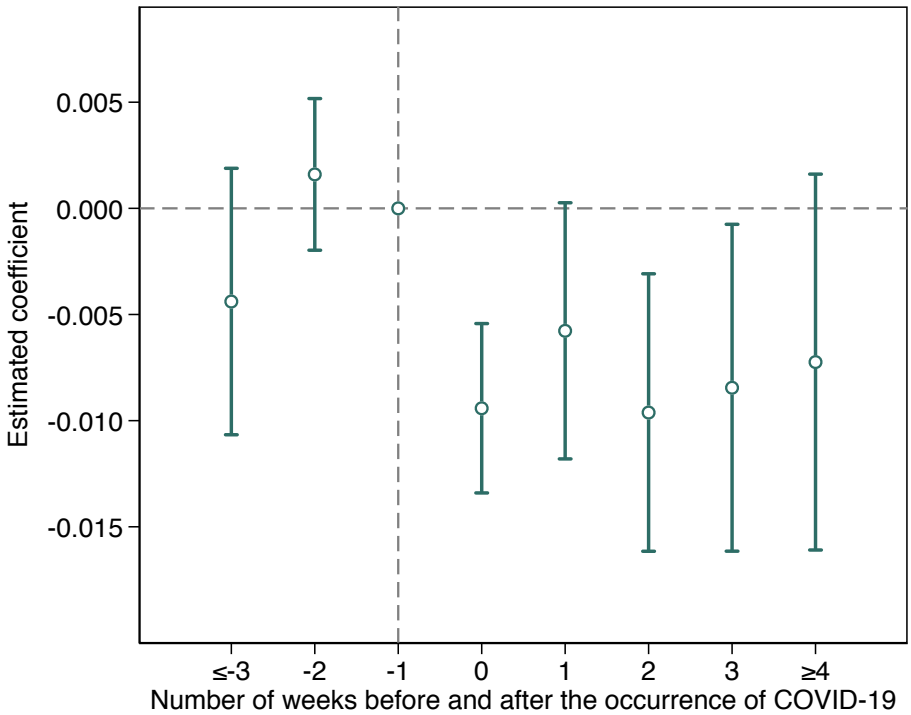
Tables

Table 1 | The effect of COVID-19 on mental health

	(1)	(2)
COVID-19	-0.0091**	-0.0097***
	(0.0028)	(0.0029)
Air pollution and weather conditions		Yes
City fixed effects	Yes	Yes
Date fixed effects	Yes	Yes
Observations	21,882	19381
R^2	0.4654	0.5539

Note. Due to some missing values of air pollution and weather data, the numbers of observations in the two columns are not the same. Standard errors are clustered at the city level and shown in parentheses. *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

Supplementary Information



Supplementary Figure 1 | The effect of COVID-19 on mental health over time using mean sentiment value as the dependent variable. The estimated coefficients from equation (2) and their 95% confidence intervals (error bars) are shown. The dummy variable indicating one week before the occurrence of COVID-19 is omitted from the regression (see Methods). Thus, the difference in mental health status between treated and control cities one week before the treatment is set to be zero and serves as the reference point. The estimation signifies the difference in mental health status in each period relative to the difference one week before the treatment.

Supplementary Table 1. Summary statistics

	All cities (1)	Treatment group		Control group (4)
		Before treatment (2)	After treatment (3)	
Dependent variable				
City-level mental health status	0.6397	0.6535	0.6311	0.6363
	(0.0684)	(0.0633)	(0.0618)	(0.1043)
Independent variable				
COVID-19	0.5441	0	1	0
	(0.4981)	(0)	(0)	(0)
Control variables				
AQI	78.1637	94.8988	68.3883	71.3907
	(52.2649)	(61.7197)	(40.0593)	(60.0207)
Mean temperature (°C)	4.4893	3.2688	6.2043	-0.7453
	(9.9080)	(10.4081)	(8.9934)	(10.4503)
Wind speed (m/s)	1.6052	1.4402	1.7470	1.4145
	(1.1122)	(1.0115)	(1.1816)	(0.9365)
Rainfall (mm)	1.3692	1.3008	1.5826	0.4021
	(4.8751)	(4.4224)	(5.4289)	(2.3889)
Cloud (%)	61.8355	66.9818	59.6237	54.6302
	(36.1747)	(34.8240)	(37.0007)	(33.7333)

Each column summarizes the mean values and standard deviations of different variables in our panel data.

Supplementary Table 2. The effect of COVID-19 on mental health after excluding cities in Hubei province

	(1)	(2)
COVID-19	-0.0082**	-0.0090**
	(0.0028)	(0.0028)
Air pollution and weather conditions		Yes
City fixed effects	Yes	Yes
Date fixed effects	Yes	Yes
Observations	20,906	18771
R^2	0.4662	0.5541

Due to some missing values of air pollution and weather data, the numbers of observations in the two columns are not the same. Standard errors are clustered at the city level and shown in parentheses. *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

Supplementary Table 3. The effect of COVID-19 on mental health using mean sentiment value as the dependent variable

	(1)	(2)
COVID-19	-0.0071**	-0.0084***
	(0.0027)	(0.0027)
Air pollution and weather conditions		Yes
City fixed effects	Yes	Yes
Date fixed effects	Yes	Yes
Observations	21,882	19381
R^2	0.5070	0.5947

Due to some missing values of air pollution and weather data, the numbers of observations in the two columns are not the same. Standard errors are clustered at the city level and shown in parentheses. *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

Supplementary Table 4. Assessing the effect of COVID-19 on mental health at the tweet level

	(1)	(2)	(3)
COVID-19	-0.0084***	-0.0087***	-0.0089***
	(0.0014)	(0.0014)	(0.0011)
Air pollution and weather conditions		Yes	Yes
User fixed effects			Yes
City fixed effects	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes
Observations	13,478,142	12,983,153	11,895,215
R^2	0.0165	0.0168	0.2958

The numbers of observations in columns (2) and (3) are different since the users only posting one tweet were dropped in column (3). Standard errors are clustered at the city level and shown in parentheses. *$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.

Supplementary Table 5. Randomized occurrence time of COVID-19 (Placebo Test)

	Randomization	
	On treated cities	On all cities
	(1)	(2)
Mean of β_{pseudo}	-0.0006	0.0000
standard deviation of β_{pseudo}	0.0014	0.0015
Estimated β	-0.0097	-0.0097
Replication times	1000	1000
Z-score	211.4830	203.2985
p-value	<0.0001	<0.0001

The randomization refers to the procedure of randomly assigning COVID-19's pseudo presence to treated cities and all cities, respectively, with 1,000 times of repetition. β_{pseudo} is the coefficient for COVID-19's pseudo presence, and β is the true coefficient for COVID-19's occurrence reported in Table 1; both were estimated using equation (1).