Human mobility restrictions and the spread of the Novel Coronavirus (2019-nCoV) in China☆

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ABSTRACT

We quantify the causal impact of human mobility restrictions, particularly the lockdown of Wuhan on January 23, 2020, on the containment and delay of the spread of the Novel Coronavirus (2019-nCoV). We employ difference-in-differences (DID) estimations to disentangle the lockdown effect on human mobility reductions from other confounding effects including panic effect, virus effect, and the Spring Festival effect. The lockdown of Wuhan reduced inflows to Wuhan by 76.98%, outflows from Wuhan by 56.31%, and within-Wuhan movements by 55.91%. We also estimate the dynamic effects of up to 22 lagged population inflows from Wuhan and other Hubei cities – the epicenter of the 2019-nCoV outbreak – on the destination cities' new infection cases. We also provide evidence that the enhanced social distancing policies in the 98 Chinese cities outside Hubei province were effective in reducing the impact of the population inflows from the epicenter cities in Hubei province on the spread of 2019-nCoV in the destination cities. We find that in the counterfactual world in which Wuhan were not locked down on January 23, 2020, the COVID-19 cases would be 105.27% higher in the 347 Chinese cities outside Hubei province. Our findings are relevant in the global efforts in pandemic containment.

1. Introduction

Human mobility contributes to the transmission of infectious diseases that pose serious threats to global health. Indeed, many countries restrict human mobility flows as part of their response plans (Bajardi et al., 2011; Wang and Taylor, 2016; Adda, 2016; Charu et al., 2017). However, restrictions on human mobility are controversial not only because of their negative economic impacts, but also because of the uncertainty about their effectiveness in controlling the epidemic. Even if restricting human movement could lead to improvements in disease control and reductions in health risks, it is empirically challenging to quantify the impact of human mobility on the spread of infectious diseases, and to understand the detailed spatial patterns of how the infectious disease spreads. Both granular disease occurrence data and human mobility data (Charu et al., 2017) are hard to obtain; moreover, it is difficult to disentangle the impact of human mobility from other potential contributing factors (Ferguson et al., 2006; Hollingsworth et al., 2006). We exploit the exogenous variations in human mobility created by lockdowns of Chinese cities, and utilize high-quality data sets to study the effectiveness of an unprecedented *cordon sanitaire* of the epicenter of COVID-19, and provide a comprehensive analysis on the role of human mobility restrictions in the delaying and the halting of the spread of the COVID-19 pandemic.[1]

The fast-moving 2019-nCoV that infected 17.5 million people and claimed 682,612 lives as of July 31, 2020 is deteriorating into one of the worst global pandemics.[2] The virus first appeared in Wuhan in

[1] Throughout the paper, we use 2019-nCoV as the official name for the Novel Coronavirus according to the World Health Organization, and use COVID-19 as the name of the disease caused by 2019-nCoV.
[2] Source: https://www.who.int/emergencies/diseases/novel-coronavirus-2019.

early December of 2019, spread mainly through person-to-person contact (Chan et al., 2020), and rapidly reached more than 183 countries as of March 21, 2020.[3]

However, the nature of the virus and its transmission was not publicly known initially. Even though the Chinese state media reported the first known death caused by the Novel Coronavirus on January 11, 2020, it did not register much public attention. On January 14, 2020, the World Health Organization (WHO) announced that Chinese authorities had seen "no clear evidence of human-to-human transmission of the Novel Coronavirus." As the Chinese New Year – which fell on January 25, 2020 – approached, Chinese citizens across the country were still traveling and gathering for various festive and social activities. In fact, on January 18, 2020, more than 10,000 Wuhan families gathered for the annual Wuhan Lunar New Year banquet.[4] These announcements and events suggest that no public panic was sparked yet as of that date. On January 19, 2020, the Chinese National Health Commission convened and sent a team of epidemiologists to Wuhan to investigate the outbreak of the Novel Coronavirus. On January 20, 2020, Dr. Zhong Nanshan, a renowned epidemiologist who was leading the investigative team, for the first time publicly confirmed on national TV that the Novel Coronavirus could spread from human to human. This confirmation caused great panic among the public. The search frequencies in Baidu, the major Chinese search engine, of COVID-19 related keywords such as "Coronavirus", "Wuhan", "Bat", "SARS", and "symptom" (in Chinese) immediately surged (see Fig. A6), and the number of people leaving Wuhan spiked (see Section 3 and Fig. A2). On January 23, 2020, the Chinese central government imposed a lockdown in Wuhan, and within a day also on the other cities in Hubei province, in an effort to quarantine the epicenter of the outbreak.

The lockdown of 11 million people in Wuhan represents by then the largest quarantine in public health history, which offers us an opportunity to rigorously examine the effects of the city lockdown and understand the relationship between human mobility and virus transmission. We should point out that the Wuhan lockdown, which lasted 76 days, was extremely strict. All air, train and bus travels into and out of Wuhan were suspended, and all the highway and local road accesses were blocked except for emergency, medical and supply personnel. Residents were not allowed to leave their residence, and food supplies were ordered via phone apps and delivered to the doorsteps by community organizations. The strictness of the lockdown measures was unprecedented.

In this paper, we study four research questions. First, how does the lockdown of Wuhan affect population movement? Second, how do population flows among Chinese cities, particularly outflows from Wuhan, affect the virus infections in the destination cities? Third, are social distancing policies in the destination cities effective in reducing the spread? Fourth, how many infections were prevented elsewhere in China by the unprecedented Wuhan lockdown? We utilize datasets on city-pair population migration and the within-city population movements of each city at the daily level from Baidu Migration, and the city-level daily number of infections from the Chinese Center for Disease Control and Prevention (CCDC) during a sample period of January 1 to February 29, 2020, covering 22 days before and 38 days after the city lockdown on January 23, 2020, as well as the matched data from the same lunar calendar period in 2019.

We first employ difference-in-differences (DID) estimation strategies to disentangle the effect of Wuhan lockdown on human mobility

reductions from other confounding effects including panic effect, virus effect, and the Spring Festival effect. Our estimates show that the Wuhan lockdown reduced inflow into Wuhan by 76.98%, outflows from Wuhan by 56.31%, and within-Wuhan movements by 55.91%. We find a clear inverted *U*-shape relationship between the lagged days of the population inflows from Wuhan or other cities in Hubei and the destination cities' new COVID-19 cases, with the largest impact from the population inflows from the epicenter about 12 to 14 days earlier. We provide evidence that imposing enhanced social distancing policies in 98 Chinese cities outside Hubei Province were effective in reducing the impact of population inflows from the epicenter cities in Hubei province on the spread of 2019-nCoV virus in the destination cities. Finally, we estimate that COVID-19 cases would be 105.27% higher in the 347 Chinese cities outside Hubei province, in the counterfactual world without the Wuhan lockdown.

Our study contributes to a fast-growing literature on 2019-nCoV infection, mostly in the medical and public health fields (Huang et al., 2020; Chan et al., 2020; Liu et al., 2020; WHO, 2003).[5] Adda (2016) uses a quasi-experimental variation to assess the effectiveness of public health measures that are aimed at reducing interpersonal contacts, and finds that the effectiveness of the measures depends on disease characteristics. Our results are also in line with the results of the latest modeling exercises (Chinazzi et al., 2020; Qiu et al., 2020; Chinazzi et al., 2020; Li et al., 2020; Tian et al., 2020; Jia et al., 2020), which mostly rely on calibrations of various virus-related parameters such as incubation period and detection rates, and changes in travel flows. Lai et al. (2020) build a travel network-based susceptible-exposed-infectious-removed (SEIR) model to simulate the outbreak across cities in mainland China. López and Rodó (2020) also use a modified stochastic SEIR model to explore different post-confinement scenarios in many countries such as Spain, Japan, New Zealand, and the U.S., and they find that the gradual de-confinement could be the best strategy to reduce the disease burden. Recent literature also shows that non-pharmaceutical interventions (NPIs) have a significant effect on reducing the virus reproduction rates in the U.S., U.K, Italy, Spain, France, Australia, New Zealand, and Singapore. The effectiveness of NPIs in reducing the estimated number of infections varies substantially across countries, ranging from only 0.8% in the U.S. to 99.3% in Singapore (Flaxman et al., 2020; Milne and Xie, 2020; Koo et al., 2020; Siedner et al., 2020).

To the best of our knowledge, this paper is the first to provide a *causal* interpretation of the impact of city lockdown on human mobility and the spread of 2019-nCoV, and to clearly disentangle the lockdown effects from other potential contributing factors such as panic and virus effect, as well as the seasonal Spring Festival effect. Although our study focuses exclusively on the impact of human mobility restrictions on the spread of 2019-nCoV virus in China, our estimated results can have general implications for other countries in their fight against the Novel Coronavirus.

The remainder of the paper is structured as follows. In Section 2, we describe the data sets and provide descriptive statistics. In Section 3, we use various DID estimations to evaluate the lockdown effect on population movements. In Section 4, we quantify the impact of lockdown on the national spread of COVID-19. Section 5 concludes.

2. Data and descriptive statistics

2.1. Population migration data

We obtain inter-city population migration data from Baidu Migration, a travel map offered by the largest Chinese search engine, Baidu. The data is based on real-time location records for every smartphone

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[3] With a population of over 11 million, Wuhan is the largest city in Hubei, the most populous city in Central China, and the seventh most populous city in China. The city is also a major transportation hub, with dozens of railways, roads and expressways passing through and connecting to other major cities, and home to 82 colleges and more than 1 million college students.

[4] See Wei, Lingling, and Chao Deng. "China's Coronavirus Response Is Questioned: 'Everyone Was Blindly Optimistic'." The Wall Street Journal, Dow Jones &; Company, 24 Jan. 2020, www.wsj.com/articles/china-contends-with-questions-over-response-to-viral-outbreak-11579825832.

[5] This study is also related to disaster-induced migration, which has often occurred during drought, flooding, earthquake and other destructive climatic phenomena (Munshi, 2003; Gray and Mueller, 2012; Lu et al., 2012).

using the company's mapping app, and thus can precisely reflect the population movements between cities.[6] The Baidu Migration data set covers 120,142 pairs of cities per day for 364 Chinese cities between January 12 and March 12 in 2019, and between January 1 and February 29 in 2020. Note that, by the lunar calendar, the data covers the same period of 24 days before and 36 days after the Spring Festivals, respectively for the year 2019 and 2020. The daily inter-city migration data consist of 2,977,899 city-pair observations each year. In addition, Baidu provides the daily *within-city* mobility data for each city in the sample period, which is a panel consisting of 21,840 city-day level observations each year.

Specifically, the Baidu Migration data provides three migration intensity indicators: the daily *in-migration* index (IMI) of a city, the daily *out-migration* index (OMI) of a city, and the daily *within-city* migration index (WCMI). We convert the three migration indices into the number of population movements using the actual number of inter-city/within-city population flows in Shanghai provided by the National Earth System Science Data Center (NESSDC). Appendix B provides the details of how we convert the Baidu indices into the number of population movements.

Appendix Table A1 presents the summary statistics of the population flows at the city-pair-day level and city-day level. It shows drastic declines in the average inflows, outflows, and within-city migration in 2020, compared to the same lunar period in 2019. The plummeting of the migration statistics due to the Wuhan lockdown is also depicted in Appendix Fig. A2.

2.2. Outbreak data

COVID-19 daily case counts are collected from China CDC, which provides daily updates on confirmed, dead, and recovered COVID-19 cases in each city.[7] Forty-one infections were first confirmed in Wuhan on January 10. We plot the geographic distributions of sample cities and cases in Appendix Fig. A1. Panel B of Appendix Table A1 presents the summary statistics of COVID-19 data, and Appendix Fig. A3 plots the trends of daily statistics of COVID-19 separately for the epicenter city of Wuhan, for other cities in Hubei, and for cities outside of Hubei.[8]

We have many reasons for treating the officially reported COVID-19 cases in Wuhan and other cities of Hubei with caution, and differently from the data of cities outside Hubei. As the epicenter of COVID-19, the health care systems in Wuhan and other cities in Hubei were overwhelmed by the sheer number of patients who needed laboratory testing, especially in the early phases of the virus outbreak. As such, the over-extended medical system in Wuhan and other cities in Hubei might have caused delays in testing the patients who contracted COVID-19; patients who contracted COVID-19 might have been self-recovered or died, before being officially tested; and some who were infected might have been asymptomatic. Also, government officials in the epicenter cities might have incentives to downplay the severity of the outbreak, at least initially. These considerations impact how we use the outbreak data in Section 4.

3. The impact of Wuhan lockdown on population movements

To suppress the spread of 2019-nCoV, the central government of China imposed an unprecedented lockdown in Wuhan starting from

10 am of January 23, 2020, and in all but one other Hubei cities a day later. As of February 29, 2020, 115 cities in 25 provinces issued different levels of lockdown policies. Table A2 in the Appendix provides detailed information about the various forms of population mobility control in different cities.

3.1. Empirical challenges

There are several confounding factors in our attempt to *causally* quantify the impact of lockdown on human mobility, and on the spread of infectious viruses. First, the virus outbreak happens right before the Spring Festival of the Chinese Lunar New Year (which fell on January 25 in 2020), which causes the largest annual human migration every year.[9] Second, the virus itself, even *in the absence* of a mandatory lockdown, may lead to curtailed human movement as people attempt to avoid the exposure to the virus. We refer to this deterrence effect as the *virus effect*. Third, for Wuhan and other nearby cities in Hubei, there is a possible *panic effect*, in reaction to the virus.[10] The panic effect can lead to an increase in the population outflow from the epicenter of the virus outbreak, and a decrease of the population inflow to the epicenter, particularly Wuhan. The panic effect is likely to peak when the government officially confirmed on January 20, 2020 that the Novel Coronavirus can transmit from person-to-person.

3.2. Effects of various factors on inter-city population mobility

We first examine the impact of city lockdown on inter-city population mobility, including inflow and outflow, between a city pair (i,j). To disentangle the contributions of these confounding factors on human mobility, we exploit many unique sources of variations in the data, and employ several DID estimation strategies by comparing different treatment and control groups. The DID specification can be described as follows:

$$Ln(Flow_{i,j,t}) = \begin{array}{l} \alpha + \beta_1 \cdot Treat * Before_{1,t} + \beta_2 \cdot Treat * Before_{2,t} \\ + \beta_3 \cdot Treat * After_t + \mu_{i,j} + \theta_t + \varepsilon_{i,j,t} \end{array} \quad (1)$$

where i, j, and t respectively index the destination city, origination city, and date; the dependent variable, $Ln(Flow_{i,j,t})$, is the logarithm of the population flows from city j to city i at date t. The definition of *Treat* varies by specific DID designs, and we will be explicit about its definition below. The city-pair fixed effect $\mu_{i,j}$ is included to absorb the city-specific and the city-pair specific heterogeneities that may contaminate the estimation of our interested coefficient β_3. We also control for the date-fixed effect θ_t to eliminate the time-specific impact, including the Spring Festival travel effect. The standard errors are clustered at the daily level.

In Eq. (1), we include two pre-lockdown period indicators: $Before_{1,t}$ is a dummy that takes value 1 for the period from January 11 to January 19, 2020 (4 to 11 days before the Wuhan lockdown), which can be used to examine the parallel pre-trend assumption in the DID analysis; $Before_{2,t}$ is a dummy that takes value 1 for the period from January 20 to January 22, 2020, three days before the unprecedented Wuhan lockdown, but after the official announcement that the virus can spread from person to person. $Before_{2,t}$ allows us to capture the panic effect. Finally, $After_t$ is a dummy that takes value 1 for the sample period after the Wuhan lockdown, between January 23 and February 29, 2020. The omitted benchmark period is from January 1 to January 10, 2020.

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[6] It is important to emphasize here that the mobility data is about the movement of people from one city to another based on geo-location services of the smartphones; as such a person flowing out of city A to city B is not necessarily a *resident* of city A, but he/she must have been to city A before moving to city B.

[7] Source: http://2019nCoV.chinacdc.cn/2019-nCoV/.

[8] The spike of confirmed cases observed on February 12 in Hubei Province is, for the most part, the result of a change in diagnosis classification for which 13,332 clinically (rather than laboratory) confirmed cases were all reported as new cases on February 12, 2020, even though they might have been clinically diagnosed in the preceding weeks. Also on February 13, 2020, a new Communist Party Secretary of Hubei started in his position.

[9] The migration across China, which officially begins from about two weeks before, and ends about three weeks after, the Lunar New Year, is often referred to as *Chunyun* (meaning Spring movement). In 2019, approximately 3 billion trips were made during Chunyun, see https://www.cnn.com/travel/article/lunar-new-year-travel-rush-2019/index.html.

[10] Keane and Neal (2020) find that both virus transmission and government policies can significantly contribute to consumers' panic purchases.

3.3. Effects of various factors on within-city population mobility

We also estimate the effect of lockdown on the within-city population movement utilizing the city-level data and a variety of DID specifications:

$$Ln(WithinCityFlow_{i,t}) = \alpha + \beta_1 \cdot Treat * Before_{1,t} + \beta_2 \cdot Treat * Before_{2,t} + \beta_3 \cdot Treat * After_t + \mu_i + \theta_t + \varepsilon_{i,t} \quad (2)$$

where i and t index the city and date. $Ln(WithinCityFlow_{i,t})$ is the logarithm of the within-city population movement for city i at date t. Similar to Eq. (1), *Treat* will be defined according to the DID design. $Before_{1,t}$, $Before_{2,t}$ and $After_t$ are defined in the same way as in Eq. (1). We include the city fixed effects μ_i and date fixed effects θ_t. The standard errors are clustered at the daily level.

3.4. Estimation results

Table 1 reports the results from three sets of regressions specified according to Eq. (1) for inter-city inflows (Panel A) and outflows (Panel B), and according to Eq. (2) for within-city movement (Panel C). We implement two models that differ in the estimation sample, and the definition of the control group.

Table 1
The effects of Wuhan lockdown on population movement.

Treatment Group	Wuhan 2020	Wuhan 2020
Control Group	Wuhan 2019	7 Cities 2020
Treatment Effects	Lockdown + Virus	Lockdown
Model	(1)	(2)
Panel A. Dep. Variable: *ln(Inflow Population)*		
Treat*Before$_1$	-0.138	0.149
	(0.098)	(0.151)
Treat*Before$_2$	-0.122	0.239
	(0.083)	(0.153)
Treat*After	-2.518***	-1.469***
	(0.212)	(0.338)
Observations	26,494	72,094
R-squared	0.803	0.761
Panel B. Dep. Variable: *ln(Outflow Population)*		
Treat*Before$_1$	0.042	0.010
	(0.079)	(0.071)
Treat*Before$_2$	0.723***	0.174**
	(0.071)	(0.071)
Treat*After	-1.295***	-0.828***
	(0.155)	(0.168)
Observations	26,326	71,533
R-squared	0.899	0.901
Panel C. Dep. Variable: *ln(Within-city Population Flow)*		
Treat*Before$_1$	-0.014	-0.015
	(0.065)	(0.014)
Treat*Before$_2$	-0.275***	-0.096
	(0.067)	(0.057)
Treat*After	-1.861***	-0.819***
	(0.093)	(0.047)
Observations	120	256
R-squared	0.952	0.938
Fixed Effects	City-Pair FE and Daily FE in Panel A and Panel B	
	City FE and Daily FE in Panel C	

Notes: This table reports the results of estimating Eqs. (1) and (2). The control and treatment groups for Models 1–2 are described in the text. Fixed effects of city-pair and daily are included in all columns in Panels A and B, and fixed effects of city and daily are included in all columns in Panel C. standard errors are clustered at the daily level. ***Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.

3.4.1. Model 1: Wuhan 2020 vs. Wuhan 2019

In Model 1, we compare the population movements of Wuhan in 2020 to *itself* in the same matched lunar calendar period in 2019, during which Wuhan is free of virus outbreak and lockdown. Thus, the estimation sample in Model 1 is the daily inflows into and outflows out of Wuhan, as well as the daily within-city movements in Wuhan for years 2019 and 2020.

Under Model 1, *Treat* takes value 1 if the destination city i (respectively, the origination city j) is Wuhan and year is 2020 in Panel A (respectively, Panel B). Panel C examines the within-city mobility, *Treat* takes value 1 if the year is 2020. The control group is Wuhan 2019. We interpret the coefficient estimate of $Treat * Before_{2,t}$ as measuring the panic effect of Wuhan 2020 relative to Wuhan 2019; and the coefficient estimate of $Treat * After_t$ as measuring both the lockdown and the virus effects. The coefficient estimate of $Treat * Before_{1,t}$ examines whether the parallel trend assumption for DID is satisfied. The possibly time-varying Spring Festival effects and the virus effects are both absorbed in the day fixed effects.

The estimated coefficients on $Treat * After_t$ remain negative, and economically and statistically significant in all panels. The estimates suggest that the lockdown of Wuhan, together with the deterrence effect of the virus (the *virus effect*), on average reduces the inflow population into, outflow population from, and within-city movements in Wuhan by 91.94% ($=1 - exp(-2.518)$), 72.61% ($=1 - exp(-1.295)$), and 84.45% ($=1 - exp(-1.861)$), respectively, relative to the same lunar calendar days in 2019. We also find that the coefficient on $Treat * Before_{2,t}$ is significantly positive in Panel B and significantly negative in Panel C, suggesting that the official confirmation of person-to-person spread of COVID-19 creates a panic effect, causing an increase of outflow from Wuhan of 106.06% ($= exp(0.723) - 1$), and a decrease of within-city movements in Wuhan of 24.04% ($=1 - exp(-0.275)$), during the three days after the confirmation of the person-to-person transmission but before the city lockdown. However, we do not observe a statistically significant panic effect for the population inflow into Wuhan, suggesting that people in other cities were not yet sufficiently concerned about the virus outbreak in Wuhan and did not avoid traveling to Wuhan, even after the official confirmation of the person-to-person transmission. Finally, the coefficient estimates for $Treat * Before_{1,t}$ are all statistically insignificant, suggesting that the parallel pre-trend assumption is plausible.

3.4.2. Model 2: Wuhan 2020 vs. seven other lockdown cities 2020

In Model 1, the coefficient estimates of $Treat * After_t$ provide an estimate of the *sum* of the lockdown and the virus effects. In order to isolate the lockdown effect from the virus deterrence effect, we consider Model 2, where the estimation sample consists of data of Wuhan and *seven other cities* that went into partial lockdown on February 2 and February 4, 2020, 10 to 12 days after the lockdown of Wuhan.[11] As we show in Table A3 in the Appendix, these seven cities are more comparable to Wuhan than other unlocked cities in terms of the epidemic situation and other economic indicators, and thus provide a more reasonable control group to partial out the virus effect. In particular, it is much more plausible than using cities that were never locked down as control cities to assume that the virus deterrence effect on human mobility in the seven cities is similar to that in Wuhan.

The estimation sample for Model 2 consists of data from Wuhan and the seven cities for the period between January 1 and February 2, 2020. Note that during this period, none of the seven control cities were locked down yet, though they soon would be. The definitions for *Treat* variables are as follows. In Panel A, *Treat* takes value 1 if the destination city i is Wuhan; in Panel B, *Treat* takes value 1 if the origination city j is Wuhan; in Panel C, *Treat* takes value 1 if city i is Wuhan. The control group consists of the seven cities.

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[11] These seven cities are summarized in Appendix Table A2.

We find that the Wuhan lockdown significantly reduces the inflow into, outflow from, and within-city movements in Wuhan by 76.98% ($=1 - exp(-1.469)$), 56.31% ($=1 - exp(-0.828)$), and 55.91% ($=1 - exp(-0.819)$), respectively. We interpret these as the *pure* lockdown effect on population mobility related to Wuhan.

3.4.3. Summary

Based on our estimation of Models 1 and 2, Table 2 summarizes our estimates of the panic effect, the virus effect, and the lockdown effect on inflows into, outflows from, and within-city population movements in Wuhan.

In Table 2, the lockdown effects are directly calculated from the corresponding coefficient estimates of *Treat ∗ After* from Model 2 discussed above; the panic effects are from the coefficient estimates of *Treat ∗ Before$_2$* in Model 1. For the virus effect, we recognize that the coefficient estimates of *Treat ∗ After* in Model 1 incorporate both the lockdown and the virus effects. Thus, we calculate the *virus effect* on inflows into Wuhan to be $exp(-2.518 - (-1.469)) - 1 = -64.97\%$, on the outflows from Wuhan to be $exp(-1.295 - (-0.828)) - 1 = -37.31\%$, and on the within-city flow in Wuhan to be $exp(-1.861 - (-0.819)) - 1 = -64.73\%$.

Because our models assume that the different effects enter exponentially in explaining the flows - recall the natural log specifications in Eqs. (1) and (2) - when we would like to calculate the impact of two or more effects on the population flows, we should not simply add the individual effects. For example, the joint impact of the panic and virus effects on outflows out of Wuhan is $(1 + 106.06\%) * (1 - 37.31\%) - 1 = 29.18\%$, instead of the simple sum of $106.06\% + (-37.31\%) = 68.75\%$.

4. Quantify the impact of lockdown on the national spread of COVID-19

4.1. Inter-city flows and the 2019-nCoV transmission

We now examine the impact of human mobility on the transmission of 2019-nCoV. Considering that almost all the new COVID-19 cases outside Wuhan were confirmed after the Wuhan lockdown, while almost all inter-city population flows occurred prior to the Wuhan lockdown (see Appendix Figs. A2 and A3), we investigate the imported infections by looking specifically at the impact of population inflows from cities in the epicenter, namely, Wuhan and other cities in Hubei province, on the new cases in the destination cities outside Hubei.

Recognizing that 2019-nCoV has a long incubation period, we estimate a *dynamic distributed lag* regression model taking into account that inflows from Wuhan with different lags may have differential impacts on the current new cases in the destination cities. Most of the medical literature states that the 2019-nCoV virus has a median incubation period of five days, and some can have an incubation period of 14 days or more (see, e.g., Lauer et al. (2020)). Luckily, our data allows us to incorporate the possibility that contact with an infected person from Wuhan or other cities in Hubei can result in confirmed infections in the destination city for up to 22 days.

The analysis focuses on the daily new confirmed cases in the post-Wuhan lockdown period from January 23 to February 29, 2020, for cities

i that are *outside Hubei province*. Specifically, we run the following regression[12]:

$$Ln(1 + NewCase_{i,t}) = \alpha + \sum_{\kappa=1}^{22} \beta_{1\kappa} \cdot Ln(Inflow_{i,WH,t-\kappa} \cdot I_{WH,t-\kappa})$$
$$+ \sum_{\kappa=1}^{22} \beta_{2\kappa} \cdot Ln\left(\sum_{j\neq i, j\neq WH, j\in HB} Inflow_{i,j,t-\kappa} \cdot \sum_{j\neq i, j\neq WH, j\in HB} I_{j,t-\kappa} \right)$$
$$+ \mu_i + \theta_t + \varepsilon_{it}, \tag{3}$$

where i indexes the cities outside Hubei, and $t \in \{23,...,60\}$ indicates the date.[13] $\kappa \in \{1,...,22\}$ indicates the time lapsed from the inflows from Wuhan or other Hubei cities until the current date t. $Ln(1 + NewCase_{i,t})$ is the logarithm of the number of new confirmed cases in city i at date t. $Inflow_{i,WH,t-\kappa}$ and $\sum_{j\neq i, j\neq WH, j\in HB} Inflow_{i,j,t-\kappa}$ are the inflows from Wuhan, and the inflows from the 16 other cities in Hubei to city i, respectively, κ days prior to the focal date t. $I_{WH,t-\kappa}$ and $\sum_{j\neq i, j\neq WH, j\in HB} I_{j,t-\kappa}$ respectively represent the *active infected cases* in Wuhan and other cities in Hubei, κ days prior to the focal date t.[14] Therefore, $Ln(Inflow_{i,WH,t-\kappa} \cdot I_{WH,t-\kappa})$ measures the impact of the infected fraction of the inflows from Wuhan κ days earlier on the new infections in city i at date t. We control for destination city fixed effects μ_i and date fixed effects θ_t.

Remark 1. The role of asymptomatic infected individuals in the transmission of 2019-nCOV virus is now well understood (Rothe et al., 2020). Our data, unfortunately, does not contain asymptomatic infection cases. However, to the extent that there is a constant ratio of asymptomatic and symptomatic cases, which seems to be a plausible assumption based on the current literature, our log-log specification using only the number of symptomatic cases would not be affected by not including the asymptomatic cases.

Note that in this regression we include only cities outside Hubei Province for two reasons. First, Wuhan and other cities in Hubei province are the outbreak epicenter, and we are interested in how population outflows from these cities affect the destination cities' COVID-19 cases. Second, the confirmed COVID-19 cases in Wuhan and other cities in Hubei are likely to be inaccurate due to the reasons aforementioned in Section 2. In contrast, the confirmed cases in other cities are likely to be accurate, as their numbers are not large enough to overwhelm their local health care system; and the incentives to under-report are much weaker in cities outside of Hubei.

The estimated coefficients $\beta_{1\kappa}$ and $\beta_{2\kappa}$ in Eq. (3) respectively represent the impact of the inflows from Wuhan and other cities in Hubei $\kappa \in \{1,...,22\}$ days ago on the destination cities' new cases today. They are respectively plotted in the left and right graphs of Panel A of Fig. 1. We also fit a spline smoothed curve of the estimated effects of the different lags of inflows from Wuhan and Hubei, which both show a clear inverted *U*-shape relationship between the lagged days of the population inflows from Wuhan or other cities in Hubei and the destination cities' new COVID-19 cases. Interestingly, both graphs show that the largest impact on the newly confirm cases today in Chinese cities outside Hubei comes from the inflow population from Wuhan or other cities in Hubei about 12 to 14 days ago. The pattern exhibited in Fig. 1 is consistent with the hypothesis that the

Table 2
Summarizing the panic effect, virus effect and lockdown effect on inter-city and within-city population movements of Wuhan.

Effect	Infows	Outflows	Within-city
Panic effect	−11.49%	106.06%***	−24.04%***
Virus effect	−64.97%***	−37.31%***	−64.73%***
Lockdown effect	−76.98%***	−56.31%***	−55.91%***

Notes: These effects are calculated based on the estimates reported in Columns (1) and (2) of Table 1.
*** Significant at the 1% level.

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[12] Our log-log specification is based on the classical susceptible-infectious-removed (SIR) model in epidemiology.

[13] Date $t = 23$ indicates the date of January 23, 2020, and $t = 60$ the date of February 29, 2020.

[14] Active infected cases stand for the cumulative active infections (total infections - total healed - total death) in Wuhan at $t - \kappa$. Note that the total populations in Wuhan and other cities in Hubei are constants that are absorbed in α in Eq. (3). Despite the fact that the confirmed cases in cities in Hubei may be under-reported, as we will show in Section 3, the active cases are still informative about the underlying true infection rates.

A: Results of Estimating Equation (3)
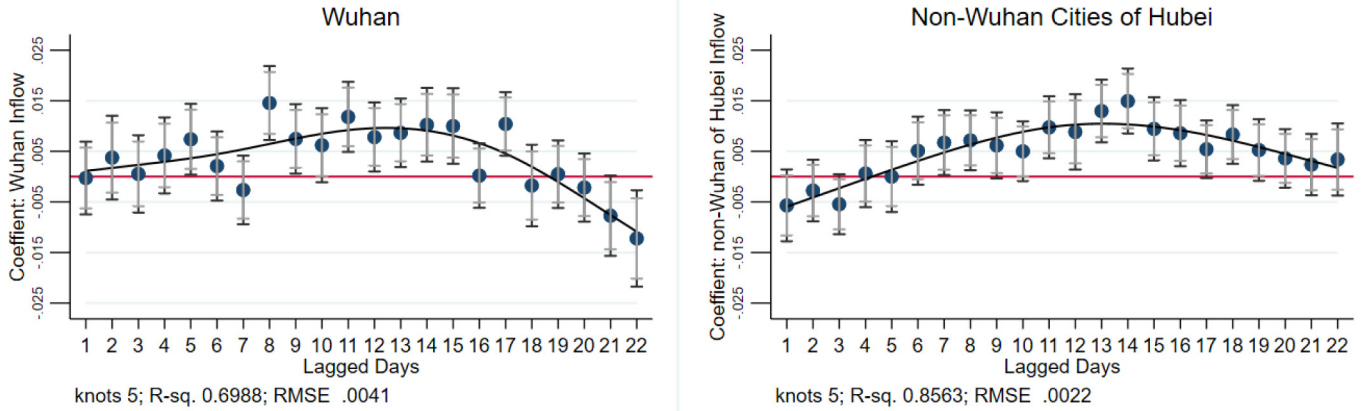
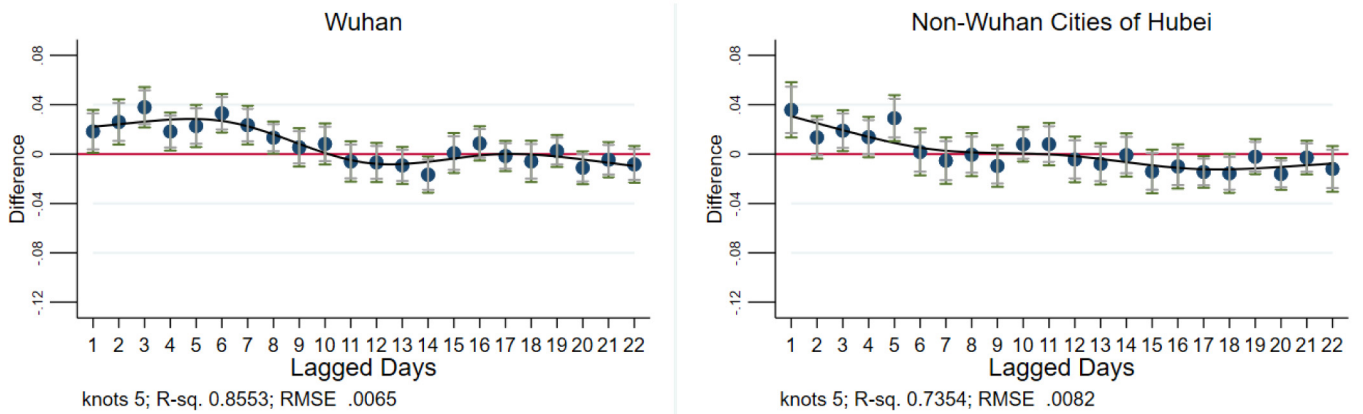## B: Results of Estimating Equation (4)

Fig. 1. Dynamic impact of past inflow from Wuhan and from other cities in Hubei on daily new cases. Panel A: Results of estimating Eq. (3). Panel B: Results of estimating Eq. (4). Notes: Panel A plots the dynamic effects of lagged inflows from Wuhan (left) and 16 other cities in Hubei (right) from estimating Eq. (3). Panel B plots the difference between the estimated effects of pre- and post-destination-lockdown inflows from Wuhan (left figure) and non-Wuhan cities in Hubei (right figure) on daily new cases in destination cities outside Hubei from estimating Eq. (4). We add spline smoothing fit curves (in red) using the *rcspline* function and plot the 90% (the vertical gray whiskers) and 95% (the vertical black whiskers) confidence intervals.

incubation period of the 2019-nCoV is up to 12 to 14 days, and also consistent with a shorter incubation period coupled with secondary infections.

4.2. Effect of social distancing on virus transmission in destination cities

Social distancing at the destination cities is crucial in preventing the possibly asymptomatic transmission from the source city (Chinazzi et al., 2020) and quantifying the effect of social distancing on virus transmission is especially relevant in the stage of pre-epidemic community spread. This section studies the effectiveness of social distancing measures in the destination cities in reducing and containing the spread of the virus.

As shown in Appendix Table A2, within weeks after the Wuhan and Hubei lockdowns, various human mobility restrictions were imposed on 98 other Chinese cities outside Hubei. As described in Table A2, the "lockdowns" in destination cities varied in their degree of strictness, from checkpoints at building entrances to establishing quarantine zones, and from public transit shutdowns to strict limits on the inflows into the city, outflows out of the city, as well as within-city population movements. We interpret the human mobility restrictions in the destination cities as an *enhanced social distancing* policy, because the "lockdown" rules in the destination cities are not as strict as those implemented in Wuhan.

Specifically, we estimate the following specification that is a modified version of the regression specification described by Eq. (3):

$$Ln(1 + NewCase_{i,t})$$

$$= \alpha + \sum_{\kappa=1}^{22} \beta_{1\kappa} \cdot Ln(Inflow_{i,WH,t-\kappa} \cdot I_{WH,t-\kappa}) \cdot (1 - Lockdown_{i,t})$$

$$+ \sum_{\kappa=1}^{22} \gamma_{1\kappa} \cdot Ln(Inflow_{i,WH,t-\kappa} \cdot I_{WH,t-\kappa}) \cdot Lockdown_{i,t}$$

$$+ \sum_{\kappa=1}^{22} \beta_{2\kappa} \cdot Ln\left(\sum_{j\neq i, j\neq WH, j\in HB} Inflow_{i,j,t-\kappa} \cdot \sum_{j\neq i, j\neq WH, j\in HB} I_{j,t-\kappa}\right) \cdot (1 - Lockdown_{i,t})$$

$$+ \sum_{\kappa=1}^{22} \gamma_{2\kappa} \cdot Ln\left(\sum_{j\neq i, j\neq WH, j\in HB} Inflow_{i,j,t-\kappa} \cdot \sum_{j\neq i, j\neq WH, j\in HB} I_{j,t-\kappa}\right) \cdot Lockdown_{i,t}$$

$$+ \mu_i + \theta_t + \varepsilon_{it}, \tag{4}$$

where $Lockdown_{i,t}$ is a dummy that takes value 1 if time t is a date after destination city i's "lockdown" date, if at all; and 0, otherwise, where the lockdown dates of the 98 cities outside Hubei are listed in Table A2. If city i never implemented any formal lockdown policy, the dummy is always 0. Therefore, the coefficients, $\beta_{1\kappa}$ and $\beta_{2\kappa}$, respectively, measure the impact of the lagged inflows from Wuhan and other cities in Hubei κ days earlier on the destination cities' current new cases before the city's imposition of its "lockdown," while $\gamma_{1\kappa}$ and $\gamma_{2\kappa}$ represent the effect on destination cities' current new cases of the inflows from Wuhan

and other Hubei cities after the imposition of the city's lockdown. If enhanced social distancing that comes from the "lockdown policies" imposed at the 98 Chinese cities outside Hubei is effective in reducing the spread of the virus from population flows from the epicenter of the virus, then we expect that $\gamma_{1\kappa}$ and $\gamma_{2\kappa}$ to be smaller than $\beta_{1\kappa}$ and $\beta_{2\kappa}$, respectively.

We plot the estimated coefficients $\beta_{1\kappa}$ and $\gamma_{1\kappa}$ (respectively, $\beta_{2\kappa}$ and $\gamma_{2\kappa}$) in Panel A (Panel B) of Appendix Fig. A4, and their differences in Panel B of Fig. 1 for the lagged effects of inflows from Wuhan (respectively, 16 non-Wuhan cities in Hubei) on the daily new cases in destination cities outside Hubei. The estimated lagged effects of inflows from Wuhan and other cities in Hubei before the destination city's lockdown, if any, show little change compared to the coefficients in Panel A of Fig. 1; however, the coefficient estimates of lagged inflows after the destination city's lockdown policies appear to be statistically insignificant on almost all lags. As shown in Panel B of Fig. 1, the differences between the estimated effects pre and post the destination cities' lockdown policies are positive and statistically significant at 10% or lower level for eight (respectively, three) of the first ten lagged population inflows from Wuhan (respectively, 16 other cities of Hubei).

These results suggest that the enhanced social distancing policies in the destination cities are effective in reducing the impact of population inflows from the source cities of Wuhan and other cities in Hubei on the spread of 2019-nCoV virus in the destination cities. This in turn implies that population inflows from the epicenter contribute to the spread of infection in the destination cities only *before* the social distancing measures are applied; it appears that after implementing their various control measures, cities adopting an enhanced social distancing policies can flatten the upward trajectory of the virus infections.

4.3. How many COVID-19 cases were prevented by the Wuhan lockdown?

We next estimate the *counterfactual* number of COVID-19 cases that would have occurred in other cities in the absence of Wuhan lockdown, which would, in turn, require a counterfactual estimate of the outflows from Wuhan to other Chinese cities, had there been no lockdown of Wuhan. As shown in Table 2, in the absence of the Wuhan lockdown, the virus effect and panic effects would have led to a 37.31% decrease and a 106.06% increase in the outflow population from Wuhan, respectively. Therefore, we would expect the outflows from Wuhan after January 23 to be

$$\underbrace{(1-0.3731)}_{\text{Reducton from Virus Effect}} * \underbrace{(1+1.0606)}_{\text{Increase from Panic Effect}} = 1.29 \qquad (5)$$

times the *normal outflows* from Wuhan to other cities in the counterfactual world.

We use the daily level of outflows from Wuhan to a city *in 2019 on the same lunar calendar day* as a measure of the normal outflow, and multiple the number by 1.29 to obtain the daily counterfactual inflows from Wuhan to the city, had there been no lockdown of Wuhan from January 23, 2020. Using this estimation method, we find that on average, the estimated counterfactual outflows from Wuhan to the 347 cities outside Hubei between January 23 and February 29, 2020 would be 2,848,496, 5.99 times the actual population outflow to those cities during the same period, which is 475,542.[15]

We denote the counterfactual inflows from $j = Wuhan$ into city i at date $s \in \{23, ..., 60\}$ from the above calculation as $\widetilde{Inflow}_{i,WH,s}$. We assume that the Wuhan lockdown did not affect the within-city and inter-city population movements in other cities, as well as the infected cases in Wuhan. We also assume that all the control measures

implemented by other cities after the Wuhan lockdown remain in place. Thus the parameter estimates of the dynamic lag effects of inflows from Wuhan and other cities in Hubei, estimated in Eq. (3), remain valid as an epidemiological diffusion equation that is not affected by human mobility restrictions that result from the Wuhan lockdown; the lockdown only affected the human flows.

With these considerations in mind, we simulate the counterfactual number of COVID-19 cases, had there been no Wuhan lockdown, on date $t \in \{23, ..., 60\}$ (i.e., from January 23 to February 29, 2020) in cities i outside Hubei by the following equation:

$$
\begin{aligned}
Ln\left(1 + \widetilde{NewCase}_{i,t}\right) = \hat{\alpha} &+ \sum_{\kappa=1}^{22} \hat{\beta}_{1\kappa} \cdot Ln\left(\widetilde{Inflow}_{i,WH,t-\kappa} \cdot I_{WH,t-\kappa}\right) \\
&+ \sum_{\kappa=1}^{22} \beta_{2\kappa} \cdot Ln\left(\sum_{j\neq i, j\neq WH, j\in HB} Inflow_{i,j,t-\kappa} \cdot \sum_{j\neq i, j\neq WH, j\in HB} I_{j,t-\kappa}\right) \\
&+ \hat{\mu}_i + \hat{\theta}_t + \hat{\varepsilon}_{i,t},
\end{aligned} \qquad (6)
$$

where $\hat{\beta}_{1\kappa}$ and $\hat{\beta}_{2\kappa}$ are coefficient estimates obtained from regressions specified in Eq. (3) and $\hat{\mu}_i$ and $\hat{\theta}_t$ are the estimated city fixed effects and date fixed effects, respectively, from the same regression. Note that in predicting the counterfactual infections without the Wuhan lockdown, we use the *counterfactual* inflows from Wuhan to city i for days after January 23 $\widetilde{Inflow}_{i,WH,s}$ discussed previously.

In Fig. 2, we present the counterfactual estimates (in the dotted curve) of COVID-19 cases had there been no Wuhan lockdown, and the officially reported cases (in the solid curve) for cities outside Hubei. The gap between the estimated counterfactual number of infection cases and the officially reported cases on the bottom figure represents the number of COVID-19 cases prevented by the Wuhan lockdown. As of February 29, 2020, the officially reported number of COVID-19 in the 347 cities outside Hubei province was 12,623, but our counterfactual simulation suggests that there would have been around 25,911 cases, had there been no Wuhan lockdown. That is, the COVID-19 cases would be 105.27% higher in 347 cities outside Hubei as of February 29, in the counterfactual world in which the city of Wuhan were not locked down from January 23, 2020. Our findings thus suggest that the lockdown of the city of Wuhan from January 23, 2020 played a crucial role in reducing the imported infections in other Chinese cities and halted the spread of 2019-nCoV virus.

We show that, the daily new infections would gradually decline and stabilize at around 400 cases from February 18 onwards in the counterfactual world. In the short term, the estimated daily new cases in the counterfactual world would not converge to the real world reported cases. The results suggest that the social distancing measures implemented elsewhere in China would not work as well in containing the spread of 2019-nCOV virus unless Wuhan was locked down on January 23, 2020. It also reflects the challenging situations many countries experienced in containing the spread of virus, where strict lockdowns of the virus epicenters were not imposed early.

We also attempt to estimate the magnitude of the undocumented infection cases in Wuhan and other cities in Hubei province during the early stages of the epidemic. In Appendix C we present the methodology and results. We find that there were substantial undocumented infection cases in the early days of the 2019-nCoV outbreak in Wuhan and other cities of Hubei province, but over time, the gap between the officially reported cases and our estimated "actual" cases narrowed significantly.

5. Conclusion

In this paper, we provide valuable causal evidence on the role of human mobility restrictions on the containment and delay of the spread of contagious viruses, including the 2019-nCoV virus that is now ravaging the world. We find that the lockdown of Wuhan reduced inflows to Wuhan by 76.98%, outflows from Wuhan by 56.31%, and within-Wuhan

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[15] Recall that outflows from Wuhan are not just residents of Wuhan; any travelers who entered Wuhan for whatever reason and then leave Wuhan would be included in the Wuhan outflows measured by Baidu Migration data.
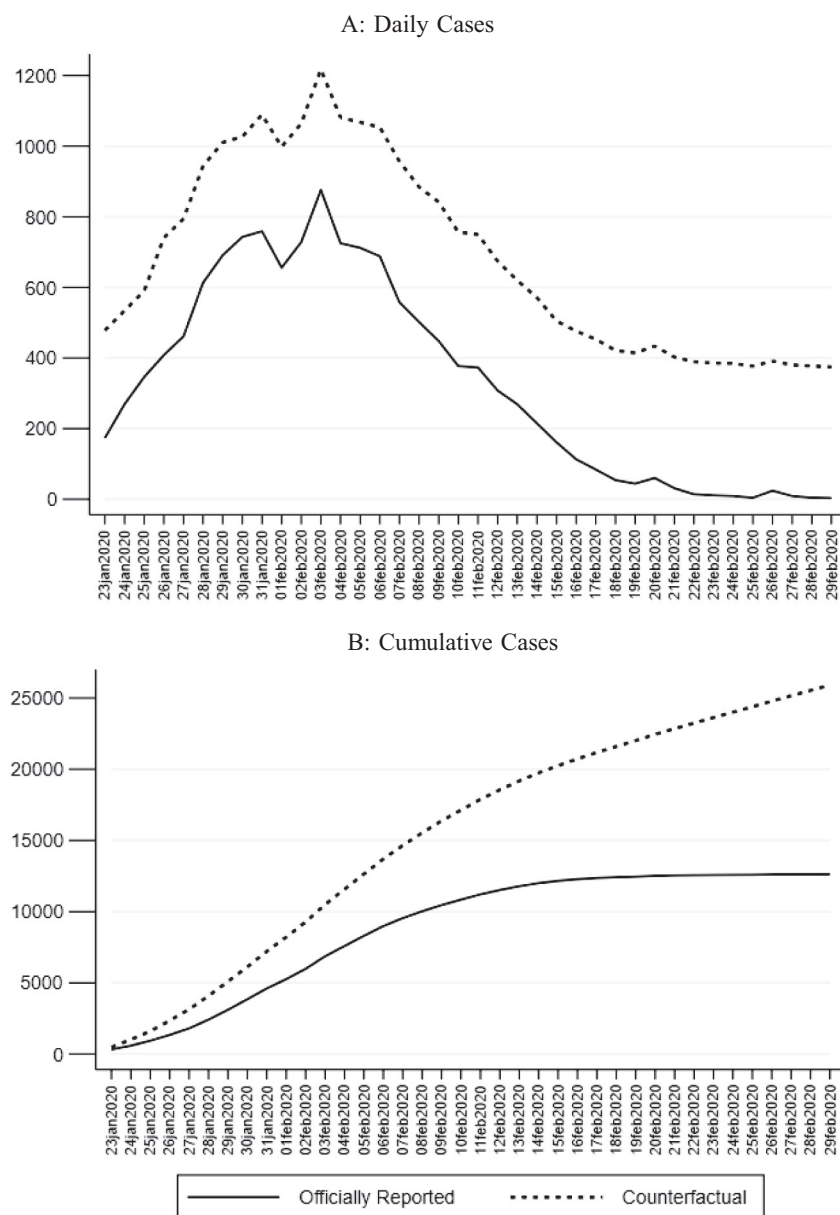
A: Daily Cases

B: Cumulative Cases

Fig. 2. Counterfactual of infected cases elsewhere in China. Panel A: Daily cases. Panel B: Cumulative cases. Notes: This figure plots the counterfactual estimation on the COVID-19 cases in 347 other cities in China if Wuhan had never been under a government-ordered lockdown (in the dotted curve), and traces the officially reported COVID-19 cases in cities outside Hubei (in the solid curve). The top figure depicts the model's counterfactual prediction and the actual of daily infection cases, and the bottom figure depicts the evolution of cumulative cases from January 23 to February 29, 2020.

movements by 55.91%; we also find a substantial virus deterrence effect on population mobility. We estimate the dynamic effects of up to 22 lagged population inflows from Wuhan and other Hubei cities, the epicenter of the 2019-nCoV outbreak, on the destination cities' new infection cases. We find that the lockdown of Wuhan significantly reduced the population mobility and that the enhanced social distancing policies in the destination cities effectively reduce the impact of population inflows from the epicenter cities in Hubei on the spread of 2019-nCoV. Using counterfactual simulations with these estimates, we find that the lockdown contributed significantly to reducing the total infections outside Hubei. Specifically, we find that in the counterfactual world in which the city of Wuhan were not locked down from January 23, 2020, infections would be 105.27% higher in the 347 Chinese cities outside Hubei province. Lockdowns of virus epicenters, if they can be identified before the virus widely spreads, may be an important policy instrument in the fight to contain a fast-moving pandemic.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpubeco.2020.104272.

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