文献导读（一）：人口流动与疫情扩散

Literature Review (1): Population Mobility and Coronavirus Spreading

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Literature Review (1)

Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China

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研究背景/Background

- 以往研究/Previous studies:
  - Human mobility contributes to the transmission of infectious diseases.
  - Many countries impose restriction of human mobility in response to pandemic threats.
  - Restrictions on human mobility are controversial in respect to their negative economic impacts and uncertainty about the effectiveness in controlling the epidemic.
- 研究挑战/Challenges of current studies:
  - It is empirically challenging to quantify the impact of human mobility on the spread of infectious disease and to understand the detailed spatial patterns of how the infectious diseases spread.
  - It is difficult to disentangle the impact of human mobility from other potential contributing factors.

研究目标/Objective

To examine the effects of the city lockdown and understand the relationship between human mobility and virus transmission.

1. How does the lockdown of the city of Wuhan amid the Novel Coronavirus outbreak affect population movement?
2. How do population flows among Chinese cities, particularly outflows from Wuhan and other cities in Hubei province, affects virus infection in the destination cities?
3. What is the magnitude of undocumented cases of COVID-19 cases in Wuhan and other cities in Hubei province during the early stages of the epidemic? And how does the extent of undocumented infection cases evolve over time?
4. How many COVID-19 cases elsewhere in China were prevented by the unprecedented Wuhan lockdown?
5. Are social distancing policies in destination cities effective in reducing the spread of the infections?

数据来源/Dataset

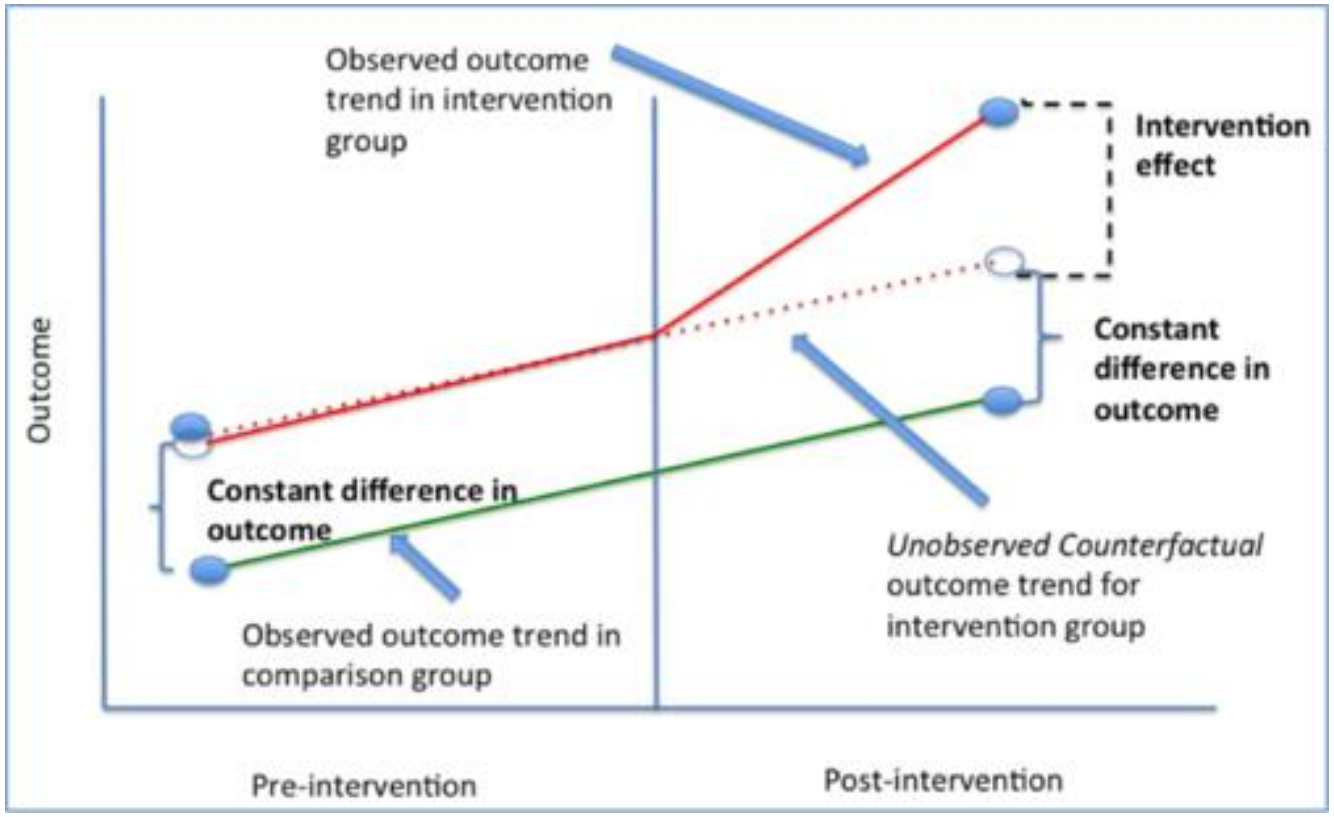
- 百度地图/**Baidu Migration**: The Baidu Migration data is based on real-time location records from every smart phone using Baidu's mapping app. It includes inter-city population migration data from 364 Chinese cities.
- 中国疾病疾病预防控制中心/**Chinese Center for Disease Control and Prevention:** the city-level daily numbers of confirmed COVID-19 cases, recovered patients, and death tolls
- 数据时间/**Timeline:** January 1-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.

数据模型/statistical model

- 双重差分模型/Difference-in-differences estimation
- 滞后解释数模型/The dynamic distributed lag regression model

数据模型/statistical model

- 双重差分模型/Difference-in-differences estimation (DID)



DID is typically used to estimate the effect of a specific intervention or treatment (such as a passage of law, enactment of policy, or program implementation) by comparing the changes in outcomes over time between a population that is enrolled in a program (the intervention group) and a population that is not (the control group).

数据模型/statistical model

- 滞后解释数模型/The dynamic distributed lag regression model
  - In the regression model includes not only the current but also the lagged values of the explanatory variables.

- 什么是滞后/What dose mean of lag?
  - Many economic models have lagged values of the explanatory variables in the regression equation. For example, it takes time before investment in research and development pays off in new inventions which in turn take time to develop into commercial products.

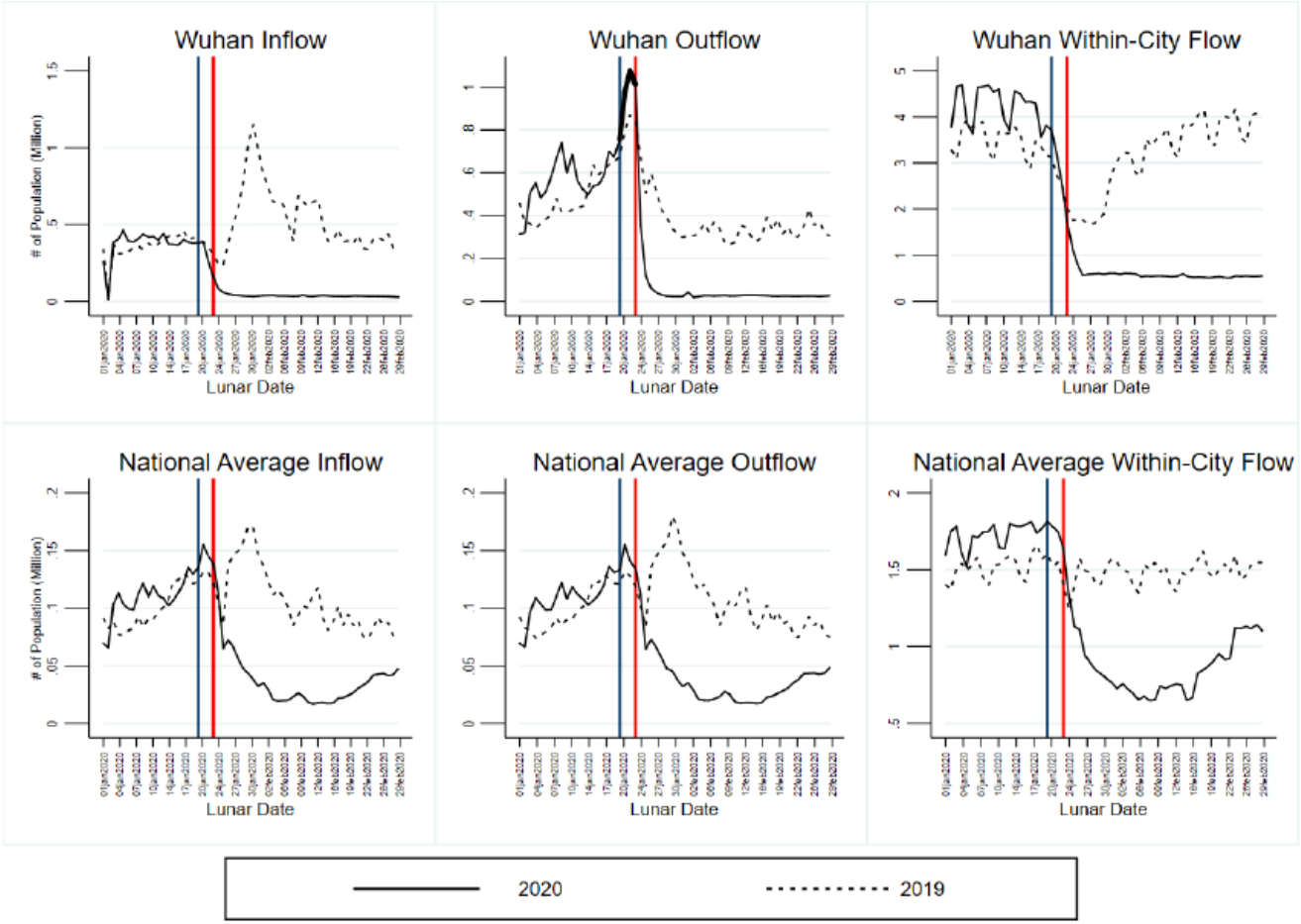
- 滞后再本研究中代表什么/What dose mean of lag in this research?
  - Incubation period of COVID-19

结果解读
Reading Results

人口流动数据
Population migration data

The inter-city and within-city population flows dropped significantly, particularly after the lockdown of Wuhan.

Figure 2: Inter-city and Within-city Population Flows



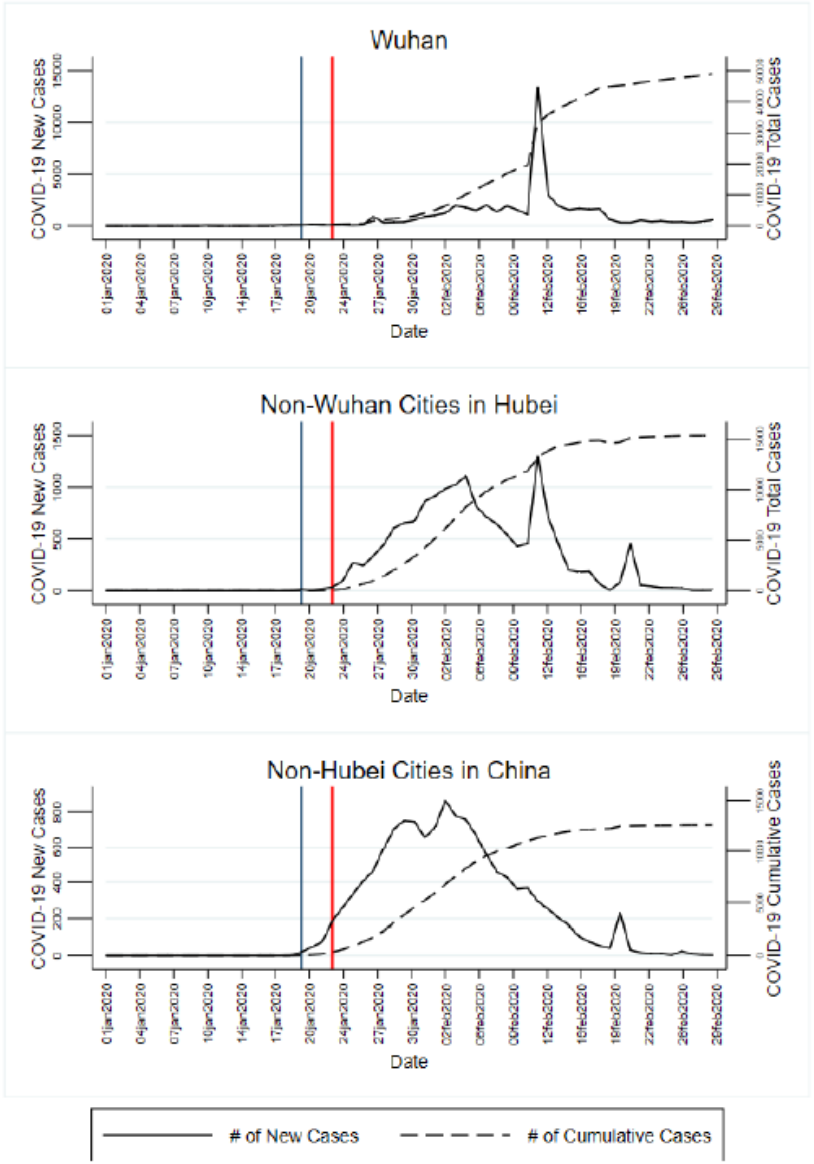
Notes: This figure presents the daily inflow into, outflow from, and within-city flow in Wuhan (top figures) and in other cities in Chi (bottom figures) during the sample lunar calendar date matched period in 2019 and 2020. The blue line indicates the date of offic confirmation of human-to-human spread of COVID-19 (January 20, 2020) and the red line indicates the date of Wuhan lockdown (Janua 23, 2020).

The first vertical line indicates the date of January 20, 2020 when experts confirmed that 2019-nCoV could transmit from human to human; and the second vertical line indicates the date of January 23, 2020 when Wuhan was locked down.

疫情数据
Outbreak data

The first vertical line indicates the date of January 20, 2020 when experts confirmed that 2019-nCoV could transmit from human to human; and the second vertical line indicates the date of January 23, 2020 when Wuhan was locked down.

Figure 3: Daily Confirmed Cases and Cumulative Confirmed Cases



Notes: This figure shows the daily confirmed, dead, and healed cases in Wuhan, other cities in Hubei Province, and cities outside of Hubei Province.

武汉封城对人口流动的影响
The impact of Wuhan lockdown on population movements

The lockdown of Wuhan reduced inflow into Wuhan by 76.64%, outflows from Wuhan by 56.35%, and within-Wuhan by 54.15%.

Difference-in-differences (DID) estimation strategies to measure the effects of Wuhan lockdown on human mobility.

Table 3: 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	-11.48%	+107.09%***	-24.19%***
Virus Effect	-65.63%***	-36.75%***	-66.41%***
Lockdown Effect	-76.64%***	-56.35%***	-54.15%***

Notes: These effects are calculated based on the estimates reported in Columns (2) and (3) of Table 2. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

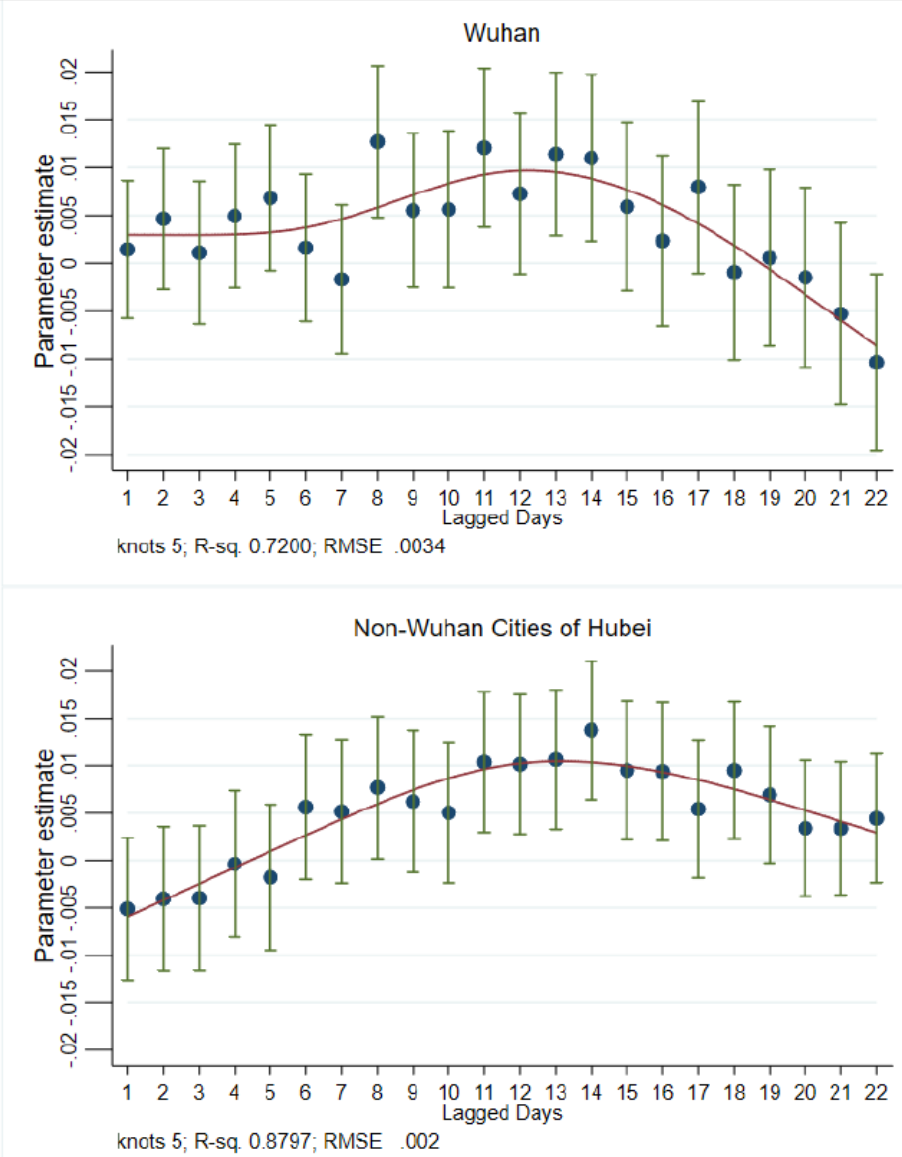
武汉封城对病毒扩散的影响
The impact of Lockdown on national spread of COVID-19

Contact with an infected person from Wuhan or other cities in Hubei can results in confirmed infections in the destination city for up to 22 days.

The largest impact on the newly confirmed cases today in other cities in China comes from inflow population from Wuhan or other cities in Hubei about 12 to 14 days ago.

The pattern is consistent with the hypothesis that the incubation period of the 2019-nCoV is up to 12 to 14 days, but also consistent with a shorter incubation period coupled with secondary infections.

The dynamic distributed lag regression model



Notes: This figure plots the dynamic effects of lagged inflows from Wuhan (left) and 16 other citi in Hubei (right) from estimating Equation (3). We add spline smoothing fit curves (in red) usi the *rcspline* function and plot the 95% confidence intervals (the vertical green whiskers).

官方数据的真实性
Estimate the “Actual” number of infection cases in Wuhan and others cities in Hubei

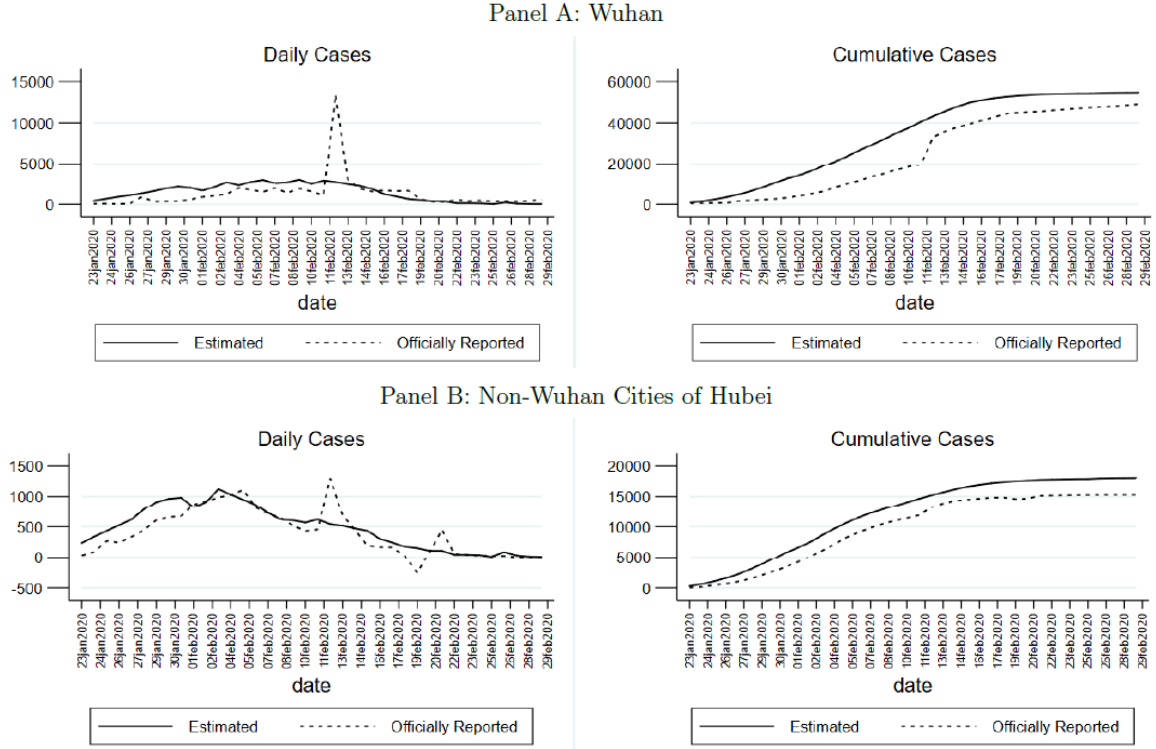
The estimated “actual” number is 2.48 times higher than the reported cases during the first 20 days after Wuhan lockdown. As of February 29, the estimated infectious is 11.33% higher than the official reported cases.

This can be explained by the unaccounted for self-healing and death that might have occurred during he early periods of outbreak between January 23 and early February.

Almost all infection cases in Wuhan were able to be treated as the stress on the health system was relieved, and the official statistics were mostly accurate.

The dynamic distributed lag regression model

Figure 5: Estimation on the “Actual” Number of Infected Cases in Wuhan and No-Wuhan Cities in Hubei



Notes: This figure compares the estimated COVID-19 cases (in solid curve) with the officially reported confirmed cases (in dotted curve) in Wuhan (top) and in 16 non-Wuhan cities in Hubei Province (bottom) from January 23 to February 29 in 2020. The left panel plots the estimated new COVID cases on each date t from 23 (January 23, 2020) to 60 (February 29, 2020) obtained from Equation (3). The right panel plots the estimated cumulative cases on each day.

武汉封城在多大程度上抑制了病毒传播
How many COVID-19 cases were prevented by the Wuhan lockdown

Without Wuhan lockdown,

outflows from Wuhan and other cities in Hubei will be 5.97 times higher than the observed inflow;

inflow from Wuhan to other cities outside Hubei will be 3.14 times higher than the actual inflow population to those cities during the same period.

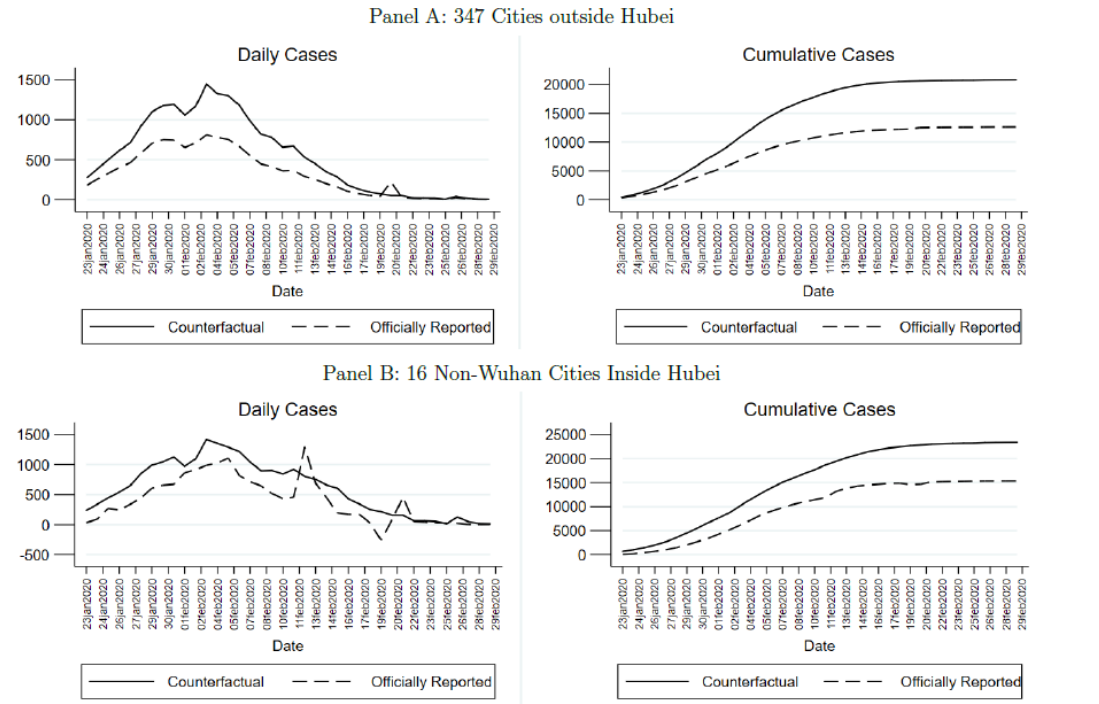
武汉封城在多大程度上抑制了病毒传播
How many COVID-19 cases were prevented by the Wuhan lockdown

As of February 29, COVID-19 cases would be 64.81% higher in 347 cities outside Hubei and 52.64% higher in 16 other cities in Hubei.

The lockdown of Wuhan played a crucial role in reducing the imported infections in other Chinese cities and the spread of 2019-nCoV virus.

The dynamic distributed lag regression model Counterfactual estimates of COVID-19 cases had there been no Wuhan lockdown and the officially reported cases.

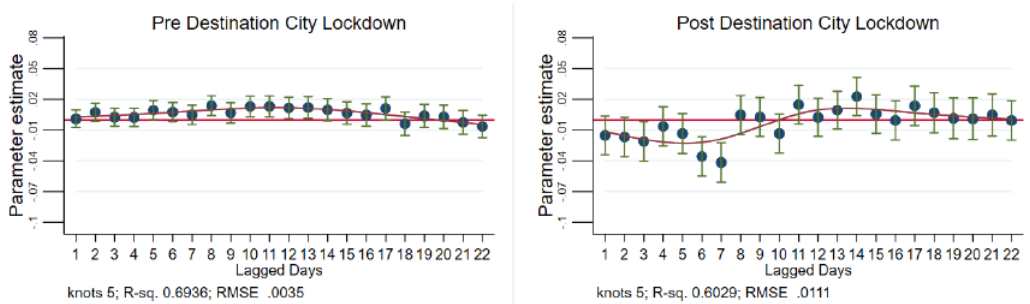
Figure 6: Counterfactual of Infected Cases Elsewhere in China If Wuhan Were Not Locked Down from January 23, 2020



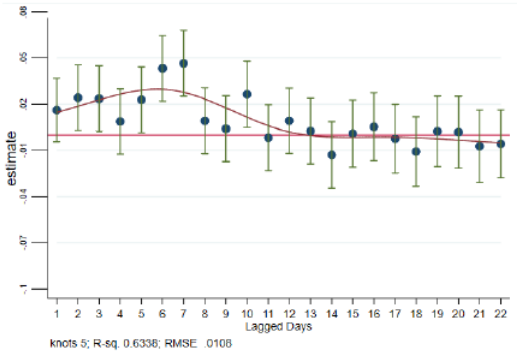
Notes: This figure plots the counterfactual estimation on the COVID-19 cases in 16 other cities outside Hubei (top) and 347 other cities in China (bottom) if Wuhan had never been under a government-ordered lockdown (in solid curve), and traces the officially reported COVID-19 cases in cities outside of Hubei (in dotted curve). The left graphs present the daily new cases and the right graphs present the cumulative daily cases.

保持社交距离对病毒传播的影响
Effects of social distancing on virus transmission in destination cities

Figure 7: Dynamic Impact of Past Inflows from Wuhan on Destination Cities' Daily New Cases: Pre and Post Destination Cities' Lockdown



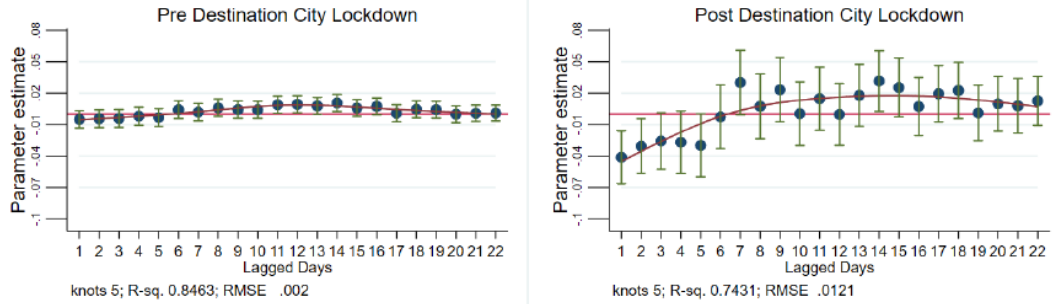
(a) Lagged Effects of Wuhan Inflows: Pre and Post Destination Cities' Lockdown



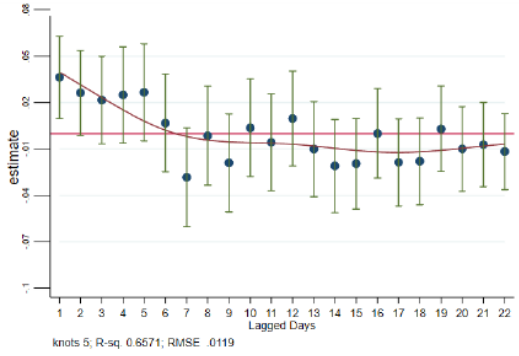
(b) Difference in the Effects

Notes: This figure plots the dynamic lagged effects of past inflows from **Wuhan** pre (left figure of Panel (a)) and post (right figure of Panel (a)) destination cities' lockdown policy, if any. Panel (b) plots the difference of the pre- and post- estimated effects. The coefficient estimates are obtained from estimating Equation (6). We add spline smoothing fit curves using the *rcspline* function and plot the 95% confidence intervals (the vertical green whiskers).

Figure 8: Dynamic Impact of Past Inflows from Non-Wuhan Hubei Cities on Destination Cities' Daily New Cases: Pre and Post Destination Cities' Lockdown



(a) Lagged Effects of Wuhan Inflows: Pre and Post Destination Cities' Lockdown



(b) Difference in the Effects

Notes: This figure plots the dynamic lagged effects of past inflows from 16 **non-Wuhan Hubei cities** pre (left figure of Panel (a)) and post (right figure of Panel (a)) destination cities' lockdown policy, if any. Panel (b) plots the difference of the pre- and post- estimated effects. The coefficient estimates are obtained from estimating Equation (6). We add spline smoothing fit curves using the *rcspline* function and plot the 95% confidence intervals (the vertical green whiskers).

保持社交距离对病毒传播的影响
Effects of social distancing on virus transmission in destination cities

The enhanced social distancing policies in the destination cities are effective in reducing the impact of population inflows from Wuhan and other cities in Hubei on the spread of 2019-nCoV virus in the destination cities.

Population inflows from the epicenter contribute to the spread of infection in the destination cities only before the social distancing measures are applied.

总结与讨论
Summary and Discussions

Summary

- How does the lockdown of the city of Wuhan amid the Novel Coronavirus outbreak affect population movement?

  The lockdown of Wuhan reduced inflow into Wuhan by 76.64%, outflows from Wuhan by 56.35%, and within-Wuhan by 54.15%.

- How do population flows among Chinese cities, particularly outflows from Wuhan and other cities in Hubei province, affects virus infection in the destination cities?

  Human mobility restrictions, particularly the lockdown of Wuhan on January 23, 2020 on the containment and delay of the spread of the virus, up to 22 lagged population inflows from Wuhan and other Hubei cities.

Summary

- How does the lockdown of the city of Wuhan amid the Novel Coronavirus outbreak What is the magnitude of undocumented cases of COVID-19 cases in Wuhan and other cities in Hubei province during the early stages of the epidemic? And how does the extent of undocumented infection cases evolve over time?

  There were substantial undocumented infection cases in the early days of the 2019-nCoV outbreak in Wuhan and other cities of Hubei province, but overtime, the gap between the officially reported cases and our estimated actual cases narrows significantly.

- How many COVID-19 cases elsewhere in China were prevented by the unprecedented Wuhan lockdown?

  COVID-19 cases would be 64.81% higher in the 347 Chinese cities outside Hubei province and 52.64% higher in 16 cities in Hubei other than Wuhan.

Summary

- Are social distancing policies in destination cities effective in reducing the spread of the infections?

  Enhanced social distancing policies in the 63 Chinese cities outside Hubei province is effective in reducing the impact of population inflows from Wuhan on the spread of virus in the destination cities elsewhere.

Discussions

- 百度地图/Baidu Migration vs. 手机数据/mobile phone data
- 寻找缺失数据/Looking for the undocumented data

寻找缺失数据/Looking for undocumented data

许刚，武汉大学特聘副研究员，博士后，入选2019年度博士后创新人才计划（“博新计划”）。在武汉大学先后获得土地资源管理专业学士（2014）和博士学位（2019）。研究兴趣为全球城市扩张及其环境效应和城市复杂系统，在《Landscape and Urban Planning》、《Journal of Cleaner Production》、《Science of the Total Environment》等国际期刊发表SCI、SSCI论文十余篇。欢迎地理信息系统、土地资源管理、遥感等专业同学联系咨询。

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Literature Review (2)

Population flow drives spatio-temporal distribution of COVID-19 in China

Jayson S. Jia, Xin Lu, Yun Yuan, Ge Xu, Jianmin Jia & Nicholas A. Christakis

Nature, Accelerated Article Preview, https://doi.org/10.1038/s41586-020-2284-y

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研究背景 Background

- **Recent research on COVID-19 using historical population flow data (e.g., previous years' chunyuan migrations) to estimate case exportation**
- Wu, J. T., Leung, K., & Leung, G. M. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study. *Lancet*. 395, 689-697 (2020).
- Wu, J.T., Leung, K., Bushman, M. et al. Estimating clinical severity of COVID-19 from the transmission dynamics in Wuhan, China. *Nat. Med*. (2020).
- Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., ... & Viboud, C. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science* (2020).
- Du, Z., Wang, L., Cauchemez, S., Xu, X., Wang, X., Cowling, B. J. & Meyers, L. A. Risk of 2019 novel coronavirus importations throughout China prior to the Wuhan. *Lancet* 361, 1761-6 (2020).
- Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W., & Shaman, J. Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV2). *Science* (2020).

研究背景 Background

- **Limitation**
- Estimating population movement, not observing
- Could lead to inaccurate predictions that can have important policy consequences for policy-making
  - Under-reaction: disease spread
  - Over-reaction: medically, socially, and economically inefficient policies

研究背景 Background

- **Previous approaches to epidemiological modelling**
- Adda, J. Economic activity and the spread of viral diseases: Evidence from high frequency data. *Q. J. Econ*. 131, 891-941 (2016).
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研究背景 Background

- **Limitation**
- Rely on assumptions regarding population mixing, population compartment size, and viral properties.
- 本文重点扩展：
- Using detailed mobile phone geolocation data to compute aggregate population movement
- “risk source” model: makes no assumptions regarding travel patterns or effective distance effects, allows for non-linear estimation, generates a non-arbitrary source-linked risk score, easily adapted to other empirical contexts

研究数据 Data

- **Mobility outflow data**
- Population flow data provided by one of the 3 national mobile carriers in China
- Aggregated from the records of mobile phone activities (including geolocation) of their users, nationwide
- A user only had to have their phone on for their location to be noted
- The number of trips made by users who moved from Wuhan to other prefectures during the period of **January 1-24, 2020**
- Exclude users who only briefly transited through Wuhan (stayed in Wuhan less than 2 hrs)

研究数据 Data

- **2018 City/Prefectures Statistical Year Book of China**
- Merge outflow data with this demographic and economic variables
- Serve as covariates and control variables
- Yields a final sample of 296 prefectures (exclude Wuhan and Sansha)
- Average population: 4.4 million; total population: 1.31 billion;
- Representing 94.07% of the country’s total population

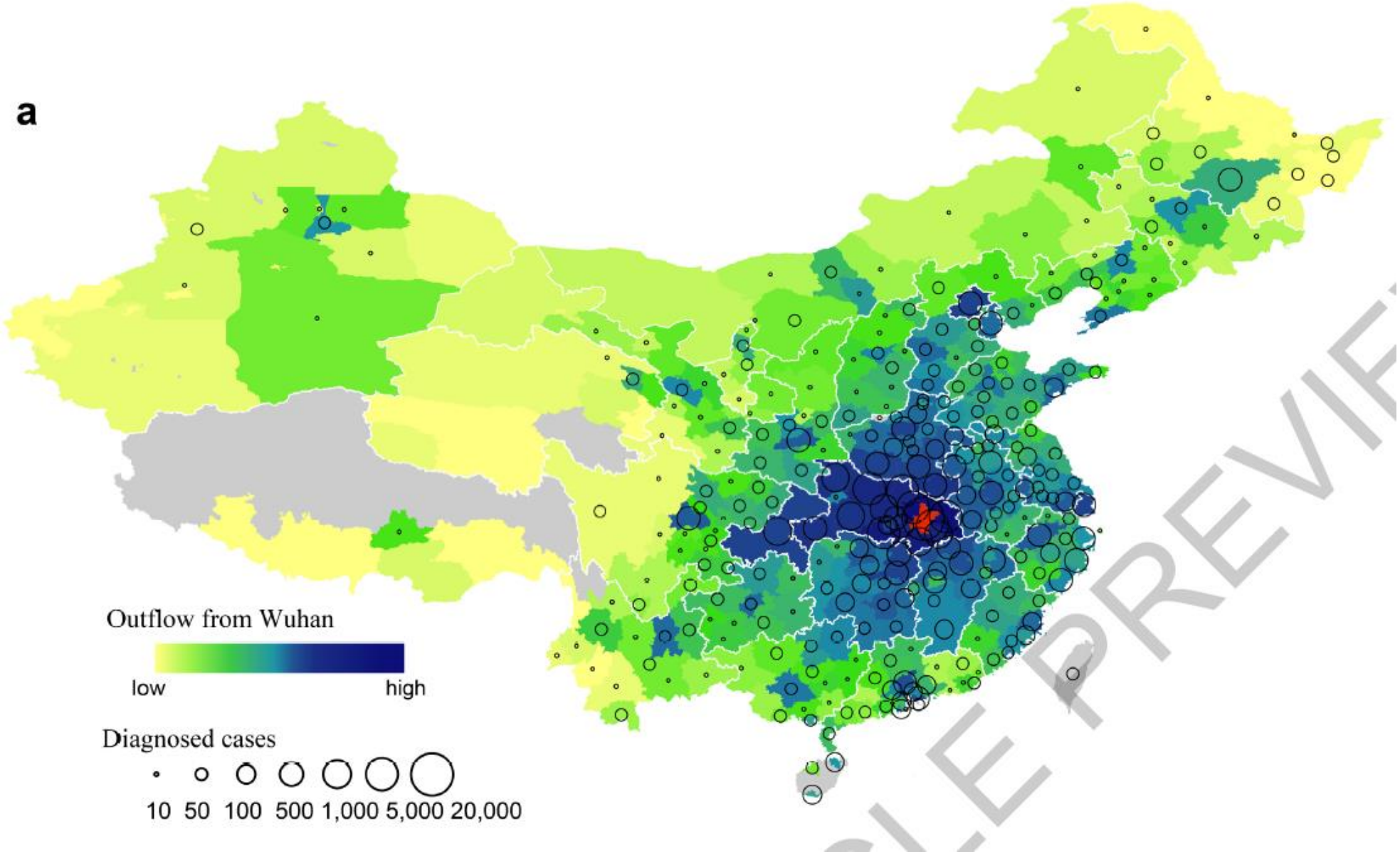
研究方法 Methodology

- **Gravity model** (Static model) $T_{ij} = cP_i^{\beta_1} P_j^{\beta_2} d_{ij}^{-\beta_3}$
- Special case: only the “recipient” prefecture’s population variable and the “donor” Wuhan is a constant
- Results: significantly negative parameter for distance

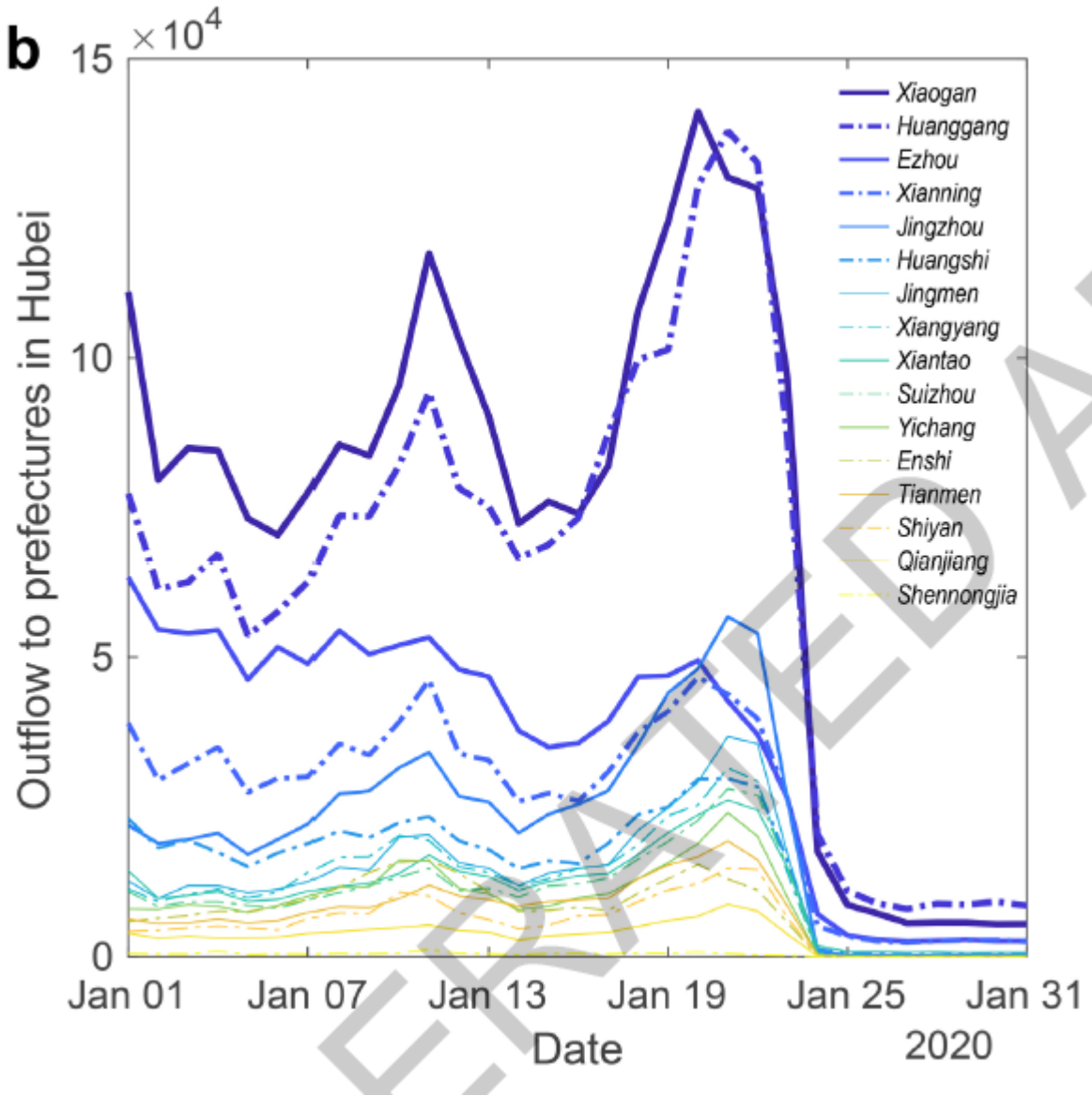
研究方法 Methodology

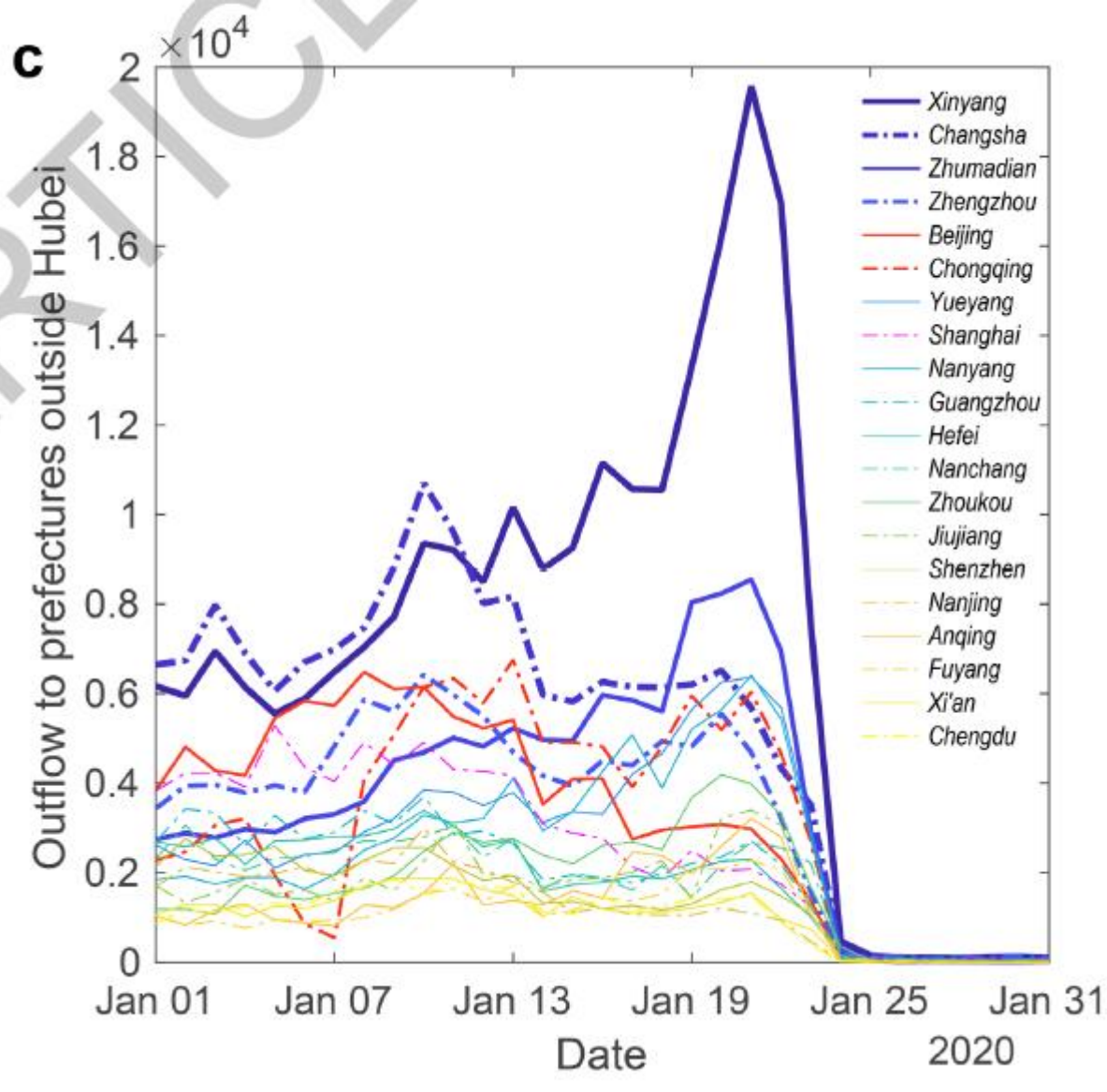
Dependent Variable	Outflow from Wuhan	Outflow from Wuhan	Confirmed Cases	Confirmed Cases	Confirmed Cases	Confirmed Cases	Confirmed Cases
Constant (c)	9623.48	15.919	21.934	2.278	13.669	4.222	3.935
Outflow (β_0)					1.821	1.507	1.565
GDP (β_1)	-0.408	0.154	0.124	0.286	0.136	0.152	0.144
Population (β_2)	0.505	0.656	0.751	0.683	0.135	0.221	0.202
Distance (β_3)	-1.250	-0.844	-1.196	-0.579			0.025
Fixed effects	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*Yes*
R^2	0.902	0.966	0.758	0.941	0.941	0.965	0.965
N	296	296	296	296	296	296	296

研究方法 Methodology



研究方法 Methodology





ERATED ARTICLE

研究方法 Methodology

- **“Risk Source” Model 1: multiplicative exponential model**
- **Cross-sectional**

$$y_i = c \prod_{j=1}^{m} e^{\beta_j x_{ji}} e^{\sum_{k=1}^{n} \lambda_k I_{ik}}$$

- yi is the cumulative (or daily) confirmed cases in prefecture *i*;
- *x*1*i* is cumulative population outflow from Wuhan to prefecture *i* from January 1 to 24;
- *x*2*i* is the GDP of prefecture *i*; *x*3*i* is the population size of prefecture *i*;
- *m* is the number of variables included; and *c* and *βi* are parameters to estimate.
- And *λk* is the fixed effect for province *k*; *n* is the number of prefectures considered in the analysis; *Iik* is a dummy for prefecture *i* and *Iik* = 1, if *i*∈*k* (prefecture *i* belongs to province *k*), otherwise *Iik* = 0.

研究方法 Methodology

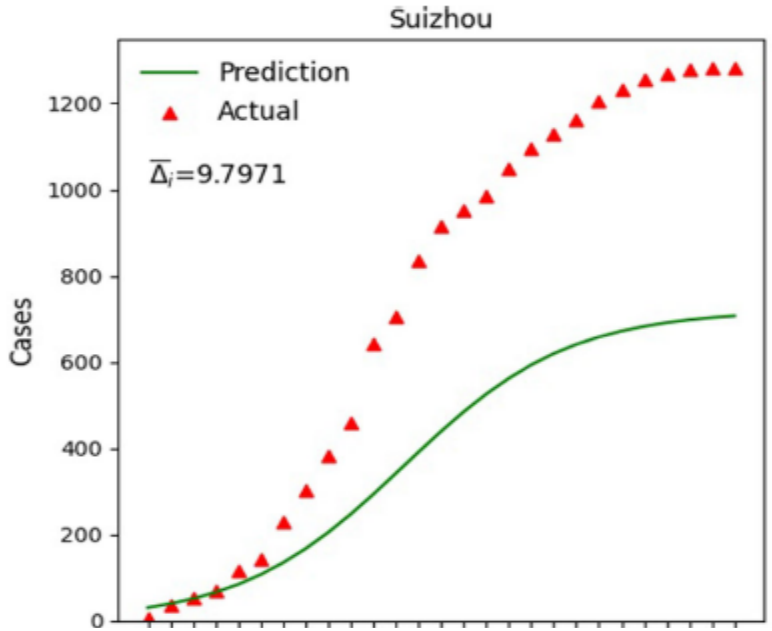
- population flow from Wuhan becomes increasingly dominant (beta 1)
- A prefecture's GDP and population become increasingly less predictive over time (beta 2 & 3)
- The spreading pattern of the virus gradually converges to the distribution of the population outflow from Wuhan to other prefectures

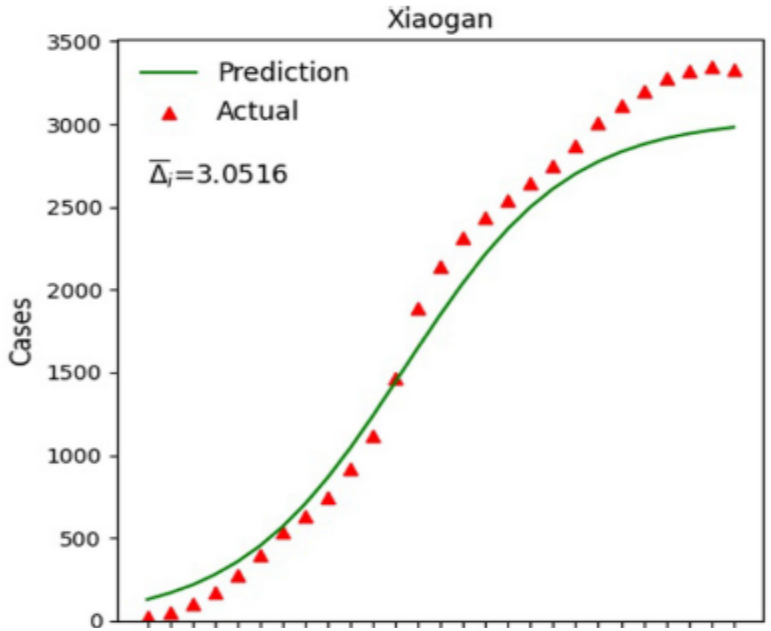
Date	R^2	c	β_1	β_2	β_3
24-Jan	0.809	0.425	1.609	-0.008	0.159
25-Jan	0.858	0.161	1.392	-0.289	1.356
26-Jan	0.871	0.631	1.131	-0.144	0.608
27-Jan	0.902	1.355	1.035	-0.030	0.380
28-Jan	0.933	1.974	1.070	-0.012	0.289
29-Jan	0.933	2.502	1.089	-0.025	0.336
30-Jan	0.938	2.244	1.156	-0.053	0.398
31-Jan	0.939	3.375	1.051	0.062	0.338
1-Feb	0.943	3.923	0.995	0.100	0.359
2-Feb	0.937	2.324	0.991	0.054	0.406
3-Feb	0.953	4.355	0.949	0.041	0.479
4-Feb	0.948	4.926	0.932	0.032	0.457
5-Feb	0.954	4.913	1.056	0.062	0.441
6-Feb	0.947	4.921	1.197	0.103	0.397
7-Feb	0.944	4.577	1.243	0.137	0.369
8-Feb	0.948	4.842	1.285	0.166	0.348
9-Feb	0.949	4.727	1.283	0.215	0.341
10-Feb	0.949	4.886	1.309	0.226	0.327
11-Feb	0.948	4.506	1.330	0.245	0.316
12-Feb	0.948	4.540	1.350	0.255	0.300
13-Feb	0.948	4.422	1.402	0.291	0.260
14-Feb	0.966	3.885	1.294	0.169	0.268
15-Feb	0.970	4.766	1.300	0.159	0.244
16-Feb	0.969	4.985	1.331	0.179	0.234
17-Feb	0.968	5.349	1.364	0.199	0.224
18-Feb	0.968	4.425	1.388	0.230	0.214
19-Feb	0.967	4.420	1.406	0.249	0.218

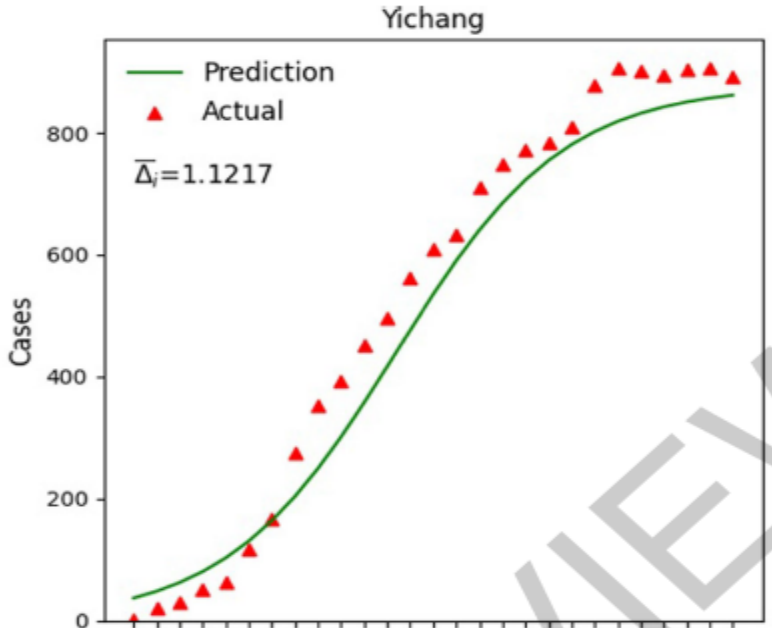
研究方法 Methodology

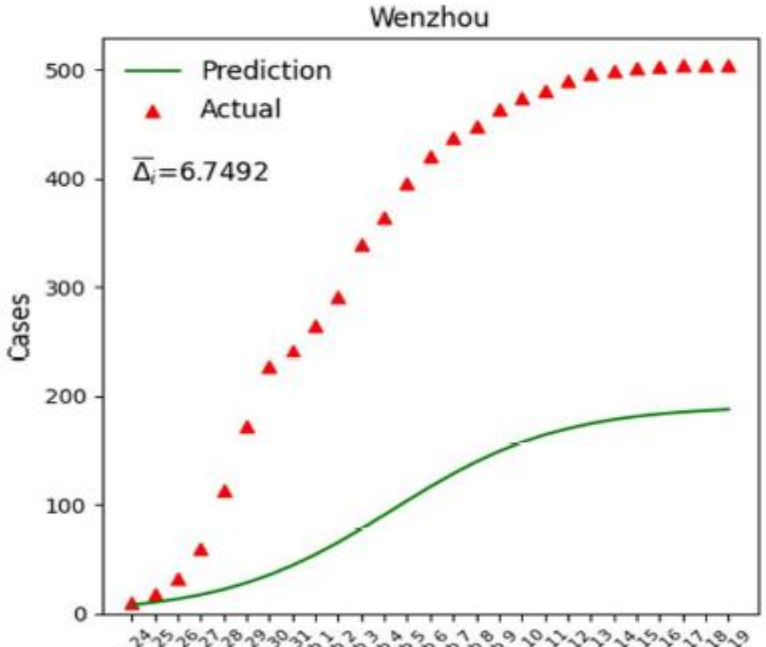
- **Daily risk score for prefectures=predicted cases-confirmed cases**
- Higher-than-expected level of infection: more community transmission
- Fewer-than-expected level of infection: implemented highly successful public health measures or inaccurate data reporting
- Over-time pattern: act as an early warning index of an epidemiological transition: if model strength declines significantly at any location, which may indicate that community transmission may be overtaking imported cases.

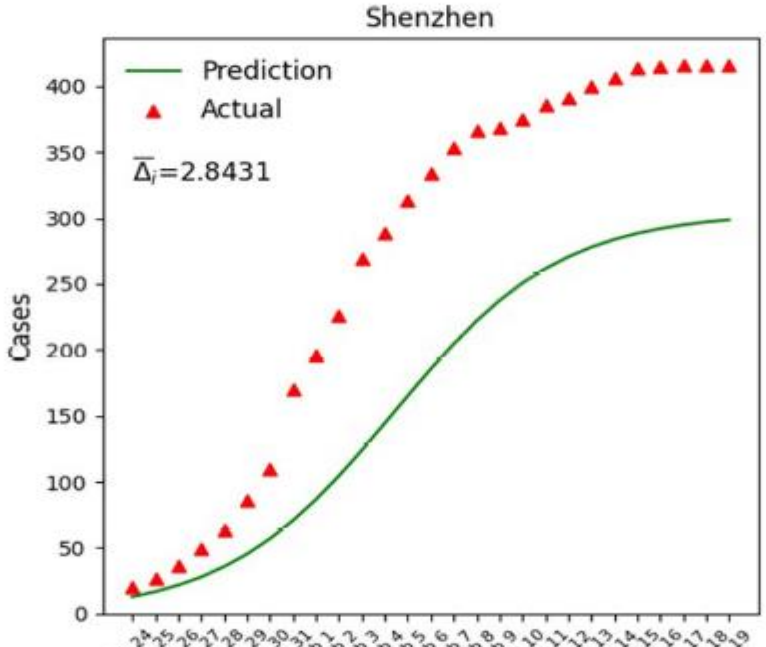
研究方法 Methodology

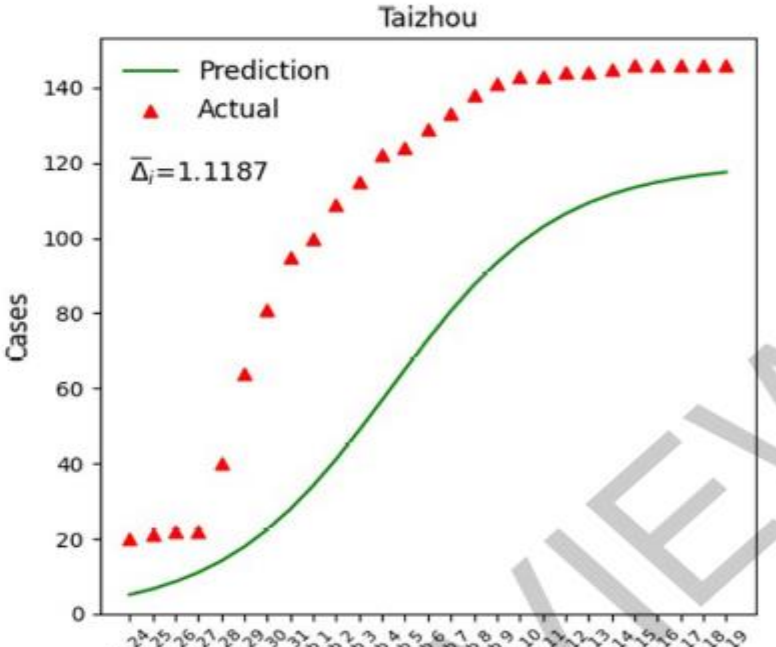












研究方法 Methodology

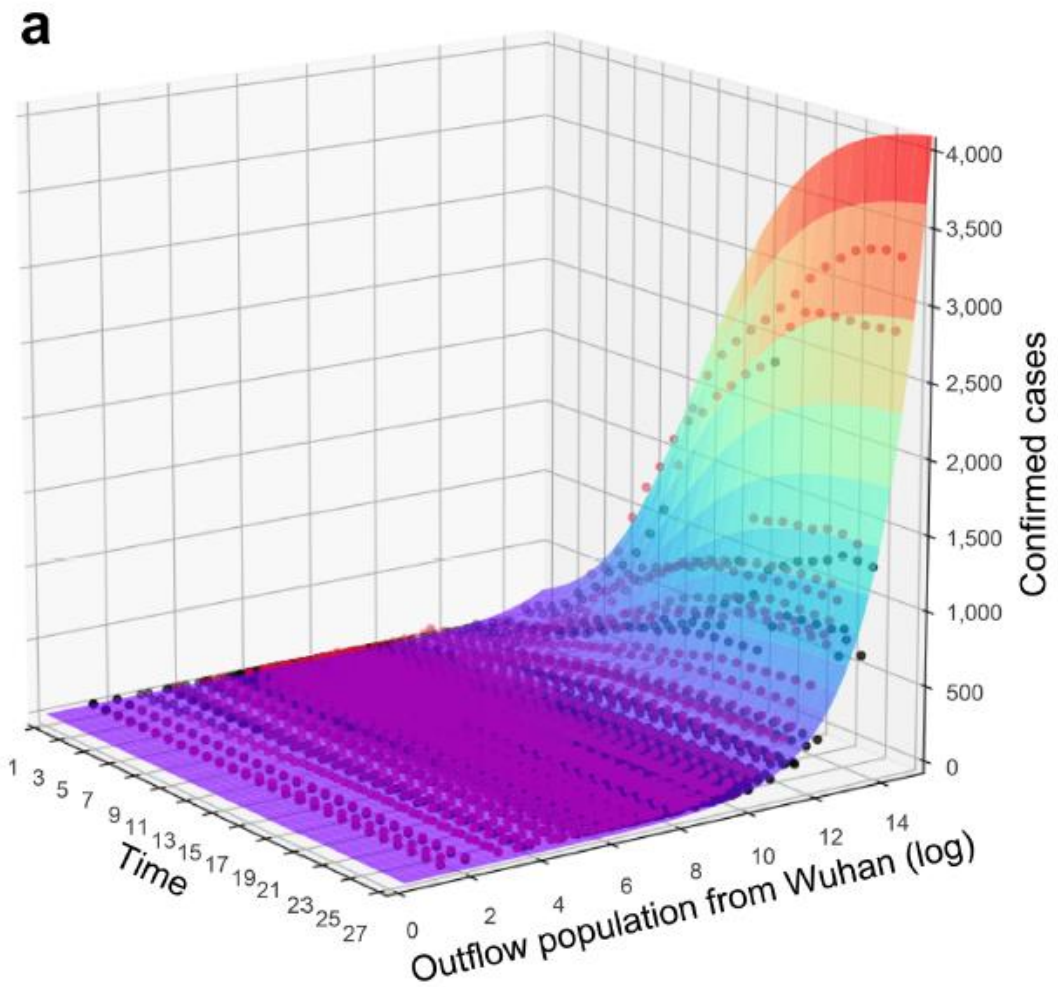
- **Risk source model 2: spatio-temporal model**
- Use a Cox proportional hazards framework

$$\lambda(t|x_i) = \lambda_0(t)\left(\prod_{j=1}^{m} e^{\beta_j x_{ji}}\right) e^{\sum_{k=1}^{n} \lambda_k I_{ik}}$$

- $\lambda(t|x_i)$ is the hazard function describing the number of cumulative confirmed cases at time t given population outflow from Wuhan to prefecture I
- $\lambda_0(t)$ is a time-varying hazard rate function, typically has an S-shape

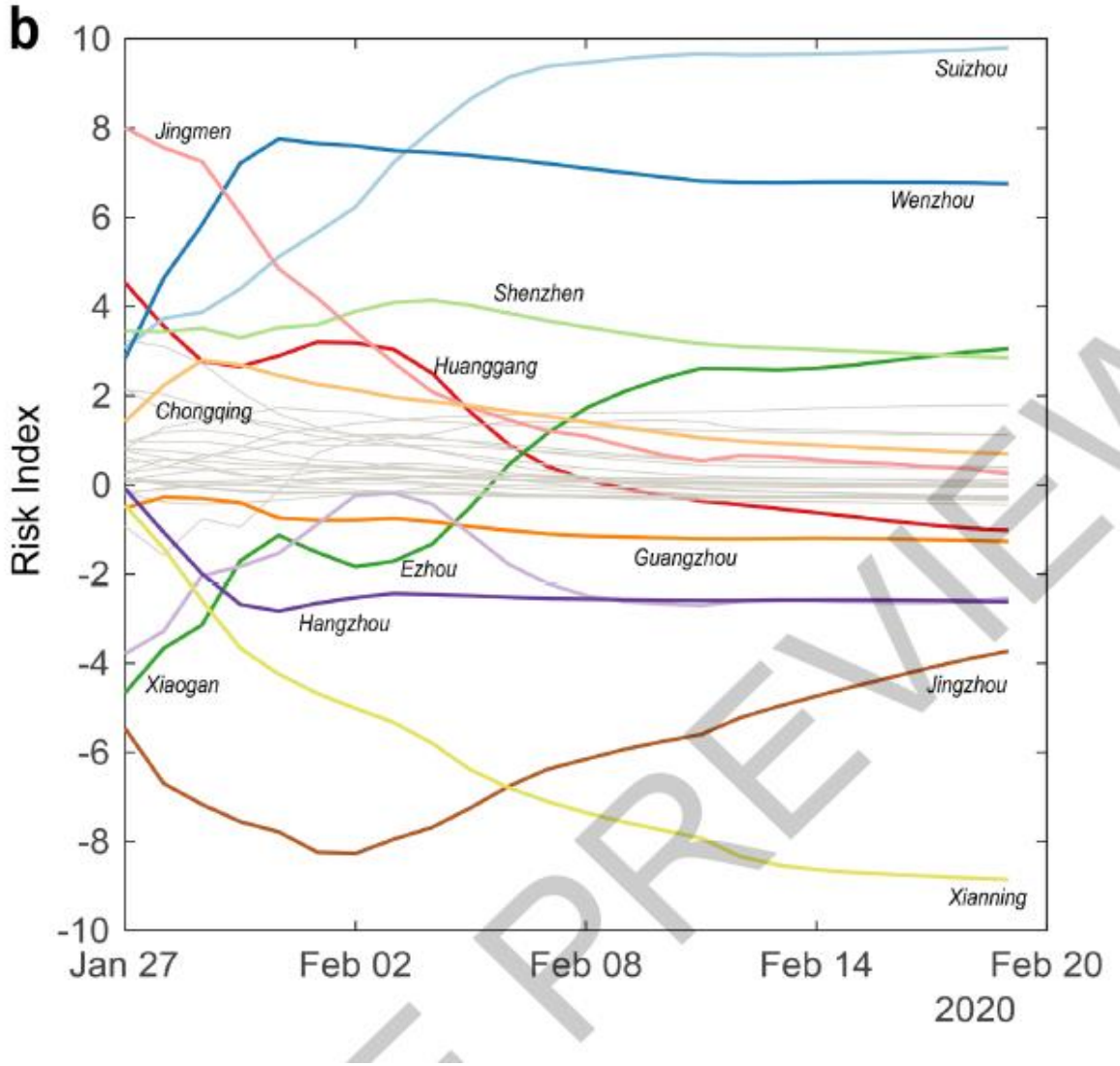
研究方法 Methodology

- The surface indicates the fitted performance of the epidemiological model with just a single variable *x1i*
- indicates outflow population from Wuhan to prefecture *i* (*log* transformed), for all prefectures, with *t* as the number of days after *chunyun* is over (i.e., *t* = 1 is January 24).
- The dots represents the actual number of confirmed cases under a given *x1i* and *t*.
- Red dots represent prefectures where the reported number of confirmed cases is greater than the model's predicted values;
- black dots are all other cases, *R2* = 0.930 (N=7,992)



研究方法 Methodology

- **Dynamic shifts in risk index score**
- Allows monitoring which prefectures performed better in controlling transmission risk over time



总结与讨论 Summary and Discussions

Primary contributions:

- robustly characterize the structure or relative distribution of cases across different geographic areas and over time, which is driven fundamentally by the cumulative outflow from Wuhan.
- non-systematic inaccuracy of COVID-19 case-finding is relatively unimportant as long as we capture the *distribution* of population flow accurately over time.

总结与讨论 Summary and Discussions

Replicability and Reproducibility:

- This approach is generalizable to any dataset that captures population movements (e.g., train ticketing or car tolling data).
- This method can also be implemented in a live fashion (if suitable data are available) to facilitate policy decisions – for example the allocation of resources and manpower across specific geographic locales based on the predicted strength of the epidemic.

Future directions for expanded research

- Hypothesis: population flow from Wuhan may export the virus to other locations, where it causes local outbreaks
- Early stage vs late stage
- Imported transmission vs community transmission
- Supervised machine learning to unsupervised machine learning

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