DISCUSSION PAPER SERIES

Uneven Recovery from the COVID-19 Pandemic: Post-lockdown Human Mobility Across Chinese Cities

Yanyan Liu
Shuang Ma
Ren Mu

Uneven Recovery from the COVID-19 Pandemic: Post-lockdown Human Mobility Across Chinese Cities

Yanyan Liu
International Food Policy Research Institute

Shuang Ma
Guangzhou University

Ren Mu
Texas A&M University and IZA

MARCH 2021

ABSTRACT

Uneven Recovery from the COVID-19 Pandemic: Post-lockdown Human Mobility Across Chinese Cities*

How quickly can we expect human mobility to resume to pre-pandemic levels after lockdowns? Does pandemic severity affect the speed of post-lockdown recovery? Using real-time cross-city human mobility data from China and a difference-in-difference-in-differences framework, we find that mobility in most cities resumed to normal six weeks after reopening. In contrast, the epicenter cities, those with the worst outbreaks, were slow to recover; twelve weeks after reopening, mobility had not returned to the pre-pandemic levels. We provide suggestive evidence that relatively undiminished pandemic concerns may have slowed down mobility recovery in the epicenter region. Our findings imply that a severe pandemic experience impedes post-lockdown mobility recovery. From a policy perspective, this study suggests that it is important to successfully contain the pandemic to achieve a faster post-lockdown recovery.

Corresponding author:
Ren Mu
The Bush School of Government and Public Service
Texas A&M University
4220 TAMU
College Station, TX 77840
USA

E-mail: rmu@tamu.edu

The world is currently seeking to contain the devastating spread of the COVID-19 virus. In the absence of effective antiviral treatments and vaccines, people must reduce social interactions to lower the risk of becoming infected. But individual voluntary prevention efforts are often not enough to achieve a socially optimal public health outcome (Toxvaerd, 2020). As a result, governments have employed various types of lockdown measures to reduce human mobility and, in turn, to reduce the social interactions that spread infection (Ferguson et al., 2006).[1] Thus far, the pandemic has followed an epidemiological curve of disease transmission, with acceleration and deceleration phases (CDC, 2018). While the number of COVID-19 cases and fatalities accelerated sharply in some countries, other countries exhibited continuing declines. This global transmission pattern was reflected in the shifting of the pandemic's epicenter, from Wuhan in China in January and February 2020, to the Lombardy region in Italy in early March, and to New York City in early April (Zhang et al., 2020). As the pandemic abated, many countries started to reopen their economies.

In this paper, we take an important early step toward understanding what may affect economic and mobility recovery from the COVID-19 pandemic. More specifically, We ask two questions: how quickly can we expect human mobility to resume to pre-pandemic levels? Does pandemic severity affect the speed of post-lockdown recovery? The answers to these questions will help us not only gain knowledge about the post-lockdown recovery process but also understand the possible linkages between the pandemic containing effort and the post-lockdown recovery experience. To shed light on these questions, we leverage multiple datasets from China, the country first hit by the pandemic and one of the first to reopen the economy, to examine how much and how soon the human mobility across cities in China has recovered from the pandemic lockdown, and how different the recovery process was for cities with acute outbreaks and cities with mild or no pandemic outbreaks. Human mobility – which we define as the number of people traveling into and out of the 327 cities throughout the country – serves as a proxy for economic vibrancy and offers a measure of societal normalcy. Change in the real-time human mobility measure also provides an alternative indicator of economic recovery other than gross domestic product (GDP) growth numbers.[2]

In the empirical analysis, we first employ an event study analysis, with two events: the lockdown and the reopening in the cities, to examine the dynamics of the population flow in the years of 2019 and 2020 before-, during-, and after- the lockdown period. Then using a difference-in-differences-in-differences (DDD) framework, we analyze the extent to which mobility has recovered to the pre-pandemic levels and how the recovery has varied across cities while controlling for

---

[1] In April 2020, about one-third of the world's population was under some form of government-mandated lockdown (Buchholz, April 23, 2020).

[2] The Chinese economy grew at 4.9 percent in the July-to-September quarter in 2020 compared with the same months in 2019, according to the National Bureau of Statistics of China (Bradsher, November 19, 2020).

city fixed effects, weather conditions, holiday fixed effects, and day-of-week effects to disentangle the pandemic-related effects from confounding factors. We find that in epicenter cities that had the first, worst outbreaks and also the most delayed responses, mobility had not fully returned to pre-pandemic levels 12 weeks after reopening; by contrast, the mobility among non-epicenter cities returned to normal six weeks after reopening. To further understand what may have driven the differences in mobility recovery, we investigate how public pandemic concerns evolved over time, and whether regional patterns of public concerns match regional patterns of mobility recovery. We measure the public pandemic concerns using the number of pandemic-related online postings and media mentions as proxies. We show that the post-lockdown public concerns about the pandemic were much higher in the epicenter regions. This provides suggestive evidence that the relatively undiminished pandemic concerns may have deterred fast mobility recovery post-lockdown in the epicenter regions.

Our investigation of the dynamics of human mobility around the time of the lockdowns in China adds to the growing number of studies on the impacts of the lockdown policies implemented by governments of different countries during this pandemic. Lockdown measures have been largely effective in inducing social distancing by reducing human interactions and mobility (Painter and Qiu, 2020; Andersen, 2020; Friedson et al., 2020; Fang et al., 2020). Consequently, these policies have achieved substantial public health benefits by helping contain virus transmission, avert hospitalizations, and lower fatalities (Friedson et al., 2020; Fang et al., 2020; Gatto et al., 2020; Glaeser et al., 2020a). However, such policy responses, combined with the pandemic outbreak itself, have tremendously strained countries' economies, leading to a steep rise in unemployment, a sharp drop in labor force participation, the closure of many small businesses, and increased indebtedness and starvation of the poor (Coibion et al., 2020; Fairlie, 2020; Montenovo et al., 2020; Ray and Subramanian, 2020). Our analysis confirms that mobility drastically reduced after the implementation of lockdown measures. Moreover, we detected a surge in mobility right before the announcement of the first lockdown ever during this pandemic.

Our focus on the post-lockdown mobility recovery of cities with different pandemic experiences provides one of the first evidence about the heterogeneous recovery process amid this pandemic. Although which reopening policies are optimal remains a subject of debate (Baqaee et al., 2020; Favero et al., 2020), recent studies show that reopening policies are associated with an overall immediate increase in human mobility, including for both work and non-work-related purposes in the United States (Nguyen et al., 2020; Cheng et al., 2020; Glaeser et al., 2020b). During the recovery phase in the United States, Lee et al. (2021) finds that the demographic and socioeconomic groups hit harder initially by the pandemic have recovered faster. Our study distinguishes from these emerg-

ing studies by investigating the recovering process in a different country and highlighting a clear linkage between the severity of the pandemic and the speed of post-lockdown recovery. The related findings contribute to our understanding of factors that may impede or facilitate mobility recovery after infection cases decline and lockdown measures are lifted.

Our study also sheds light on the effectiveness of China's pandemic response in terms of its post-lockdown mobility recovery. China is known for mishandling the very early stages of the epidemic in the epicenter region (Murphy, 2020). On December 31, 2019, the World Health Organization picked up a media statement by the Wuhan Municipal Health Commission from their website on cases of 'viral pneumonia' (WHO, June 29, 2020), but an open and public policy response was not initiated until January 23, 2020, when Wuhan City was locked down. Since then China has been vigilant in its domestic pandemic responses. Within one week after the lockdown of Wuhan, all 31 province-level divisions (or provinces for simplicity) in mainland China activated a first-level public health emergency response.[3] By the end of January 2020, all cities and rural areas across the country were under lockdown (Zhang et al., 2020). In response to the different pandemic phases, China's policies shifted from strict containment measures to a gradual easing of those measures to reopen the economy. As the number of confirmed infection cases decreased in late February, 9 provinces downgraded the level of emergency response and began to reopen their economies.[4] As of March 24, according to one estimate, three-quarters of China's workforce was back on the job (Normile, 2020). The final lifting of all lockdowns in Hubei Province on May 2, 2020, signaled the start of the return of normalcy in the country. Our analysis reveals that the recovery of human mobility in a region depends on its pandemic experience, which is closely linked to the timeliness of policy responses. Epicenter cities, where the policy responses were delayed, suffered the most severe outbreaks and also experienced the slowest mobility recovery. The findings emphasize the importance of successfully containing the pandemic to achieve a faster restoration of economic and social activities after the lockdown.

The paper proceeds as follows. Section I describes the data. Section II explains the empirical methods. Section III presents our results, and Section IV concludes.

I.   Data

For the empirical analysis, we use data on daily human mobility across cities, supplemented by weather data, administrative data on daily COVID-19 cases by city, policy data on lockdown and

---

[3]This response involved mobilizing resources for the public health sector and implementing measures to curb mass gatherings and population mobility.

[4]The 9 provinces were Shanxi, Jilin, Jiangsu, Anhui, Fujian, Guangdong, Sichuan, Niangxia, and Xinjiang.

reopening dates by city, and province-level data on social media postings and local news coverage.

Human Mobility Data   We collected population flow data from Gaode Map,[5] which is the most popular map app in China.[6] This dataset provides information on the daily human mobility index (an index of 1 representing 152,624 persons) based on real-time location records for every smartphone using the Gaode Map app in 327 Chinese cities from December 21, 2019, to June 15, 2020. Fig. 1 depicts daily total population flow (including both inflow and outflow) during the study period. As the lockdown dates coincide with the annual Spring Festival travel rush, the world's biggest annual human migration (Wang and Cripps, January 23, 2019), in Fig. 1 we also show the daily population flow from January 1, 2019, to June 27, 2019, as a reference (depicted by the blue line). The dates in 2019 and 2020 are matched based on the lunar calendar and marked by the number of days relative to the lockdown date of Wuhan. The average daily cross-city population flow was about 29.3 million in 2019 and 30.4 million in 2020. Population flows peaked at the times of national holidays, such as the Qingming Festival, Labor Day, and the Duanwu Festival,[7] with the exception of the Spring Festival of 2020 (January 23, 2020) after the lockdown measures were implemented. Population flows of the two years diverged widely which occurred during the lockdown period and mobility dipped significantly in 2020.

Weather Data   Weather conditions are an important factor influencing human travel behavior. To control for these confounding factors, we merged the population flow data with daily temperature and precipitation data from the European Center for Medium-Range Weather Forecasts (ECMWF) by linking the centroid of a city with the nearest grid point from the weather data.

Daily Infection Cases Data   To capture the severity of the pandemic over time and space, we collected the daily number of confirmed new COVID-19 cases for each city from the Chinese Center for Disease Control and Prevention (China CDC). This data is based on laboratory test results throughout China. The overall accuracy of these officially reported numbers has been questioned and it is reasonable to expect that the data is less reliable in cities in Hubei, the epicenter province than in other provinces, especially during the early stage of the outbreak. This is due to the lack of medical and test capacity, and the incentives of local governments at that time to downplay the

---

[5]For more information on Gaode Map, see https://trp.autonavi.com/migrate/page.do.

[6]In 2019, Gaode Map was used by 33 percent of e-map users. Baidu Map, used by 32.7 percent of users, was the second-most popular map app.

[7]In the figure, the Qingming Festival corresponds to around 60 days after Wuhan lockdown in 2019 and 70 days after Wuhan lockdown in 2020; Labor Day is around 90 days in 2019 and 100 days in 2020; the Duanwu Festival is around 125 days in 2019 and out of the study period for 2020.

severity of the outbreak (Fang et al., 2020). According to the data, three cities in Hubei Province — Wuhan, Xiaogan, and Erzhou — accounted for 69 percent of all confirmed infection cases before June 2020. These three cities are categorized as epicenter cities in our study.

Lockdown and Reopening Dates   In all provinces except Hubei Province, lockdown and reopening orders were made at the province level. The lockdown order was signaled by the declaration of the first and highest level of public health emergency response; the reopening order was declared by downgrading the emergency response level from the first to the second grade. Hubei Province implemented lockdown measures to restrict population mobility and later lifted such restrictions city by city, based on the pandemic severity at the city level. We collected all lockdown and reopening dates for each city in Hubei Province and each province other than Hubei from news media and government announcements.[8]

Fig. 2 presents the daily number of newly confirmed COVID-19 cases, marked with the average lockdown and reopening dates for epicenter cities and other cities. Lockdown measures began in epicenter cities first, with Wuhan being the first city locked down on January 23, 2020. Within a week, similar measures were also imposed on non-epicenter cities, which initially had only a small number of confirmed cases. Subsequently, after the number of daily new cases per 10,000 dropped close to zero, those non-epicenter cities reopened. The reopening of these cities took place, on average, 42 days after their lockdowns. By comparison, the lockdown period in epicenter cities averaged 32 days longer. All cities had a small number of new cases after reopening, with occasional flareups over our study period (December 21, 2019 – June 15, 2020).[9]

Social Media Posts and Local News Coverage Data   We collected the daily number of online posts containing keywords related to COVID-19 (including "COVID," "pneumonia," "infection," "suspected cases," and "symptoms") from the East Money Forum (https://guba.eastmoney.com/). The Forum is one of the largest online forums in China, hosting 62.52 million active users. We also collected the daily number of relevant media mentions of COVID based on 299 major newspapers and online media. The online posts and media mentions were traced to source provinces where the users and media headquarters are located.

---

[8]Appendix Figure B.1 presents the distribution of the lockdown and reopening dates of the 327 cities in our sample.

[9]The near elimination of local virus transmission allowed the reopening of most businesses, the reintroduction of transport services, and the resumption of some social activities. A general state of emergency was replaced by more targeted interventions: temperature checks at the entrance of shops and workplaces, quick quarantines for anyone showing symptoms, mandatory mask-wearing in most indoor spaces, required proof of health for entrance to many venues, and extensive monitoring through contact tracing (Allen and West, 2020).

II. Methods

Using the mobility data from January 1, 2019, to June 27, 2019, and from December 21, 2019, to June 15, 2020, we first employ an event study analysis, with two distinct events, the lockdown and the reopening, to examine the dynamics in population flows across cities. We then apply the difference-in-differences-in differences (DDD) method to estimate the difference in population mobility between epicenter and non-epicenter cities. In the DDD framework, we compare population mobility across the two years before-, during-, and after- the lockdown period between epicenter and other cities.

Event Study We use the 2019 mobility pattern as the baseline and match the 2019 data with the 2020 data based on the lunar calendar. We then analyze the aggregation of population inflow and outflow of city i during the event window of 5 weeks before the lockdown and 12 weeks after the reopening conditional on a rich set of fixed effects, as summarized in the following regression framework:

$$
\begin{aligned}
\ln(M_{ity}) = & \sum_{l_i=-4}^{3} \gamma_{l_i} \cdot p_t(l_i) + \sum_{r_i=-2}^{12} \beta_{r_i} \cdot p_t(r_i) + \phi \cdot p_t(l_i > 3, r_i \leq -3) \\
& + \sum_{l_i=-4}^{3} \xi_{l_i} \cdot p_t(l_i) \cdot \mathbb{1}[y = 2020] + \sum_{r_i=-2}^{12} \lambda_{r_i} \cdot p_t(r_i) \cdot \mathbb{1}[y = 2020] \\
& + \psi \cdot p_t(l_i > 3, r_i \leq -3) \cdot \mathbb{1}[y = 2020] + \delta_i + \tau_{ty} + x_{ity} \cdot \alpha + \varepsilon_{ity}, \quad (1)
\end{aligned}
$$

where M_{ity} is population flow of city i on day t in year y, and $\mathbb{1}[y = 2020]$ indicates year 2020. The event week l_i is relative to when the lockdown of city i occurs ($l_i = -1$ is the reference bin, which indicates the interval from two weeks to one week before the lockdown, $l_i = 0$ is the one-week period before the lockdown, $l_i = 1$ is the one-week period after the lockdown, etc.). Event week r_i is relative to when the reopening of city i occurs. We define the (hypothetical) event dates in 2019 according to the corresponding lunar calendar dates in 2020. We choose $l_i = -1$ rather than $l_i = 0$ (the one-week interval before lockdown) as the base bin because the migration pattern in $l_i = 0$ may have reflected the panic effects. (That is, people rushed out of or refrained from entering epicenter cities during the week before the lockdown (Fang et al., 2020).) $p_t(l_i)$ indicates that t of city i falls in the one-week interval, l_i. $p_t(r_i)$ indicates that t of city i falls in the one-week interval, r_i. We define a separate time interval between the two events, lockdown and reopening, as the period from three weeks after the lockdown to three weeks before the reopening. This interval is modeled as one effect window, indicated by $p_t(l_i > 3, r_i \leq -3)$ for city i. Cross-city human mobility is likely affected by not only city-specific socioeconomic and weather conditions but also time factors such as holidays

and weekends. Hence we control for a rich set of fixed effects, denoted by τ_{ty}, including the lunar-calendar-week fixed effects, day-of-week effects, holiday fixed effects, and year fixed effects. x_{ity} denotes weather conditions, including daily aggregate precipitation, mean temperature, and their quadratic terms. ε_{ity} is the error term.

To allow different patterns of population flows for epicenter and other cities, we include in (1) the interaction terms between T_i, the indicator of epicenter cities, and the event bins (the first six terms in (1)).

Difference-in-Difference-in-Differences In the DDD framework, we estimate population mobility measures while controlling for the same weather variables and fixed effects as in the event study. Our baseline specification is:

$$
\begin{aligned}
\ln(M_{ity}) \;=\; & \beta_1 \cdot 3DaysWithin_{it} + \beta_2 \cdot Lockdown_{it} + \beta_3 \cdot Reopen1_{it} + \beta_4 \cdot Reopen2_{it} \\
+\; & \beta_5 Reopen3_{it} + \gamma_1 \cdot 3DaysWithin_{it} \cdot \mathbb{1}[y = 2020] + \gamma_2 \cdot Lockdown_{it} \cdot \mathbb{1}[y = 2020] \\
+\; & \gamma_3 \cdot Reopen1_{it} \cdot \mathbb{1}[y = 2020] + \gamma_4 \cdot Reopen2_{it} \cdot \mathbb{1}[y = 2020] \\
+\; & \gamma_5 \cdot Reopen3_{it} \cdot \mathbb{1}[y = 2020] + \delta_i + \tau_{ty} + X_{ity} \cdot \alpha + \varepsilon_{ity},
\end{aligned}
\tag{2}
$$

where the study period is divided into six city-specific intervals: (i) the days from the start of the data period until three days before the lockdown of city i, denoted as $3DaysBefore_{it}$ and used as the reference period; (ii) the two days before and the day when the lockdown is implemented in city i, denoted by $3DaysWithin_{it}$; (iii) the lockdown period, $Lockdown_{it}$, referring to the period that the city is under lockdown; (iv) Reopening Phase 1, $Reopen1_{it}$, which covers the two-week period right after the reopening of city i, matching the virus' incubation period; (v) Reopening Phase 2, $Reopen2_{it}$, which captures the period from 15 to 28 days after the reopening of city i; and (vi) Reopening Phase 3, $Reopen3_{it}$, which refers to the period from 29 days after reopening until the end of our study period. The six intervals in 2019 are based on the lunar dates corresponding to the 2020 intervals. The coefficients of the difference-in-difference (DID) terms, γ_1 to γ_5, capture the differences in population mobility changes from 2019 to 2020 between the corresponding interval and the reference interval.

To compare epicenter cities with the other cities, in (2), we interact T_i, the indicator of epicenter cities, with the first difference and the DID terms (that is, the first 10 terms).

III. Results

A. Post-lockdown Mobility Recovery in Epicenter and Other Cities

To assess how human mobility responded to city lockdowns and reopening, we first present in Fig. 3 a visualization of the percentage changes in mobility, separately for the epicenter and other cities, based on the regression results of the event study outlined in the model section.[10]

Fig. 3 shows that the pre-lockdown mobility changes over 2019 and 2020 are largely indistinguishable between the epicenter and other cities, except in the week before the start of the lockdown when the mobility measures diverged between the epicenter and other cities. In response to the start of the lockdown, cross-city mobility exhibits a sharp drop in all cities, with a 90 percent decrease in epicenter cities and a 70 percent reduction in other cities. Human mobility to and from epicenter cities almost completely halted for about four weeks. In the non-epicenter cities, cross-city mobility started to bounce back three weeks into the lockdown.

When evaluating reopening measures, it is important to note that in all cities no abnormal mobility change occurred around the start date of reopening. Because the reopening started weeks after the number of newly confirmed cases began to drop (Fig. 2), the timing of the reopening might endogenously reflect an initial mobility recovery that had already occurred following the continued decline in the infection cases. After reopening, the population flow to and from epicenter cities initially increased quickly, exhibiting a trend similar to those seen in other cities. However, as mobility among non-epicenter cities continued to recover, reaching pre-pandemic level six weeks after reopening, mobility recovery in epicenter cities did not. In these epicenter cities, mobility slowed down three weeks after reopening, and cross-city mobility remained significantly lower for epicenter cities 12 weeks after reopening. At the end of our study period (June 15, 2020), the level of population flows to and from epicenter cities had still not returned to pre-pandemic levels.

To assess the statistical significance of the mobility trend difference between epicenter cities and other cities, we apply the DDD model outlined in the Methods section and separately estimate population inflow and outflow. Fig. 4 presents the estimates of the differences in the mobility percentage changes between the two types of cities.[11]

The left panel of Fig. 4 shows the results based on all cities in the total sample. During the three days before the lockdown, population flows out of epicenter cities (the outflow) increased by more than 10 percent compared to the flows out of other cities. This likely reflects a panic response to the official acknowledgement on January 20, 2020, that the disease was transmissible from person to

---

[10]The calculation of the percentage changes is explained in the Technical Note of the Appendix. The regression results of the event study are reported in Appendix Table B.1.

[11]The regression results of the DDD estimations are reported in Appendix Table B.2.

person, and to the declaration of the lockdowns of Wuhan (January 23, 2020). At the same time, the population flows into epicenter cities also increased but by a smaller magnitude and the difference between epicenter cities and other cities is not statistically significant at the 5 percent level. The lockdown period was characterized by a further drop in human mobility, with flows into and out of epicenter cities falling by an additional more than 70 percent. After reopening, the mobility gap between epicenter cities and other cities narrowed to 20-30 percent in the first phase and 10-20 percent in the next two phases. All mobility gaps remain statistically significant at the 5 percent level throughout the reopening period, with the exception of the inflow gap during the first phase.

Being hardest hit by the pandemic, epicenter cities had the strictest lockdown measures implemented for the longest period. To make comparisons, we selected 89 non-epicenter cities that implemented lockdown measures that were of similar strictness to those imposed in epicenter cities. These non-epicenter cities announced additional lockdown measures that included both neighborhood lockdown and transportation restrictions, as defined in He et al. (2020). With this restricted comparison sample, the estimated differences between epicenter and non-epicenter cities (the right panel of Fig. 4) are very similar to the estimated differences based on the full sample. This analysis suggests that the slower mobility recovery in epicenter cities is unlikely to be driven by their strict lockdown measures alone. Instead, the longer lockdown period and the more severe pandemic experience are the more likely causes of the epicenter cities' lagging mobility recovery.

B. Understanding the Difference between Epicenter and Other Cities

The mobility trends and differences observed in Fig. 3 and Fig. 4 are simultaneously shaped by two factors: the pandemic itself and the pandemic-induced lockdown policies. The pandemic effect refers to changes in individual behavior due to concerns about infection risks, leading to fewer social interactions and reduced human mobility. The pandemic-induced policy impact refers to changes in mobility caused by lockdown measures and other regulatory interventions that restrict mobility. The strength of the pandemic effect relates positively to pandemic severity, because the perceived infection risk is expected to be high under a more severe pandemic condition. Perceived high infection risk, in turn, often leads to more precautionary behaviors (Brewer et al., 2004). Therefore, the pandemic impact is expected to be larger in epicenter cities than in other cities.

The strength of the policy impact is determined by both the strictness of lockdown measures and the duration of the lockdown period. Local officials in China at various levels were mandated to contain the pandemic. Perceived failure to control the pandemic can lead to public criticism, and disciplinary actions such as suspension, dismissal, or demotion. Our news search shows that government officials in 11 provinces were disciplined due to pandemic-related charges. Due to this

enforceable mandate to contain the spread of the virus, officials in areas with few reported cases also carried out measures to prevent the spread of the virus to their region. For example, Tibet, then with zero confirmed cases, declared the first and highest level public health emergency on January 29, 2020. Nevertheless, the details of the resulting lockdown measures were city-specific, tailored to disease prevalence conditions in each city. The lockdown measures implemented in epicenter cities were among the strictest (He et al., 2020) and the longest-lasting (Fig. 2). Therefore, the pandemic-induced policy impact is expected to be bigger in epicenter cities than in other cities. In sum, the difference in human mobility between epicenter cities and other cities observed in Fig. 3 and Fig. 4 captures a bigger pandemic effect and a bigger pandemic-induced policy effect in epicenter cities.

We further elucidate the estimated differences between the epicenter and other cities by comparing the trends in the number of pandemic-related social media posts and the volume of pandemic-related local news coverage between Hubei Province and other provinces.[12] As shown in Fig. 5, in late January 2020 the number of pandemic-related online posts and local news coverage surged drastically in Hubei Province, while other provinces exhibited a relatively modest increase. By the time non-epicenter cities started to reopen in early March, the numbers of such posts and the extent of news coverage had declined across all provinces; nevertheless, the volume of pandemic-related posts and news coverage remained higher in Hubei Province. This difference continued after epicenter cities reopened, likely reflecting sustained pandemic concerns in the epicenter province. To rule out that social media users and news media in Hubei Province were somehow more active in discussing issues related to respiratory diseases, we tabulate the number of per million population online posts and local news mentions containing keywords related to respiratory diseases ("pnumo-nia", "infections", and "symptoms") separately for Hubei Province and other provinces during a pre-pandemic period (October 1, 2019, to January 19, 2020). We find no sign that more posts or news related to respiratory diseases were Hubei sourced.[13] Hence the patterns shown in Fig. 5 are not driven by higher usage of the online forum for or higher media coverage of issues related to respiratory disease in Hubei than in other provinces.

As the objective infection risks were higher in the epicenter region, the relatively undiminished pandemic concerns there, observed in Fig. 5, likely reflect higher perceived risks (Weinstein and Nicolich, 1993). Perceived higher infection risk often induces more precautionary behaviors (Brewer et al., 2004). In this pandemic context, the precautionary behaviors are partly reflected in reduced mobility across cities. The evidence presented here is consistent with the finding in Italy that indicates that people in regions hardest hit by the pandemic tended to have more pandemic-related

---

[12]The data used for this analysis are not available at the city level.

[13]Appendix Table B.3 summarizes those number of online posts and news coverage.

worries and engaged in more preventive behaviors (Pagnini et al., 2020).

IV.   Conclusion

As many countries around the world have relaxed the initial lockdown measures taken to control the spread of the COVID-19 virus, it is important to understand how fast human mobility recovers and what factors affect this recovery. This work shows that cross-city human mobility in China recovered considerably after the reopening, but that the post-lockdown recovery varied significantly with the pandemic's severity level. Among non-epicenter cities, cross-city mobility fully recovered to normal six weeks after the reopening started; by contrast, in epicenter cities, mobility remained lower than pre-pandemic levels 12 weeks after reopening (Fig. 3, Fig. 4). The slower recovery of epicenter cities is likely shaped by both their severe pandemic experience and longer lockdown periods. Citizens in the epicenter exhibited relatively undiminished pandemic concerns, as evidenced in the larger number of pandemic-related postings in social media and media mentions, which continued after the lockdown ended (Fig. 5). Continued pandemic concerns in the epicenter regions may have contributed to their sluggish mobility recovery. Besides the sustained public concerns of the pandemic, other pandemic-induced problems may contribute to the slower mobility recovery in the wake of lockdown. For example, if the economic slowdown was particularly acute in epicenter cities, it also might have contributed to the slower pace of mobility recovery. These factors shall be examined in future research.

From a policy perspective, the difference in the human mobility recovery identified in this study suggests that containing the spread of the virus is a precondition for speedy post-lockdown recovery, as exemplified by the experience of non-epicenter cities. Under the nationwide effort to contain the pandemic after the initial mishandling of the pandemic's first outbreaks in the epicenter region, aggressive and comprehensive mitigation measures, including lockdown of all cities, were implemented in China (Zhang et al., 2020). With those measures in place, non-epicenter cities avoided severe outbreaks. The mild pandemic experiences, in turn, facilitated faster post-lockdown recoveries in these cities. The evidence presented in this paper suggests that fast recovery in human mobility once a pandemic is under control can be considered an economic and social benefit of implementing swift and effective containment measures during a pandemic outbreak.

References

Allen, John R and Darrell M West, "How to Save Lives and Livelihoods," 2020. The Brookings Institution.

Andersen, Martin, "Early Evidence on Social Distancing in Response to COVID-19 in the United States," 2020. SSRN Scholarly Paper No.3569368.

Baqaee, David, Emmanuel Farhi, Michael J Mina, and James H Stock, "Reopening Scenarios," Working Paper 27244, National Bureau of Economic Research May 2020. Series: Working Paper Series.

Bradsher, Keith, "With Covid-19 Under Control, China's Economy Surges Ahead," October November 19, 2020. The New York Times https://www.nytimes.com/2020/10/18/business/china-economy-covid.html.

Brewer, Noel T., Neil D. Weinstein, Cara L. Cuite, and James E. Herrington, "Risk perceptions and their relation to risk behavior," *Annals of Behavioral Medicine*, April 2004, *27* (2), 125–130.

Buchholz, K, "What share of the world population is already on COVID-19 Lockdown," April 23, 2020. Statista, https://www.statista.com/chart/21240/enforced-covid-19-lockdowns-by-people-affected-per-country/.

CDC, *Preparedness and response framework for novel influenza A virus pandemics: CDC intervals 508 | Pandemic Influenza (Flu)* 2018.

Cheng, Wei, Patrick Carlin, Joanna Carroll, Sumedha Gupta, Felipe Lozano Rojas, Laura Montenovo, Thuy D Nguyen, Ian M Schmutte, Olga Scrivner, Kosali I Simon, Coady Wing, and Bruce Weinberg, "Back to Business and (Re)employing Workers? Labor Market Activity During State COVID-19 Reopenings," Working Paper 27419, National Bureau of Economic Research June 2020. Series: Working Paper Series.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, "Labor Markets During the COVID-19 Crisis: A Preliminary View," Working Paper 27017, National Bureau of Economic Research April 2020. Series: Working Paper Series.

Fairlie, Robert W, "The Impact of Covid-19 on Small Business Owners: Evidence of Early-Stage Losses from the April 2020 Current Population Survey," Working Paper 27309, National Bureau of Economic Research June 2020. Series: Working Paper Series.

Fang, Hanming, Long Wang, and Yang Yang, "Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China," Working Paper 26906, National Bureau of Economic Research March 2020. Series: Working Paper Series.

Favero, Carlo A, Andrea Ichino, and Aldo Rustichini, "Restarting the economy while saving lives under Covid-19," 2020. Publisher: CEPR Discussion Paper No. DP14664.

Ferguson, Neil M, Derek AT Cummings, Christophe Fraser, James C Cajka, Philip C Cooley, and Donald S Burke, "Strategies for mitigating an influenza pandemic," *Nature*, 2006, *442* (7101), 448–452. Publisher: Nature Publishing Group.

Friedson, Andrew I, Drew McNichols, Joseph J Sabia, and Dhaval Dave, "Did California's Shelter-in-Place Order Work? Early Coronavirus-Related Public Health Effects," Working Paper 26992, National Bureau of Economic Research April 2020. Series: Working Paper Series.

Gatto, Marino, Enrico Bertuzzo, Lorenzo Mari, Stefano Miccoli, Luca Carraro, Renato Casagrandi, and Andrea Rinaldo, "Spread and dynamics of the COVID-19 epidemic in Italy: Effects of emergency containment measures," *Proceedings of the National Academy of Sciences*, 2020, *117* (19), 10484–10491. Publisher: National Acad Sciences.

Glaeser, Edward L, Caitlin S Gorback, and Stephen J Redding, "How Much does COVID-19 Increase with Mobility? Evidence from New York and Four Other U.S. Cities," Working Paper 27519, National Bureau of Economic Research July 2020. Series: Working Paper Series.

_ **, Ginger Zhe Jin, Benjamin T Leyden, and Michael Luca**, "Learning from Deregulation: The Asymmetric Impact of Lockdown and Reopening on Risky Behavior During COVID-19," Working Paper 27650, National Bureau of Economic Research August 2020. Series: Working Paper Series.

He, Guojun, Yuhang Pan, and Takanao Tanaka, "The short-term impacts of COVID-19 lockdown on urban air pollution in China," *Nature Sustainability*, 2020, *July 7*.

Lee, Sang Yoon (Tim), Minsung Park, and Yongseok Shin, "Hit Harder, Recover Slower? Unequal Employment Effects of the Covid-19 Shock," Technical Report w28354, National Bureau of Economic Research, Cambridge, MA January 2021.

Montenovo, Laura, Xuan Jiang, Felipe Lozano Rojas, Ian M Schmutte, Kosali I Simon, Bruce A Weinberg, and Coady Wing, "Determinants of Disparities in Covid-19 Job Losses," Working Paper 27132, National Bureau of Economic Research May 2020. Series: Working Paper Series.

Murphy, Flynn, "Inside China's response to COVID," *Nature*, December 2020, *588* (7836), S49–S51. Number: 7836 Publisher: Nature Publishing Group.

Nguyen, Thuy D, Sumedha Gupta, Martin Andersen, Ana Bento, Kosali I Simon, and Coady Wing, "Impacts of State Reopening Policy on Human Mobility," Working Paper 27235, National Bureau of Economic Research May 2020. Series: Working Paper Series.

Normile, Dennis, "As normalcy returns, can China keep COVID-19 at bay?," *Science*, 2020, *368*, 18–19. Publisher: American Association for the Advancement of Science.

Pagnini, Francesco, Andrea Bonanomi, Semira Tagliabue, Michela Balconi, Mauro Bertolotti, Emanuela Confalonieri, Cinzia Di Dio, Gabriella Gilli, Guendalina Graffigna, Camillo Regalia, Emanuela Saita, and Daniela Villani, "Knowledge, Concerns, and Behaviors of Individuals During the First Week of the Coronavirus Disease 2019 Pandemic in Italy," *JAMA Network Open*, July 2020, *3* (7), e2015821–e2015821. Publisher: American Medical Association.

Painter, Marcus and Tian Qiu, "Political beliefs affect compliance with covid-19 social distancing orders," 2020. SSRN Scholarly Paper No. 3569098.

Ray, Debraj and S. Subramanian, "India's Lockdown: An Interim Report," Working Paper 27282, National Bureau of Economic Research May 2020. Series: Working Paper Series.

Toxvaerd, FMO, "Equilibrium social distancing," 2020. Publisher: Faculty of Economics, University of Cambridge.

Wang, Erenitie and Karla Cripps, "World's largest annual human migration now underway in China," January 23, 2019. CNN https://www.cnn.com/travel/article/lunar-new-year-travel-rush-2019/index.html.

Weinstein, Neil D. and Mark Nicolich, "Correct and incorrect interpretations of correlations between risk perceptions and risk behaviors," *Health Psychology*, May 1993, *12* (3), 235–245. Publisher: American Psychological Association.

WHO, "Listings of WHO's response to COVID-19," June 29, 2020. WHO Statement: https://www.who.int/news/item/29-06-2020-covidtimeline.

Zhang, Renyi, Yixin Li, Annie L. Zhang, Yuan Wang, and Mario J. Molina, "Identifying airborne transmission as the dominant route for the spread of COVID-19," *Proceedings of the National Academy of Sciences*, 2020, *117* (26), 14857–14863. Publisher: National Academy of Sciences.
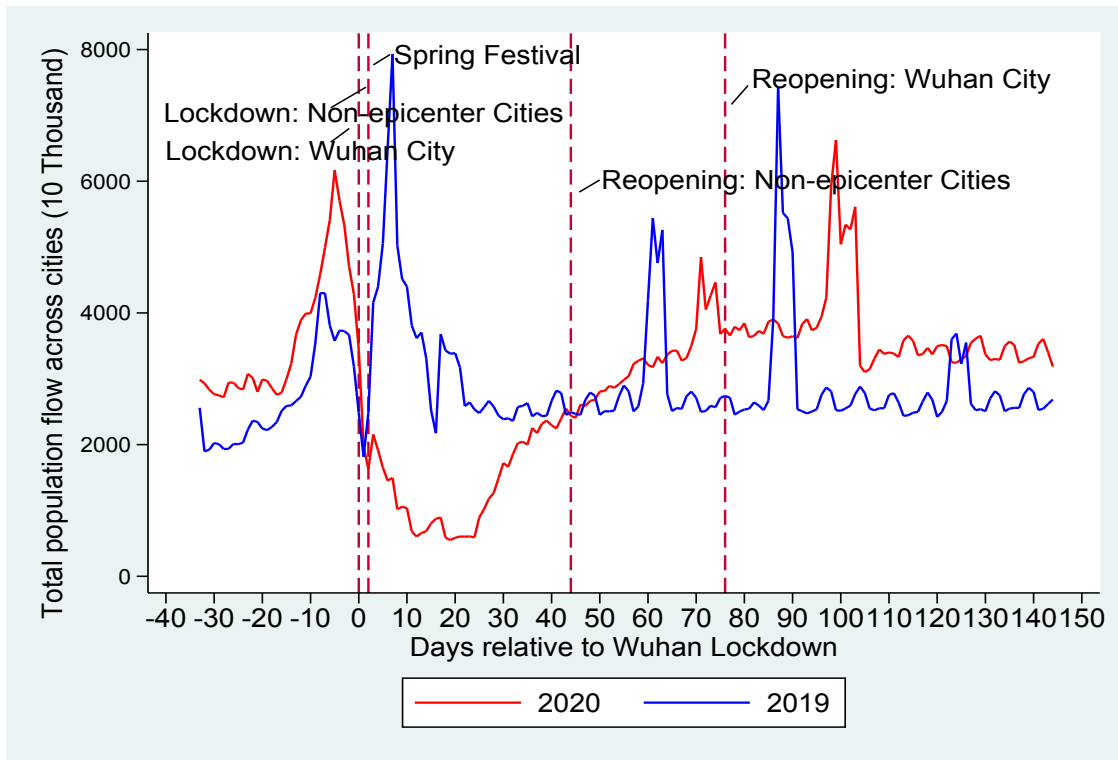
Figure 1: Daily cross-city population flow in 2020 and 2019

Note: This figure plots the total daily cross-city population flows among 327 cities in China. The 2019 (blue curve) and the 2020 (red curve) population flows are plotted for the same dates based on the lunar calendar. We mark the five critical dates: Spring Festival (the Chinese New Year), the lockdown date of Wuhan (Day 0), the lockdown date of non-epicenter cities, the reopening date of non-epicenter cities, and the reopening date of Wuhan. The lockdown (reopening) date of non-epicenter cities is the average of the lockdown (reopening) dates of these cities relative to the lockdown (reopening) date of Wuhan.
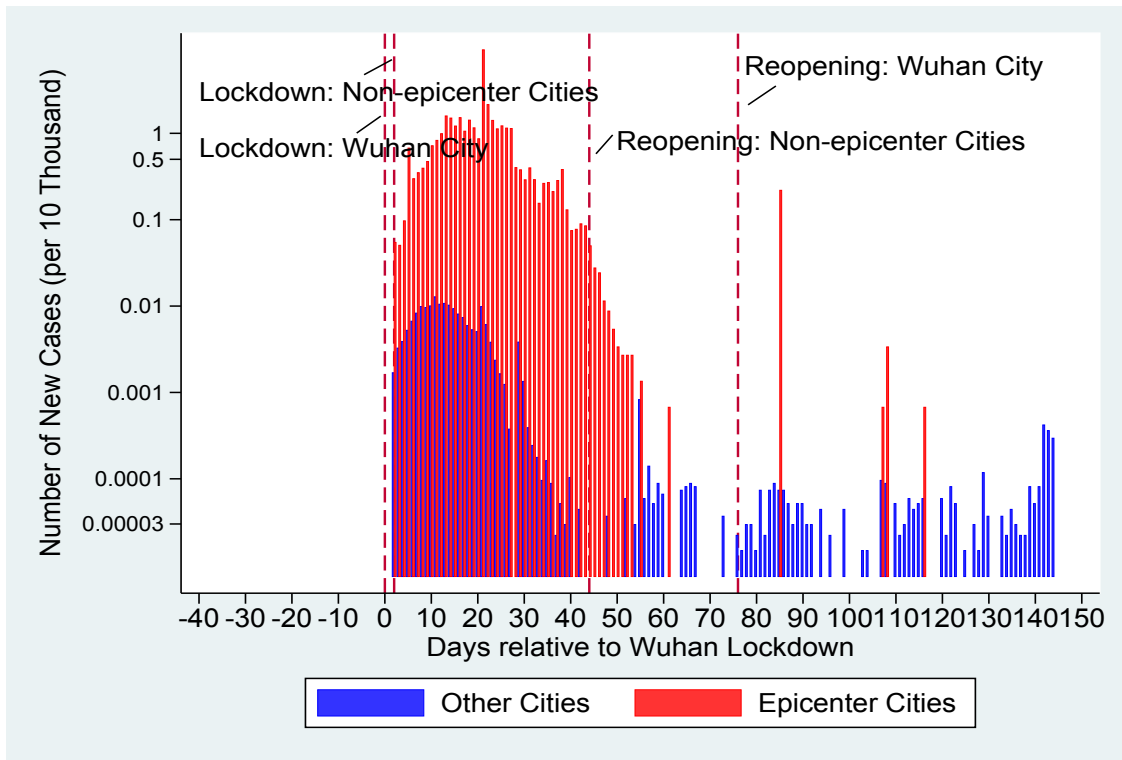
Figure 2: The number of confirmed new COVID-19 infection cases

Note: This figure graphs the daily number of new cases per ten thousand people from Day 2 to Day 144 since the lockdown date of Wuhan City (Day 0), for epicenter cities in red columns and the other 324 cities in blue columns. We mark the four critical dates: the lockdown date of Wuhan (Day 0), the lockdown date of non-epicenter cities, the reopening date of non-epicenter cities, and the reopening date of Wuhan. The lockdown (reopening) date of non-epicenter cities is the average of the lockdown (reopening) dates of these cities relative to the lockdown (reopening) date of Wuhan.
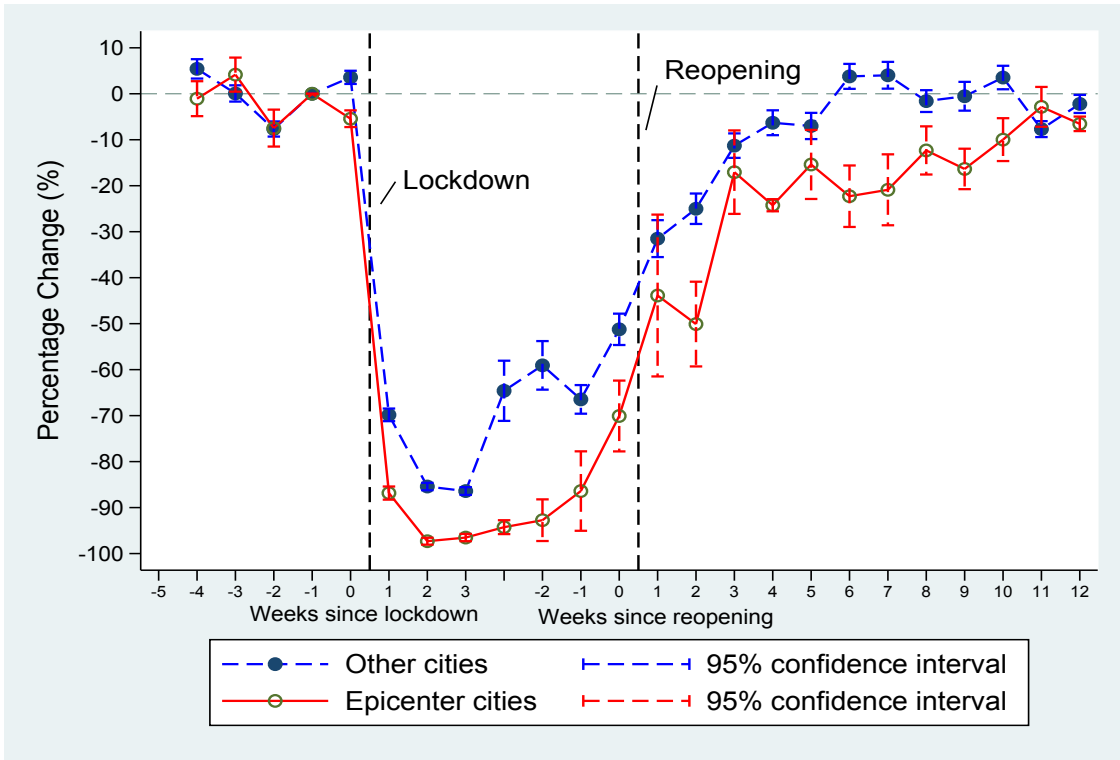
Figure 3: Event study: The change in cross-city mobility 2019-2020

Note: This figure depicts the percentage changes of the total daily cross-city population flows for epicenter cities (the blue curve) and other cities (the red curve), based on the regression results of the event study outlined in the model section. The regression results, reported in Appendix Table B.1, are based on a sample of 327 cities (three epicenter cities and 324 non-epicenter cities) for 356 days (December 21, 2019 - June 15, 2020, and January 1, 2019 - June 27, 2019). The calculation of the percentage changes is explained in the Technical Note of the Appendix.
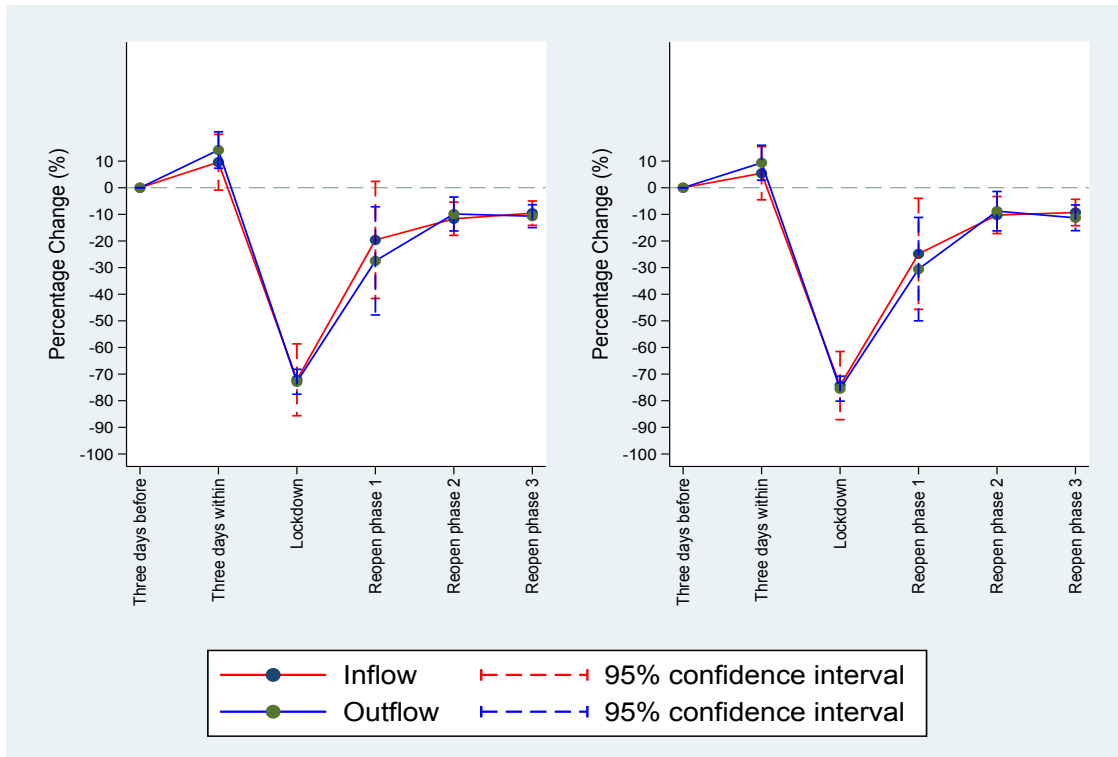
Figure 4: The difference-in-difference-in-differences (DDD) estimation: Differences between epicenter and other cities

Note: The figure reports the estimates of the differences in the mobility percentage changes between the epicenter cities and other cities, based on the DDD model described in the model section. The blue curves represent population outflows and the red curves represent population inflows. The left panel is based on the results from all of the 327 cities in the total sample (three epicenter cities and 324 non-epicenter cities) and the right panel is based on the results from the restricted sample of 92 cities, including three epicenter cities and 89 non-epicenter cities which were under strict lockdown measures. The regression results of the DDD model, on which this figure is based, are reported in Appendix Table B.2. The calculation of the percentage changes is explained in the Technical Note of the Appendix.
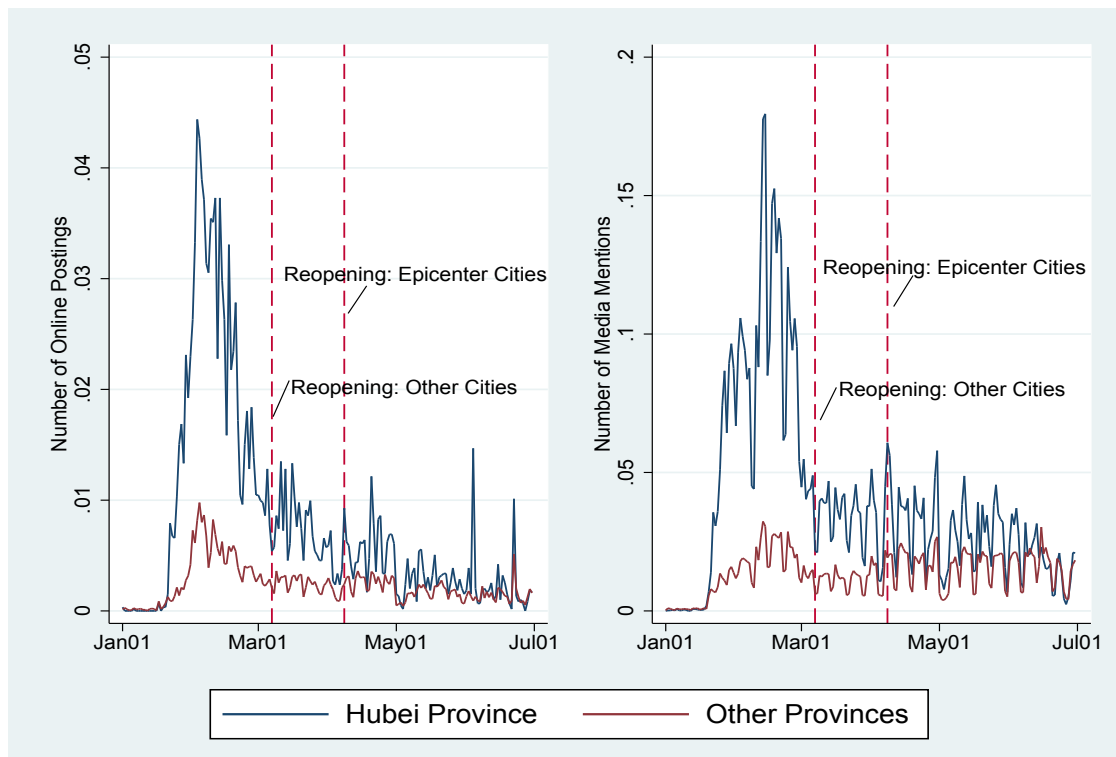
Figure 5: Number of pandemic-related online postings and media mentions

Note: The left panel plots the daily number of pandemic-related social media postings per 10,000 people in Hubei Province (blue curve) and other provinces (red curve) from January 1, 2020, to July 1, 2020. The right panel plots the daily number of pandemic-related media mentions per 10,000 people in Hubei Province (blue curve) and other provinces (red curve) from January 1, 2020, to July 1, 2020. The online postings are from the East Money Forum (https://guba.eastmoney.com/). The media mentions are based on news reports from 299 major newspapers and online media. The online postings and media mentions are traced to the provinces where the authors and the media organizations were located.

<div align="center">

Appendix

Uneven Recovery from the COVID-19 Pandemic: Post-lockdown Human Mobility Across Chinese Cities

Yanyan Liu   Shuang Ma   Ren Mu

</div>

A   Technical Note on Calculations of Percentage Changes

To facilitate interpretation, Figures 3 and 4 plot the percentage changes calculated based on the regression results of the event study and the Difference-in-Difference-in-Differences (DDD) estimations, reported in Tables B.1 and B.2 respectively.

In the event study, for the non-epicenter cities, we calculate the percentage change in population flow for each event bin following the formula proposed by Kennedy (1981):

$$\hat{p} = 100\left\{\exp\left[\hat{c} - 0.5\hat{V}(\hat{c})\right] - 1\right\}, \tag{A.1}$$

where $\hat{c}$ is the corresponding coefficient estimate reported in Column (1) of Table B.1. $\hat{V}(\hat{c})$ is the estimated variance of $\hat{c}$. For the epicenter cities, $\hat{c}$ is the summation of the corresponding coefficient estimates reported in Columns (1) and (2) of Table B.1. In calculating the percentage changes in the DDD regressions, $\hat{c}$ is the coefficient estimate corresponding to each of the five intervals (Three-DaysWithin, Lockdown, Reopen1, Reopen2, and Reopen3) reported in Table B.2.

We follow van Garderen and Shah (2002) to calculate the variance of $\hat{p}$ using the delta method:

$$\hat{V}(\hat{p}) = 100^2 \exp(2\hat{c})\left\{\exp\left[-\hat{V}(\hat{c})\right] - \exp\left[-2\hat{V}(\hat{c})\right]\right\} \tag{A.2}$$

References

Kennedy, Peter E, "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic

Equations [The Interpretation of Dummy Variables in Semilogarithmic Equations]," *American Economic Review*, 1981, *74* (4), 801–801.

van Garderen, Kees J and Chandra Shah, "Exact interpretation of dummy variables in semilogarithmic equations," *Econometrics Journal*, 2002, *5*, 149–159.
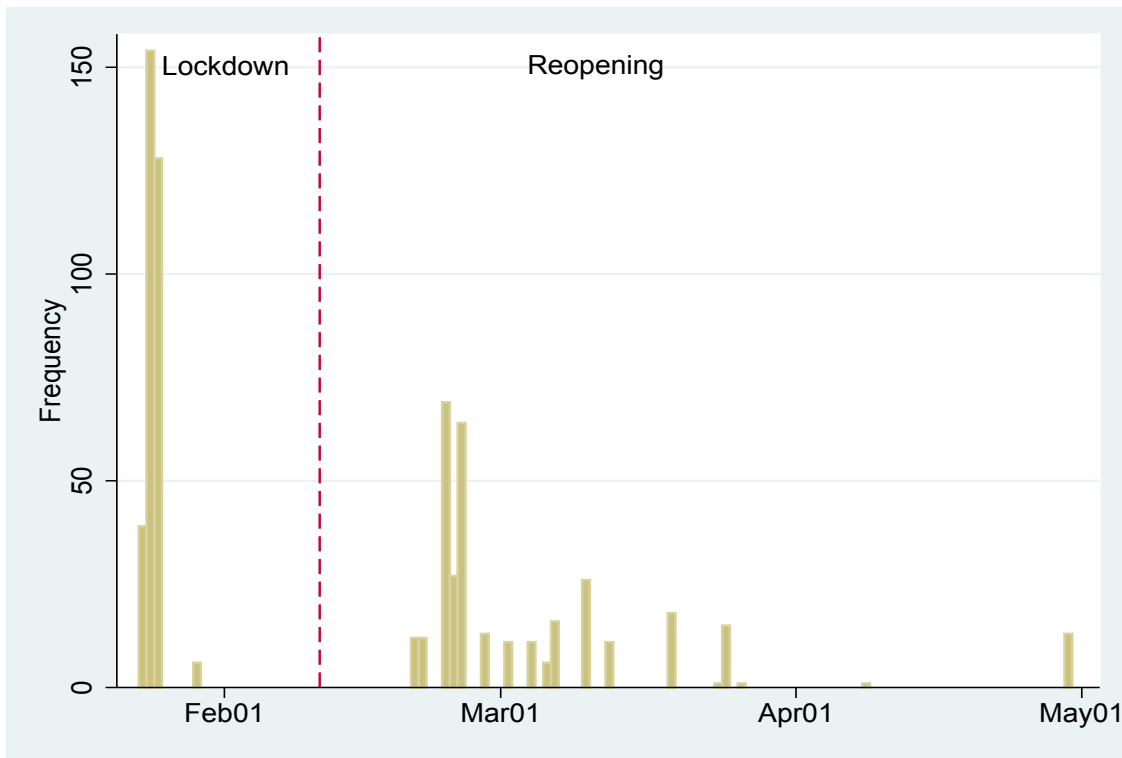
B Appendix Figures and Tables

Figure B.1: The lockdown and reopening dates of the 327 cities

Note: On the left side of the vertical red dashed line, the graph shows the frequency of the lockdown dates of the 327 cities. On the right side of the line, the graph shows the frequency of the reopening dates of these cities.

Table B.1: Event study estimations: epicenter cities versus non-epicenter cities

Dependent variable: log population flow	(1)		(2)
Lockdown Event Week -4 × 2020	0.0528*** (0.0102)	Lockdown Event Week -4 × 2020 × Epicenter	-0.0634*** (0.0172)
Lockdown Event Week -3 × 2020	0.000757 (0.00903)	Lockdown Event Week -3 × 2020 × Epicenter	0.0402** (0.0184)
Lockdown Event Week -2 × 2020	-0.0797*** (0.00911)	Lockdown Event Week -2 × 2020 × Epicenter	0.00237 (0.0220)
Lockdown Event Week 0 × 2020	0.0351*** (0.00706)	Lockdown Event Week 0 × 2020 × Epicenter	-0.0909*** (0.0117)
Lockdown Event Week 1 × 2020	-1.198*** (0.0233)	Lockdown Event Week 1 × 2020 × Epicenter	-0.829*** (0.0600)
Lockdown Event Week 2 × 2020	-1.925*** (0.0282)	Lockdown Event Week 2 × 2020 × Epicenter	-1.680*** (0.146)
Lockdown Event Week 3 × 2020	-1.995*** (0.0315)	Lockdown Event Week 3 × 2020 × Epicenter	-1.355*** (0.121)
Interval bin × 2020	-1.034*** (0.0945)	Interval bin × 2000 × Epicenter	-1.814*** (0.165)
Reopening Event Week -2 × 2020	-0.891*** (0.0659)	Reopening Event Week -2 × 2020 × Epicenter	-1.678*** (0.334)
Reopening Event Week -1 × 2020	-1.092*** (0.0474)	Reopening Event Week -1 × 2020 × Epicenter	-0.848** (0.337)
Reopening Event Week 0 × 2020	-0.717*** (0.0357)	Reopening Event Week 0 × 2020 × Epicenter	-0.480*** (0.137)
Reopening Event Week 1 × 2020	-0.378*** (0.0299)	Reopening Event Week 1 × 2020 × Epicenter	-0.187 (0.164)
Reopening Event Week 2 × 2020	-0.287*** (0.0225)	Reopening Event Week 2 × 2020 × Epicenter	-0.403*** (0.0969)
Reopening Event Week 3 × 2020	-0.120*** (0.0153)	Reopening Event Week 3 × 2020 × Epicenter	-0.0657 (0.0571)
Reopening Event Week 4 × 2020	-0.0650*** (0.0147)	Reopening Event Week 4 × 2020 × Epicenter	-0.213*** (0.0191)
Reopening Event Week 5 × 2020	-0.0725*** (0.0156)	Reopening Event Week 5 × 2020 × Epicenter	-0.0934* (0.0475)
Reopening Event Week 6 × 2020	0.0372*** (0.0133)	Reopening Event Week 6 × 2020 × Epicenter	-0.288*** (0.0465)
Reopening Event Week 7 × 2020	0.0396*** (0.0143)	Reopening Event Week 7 × 2020 × Epicenter	-0.273*** (0.0513)
Reopening Event Week 8 × 2020	-0.0160 (0.0123)	Reopening Event Week 8 × 2020 × Epicenter	-0.115*** (0.0332)
Reopening Event Week 9 × 2020	-0.00528 (0.0161)	Reopening Event Week 9 × 2020 × Epicenter	-0.173*** (0.0317)
Reopening Event Week 10 × 2020	0.0348*** (0.0126)	Reopening Event Week 10 × 2020 × Epicenter	-0.139*** (0.0296)
Reopening Event Week 11 × 2020	-0.0799*** (0.00959)	Reopening Event Week 11 × 2020 × Epicenter	0.0513** (0.0250)
Reopening Event Week 12 × 2020	-0.0223** (0.0103)	Reopening Event Week 12 × 2020 × Epicenter	-0.0453*** (0.0144)

Note: The unit of analysis is city-day. The sample includes 327 cities (three epicenter cities and 324 non-epicenter cities) for 356 days (December 21, 2019 - June 15, 2020 and January 1, 2019 - June 27, 2019). Other explanatory variables include the event bins (the lockdown event weeks from -4 to 3, the interval bin, the reopening event weeks from -2 to 12), Year 2020, the interactions between the epicenter indicator and the event bins, the lunar-calendar-week fixed effects, the day-of-week fixed effects, the holiday fixed effects, the precipitation mean and its quadratic term, the temperature mean and its quadratic term. Robust standard errors clustered at the city level are in the parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table B.2: DDD estimates: Comparing epicenter cities with non-epicenter cities

	(1) Inflow	(2) Outflow	(3) Inflow	(4) Outflow
ThreeDaysWithin× Epicenter× 2020	0.0928*	0.133***	0.0541	0.0902***
	(0.0488)	(0.0306)	(0.0483)	(0.0306)
Lockdown × Epicenter × 2020	-1.247***	-1.301***	-1.326***	-1.401***
	(0.251)	(0.0882)	(0.258)	(0.0976)
Reopen1× Epicenter × 2020	-0.208	-0.311**	-0.275*	-0.355**
	(0.140)	(0.144)	(0.142)	(0.143)
Reopen2 × Epicenter × 2020	–0.123***	-0.103***	-0.107***	-0.0913**
	(0.0361)	(0.0360)	(0.0395)	(0.0414)
Reopen3 × Epicenter × 2020	-0.100***	-0.113***	-0.0972***	-0.120***
	(0.0258)	(0.0245)	(0.0279)	(0.0278)
Observations	116,409	116,407	32,752	32,752
R^2	0.631	0.597	0.648	0.658

Note: The unit of analysis is city-day. In Columns (1) and (3), the dependent variable is log population inflow. in Columns (2) and (4), the dependent variable is log population outflow. In Columns (1) and (2), the sample includes 327 cities (three epicenter cities and 324 non-epicenter cities) for 356 days (December 21, 2019 - June 15, 2020 and January 1, 2019 - June 27, 2019). Three observations are missing in the regression reported in column (1) and five observations are missing in Column (2), due to missing values in the dependent variable. In Columns (3) and (4), the sample includes 92 cities (three epicenter cities and 89 non-epicenter cities which were under strict lockdown measures). Other explanatory variables include indicators of the six time intervals (ThreeDayBefore, ThreeDay-Within, Lockdown, Reopen1, Reopen2, Reopen3), Year 2020, the interactions between the epicenter indicator and the time intervals, the lunar-calendar-week fixed effects, the day-of-week fixed effects, the holiday fixed effects, the precipitation mean and its quadratic term, the temperature mean and its quadratic term. Robust standard errors clustered at the city level are in the parentheses. *Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table B.3: Pre-pandemic number of online posts and media mentions per million people for Hubei Province (Epicenter) and other provinces (Non-Epicenter)

	Online posts		Media mentions	
	Non-Epicenter	Epicenter	Non-Epicenter	Epicenter
	(1)	(2)	(3)	(4)
Infection	48.19	9.36	191.56	80.53
Vaccine	94.17	24.35	398.87	202.26
Pneumonia	13.80	14.98	63.09	26.22
Corona virus	0.76	0.00	10.33	11.24
Fever	2.12	1.87	18.38	7.49
Cough	3.81	1.87	14.40	11.24

Note: The table reports the total numbers of online posts and media mentions as per million population containing keywords related to respiratory diseases from October 1, 2019 to January 19, 2020 (a pre-pandemic period). The online posts are from the East Money Forum (https://guba.eastmoney.com/). The media mentions are based on 299 major newspaper and online media. The online posts and media mentions are traced to the provinces where the senders and media were located. Columns (2) and (4) are for Hubei Province (Epicenter). Columns (1) and (3) are for other provinces (Non-epicenter).