Impacts of Social and Economic Factors on the Transmission of Coronavirus Disease 2019 (COVID-19) in China

Yun Qiu[1], **Xi Chen[2]**, Wei Shi[1]

[1] Institute for Economic and Social Research, Jinan University

[2] Department of Health Policy and Management, Yale School of Public Health;
Department of Economics, Yale University

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This paper

1. Quantitatively examines the transmission patterns of Coronavirus Disease 2019 (COVID-19) in China.
    - How infections in the past generate new infections?
    - Use variations in infections that are induced by changes in weather conditions to obtain causal estimates.
2. Consider both local and between city virus spreading.
3. The role of social and economic factors in mediating the virus spread
    - Does real-time population flow data help explain between-city spread of the virus?
    - The effects of public health measures in reducing infections

Preview of results

1. The spread of COVID-19 has been effectively contained by mid February, especially for cities outside Hubei province.
2. Data on real-time population flows is valuable in explaining between city transmissions of COVID-19, even after controlling for traditional measures of geographic and economic proximity.
3. Suppressing local transmissions so that new hotspots of infections had not emerged outside Hubei is crucial in forestalling large numbers of infections.
    - The lockdown around Wuhan might have played an essential role.

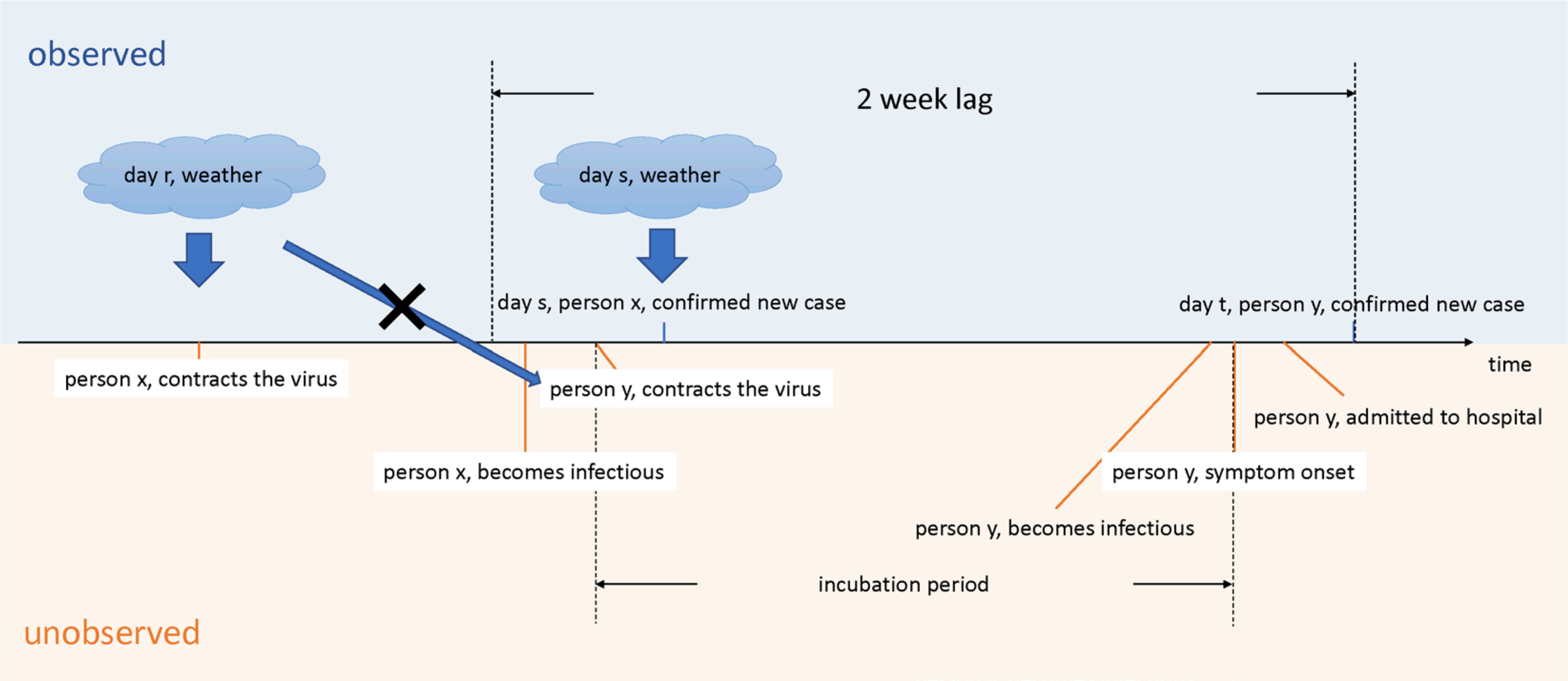
Empirical model

$$y_{ct} = \sum_{\tau=1}^{2} \sum_{k=1}^{K_{\text{within}}} \alpha^{k}_{\text{within},\tau} \bar{h}^{k\tau}_{ct} \bar{y}^{\tau}_{ct} + \sum_{\tau=1}^{2} \sum_{k=1}^{K_{\text{between}}} \sum_{r \neq c} \alpha^{k}_{\text{between},\tau} \bar{m}^{k\tau}_{crt} \bar{y}^{\tau}_{rt} + \sum_{\tau=1}^{2} \sum_{k=1}^{K_{\text{Wuhan}}} \rho^{k}_{\tau} \bar{m}^{k\tau}_{c,\text{Wuhan},t} \bar{z}^{\tau}_{t} + x_{ct}\beta + \varepsilon_{ct}.$$

$\bar{y}^{\tau}_{ct}$ denotes the average number of new cases in city c, in the preceding τ-th week from day t.

- To measure the spread of the virus from Wuhan, we examine the mediating effect of the number of people traveling from Wuhan.
- The unobserved determinants of new infections are likely correlated over time, causing correlations between the error term and the lagged dependent variables.
  - e.g. clusters that generate large numbers of infections, residents' and government's preparedness
- We use instrumental variables for the lagged dependent variables. Adda (2016)
- IVs include weekly averages of daily maximum temperature, precipitation, wind speed, and the interaction between precipitation and wind speed, in the *preceding third and fourth weeks*.

Timeline of key variables



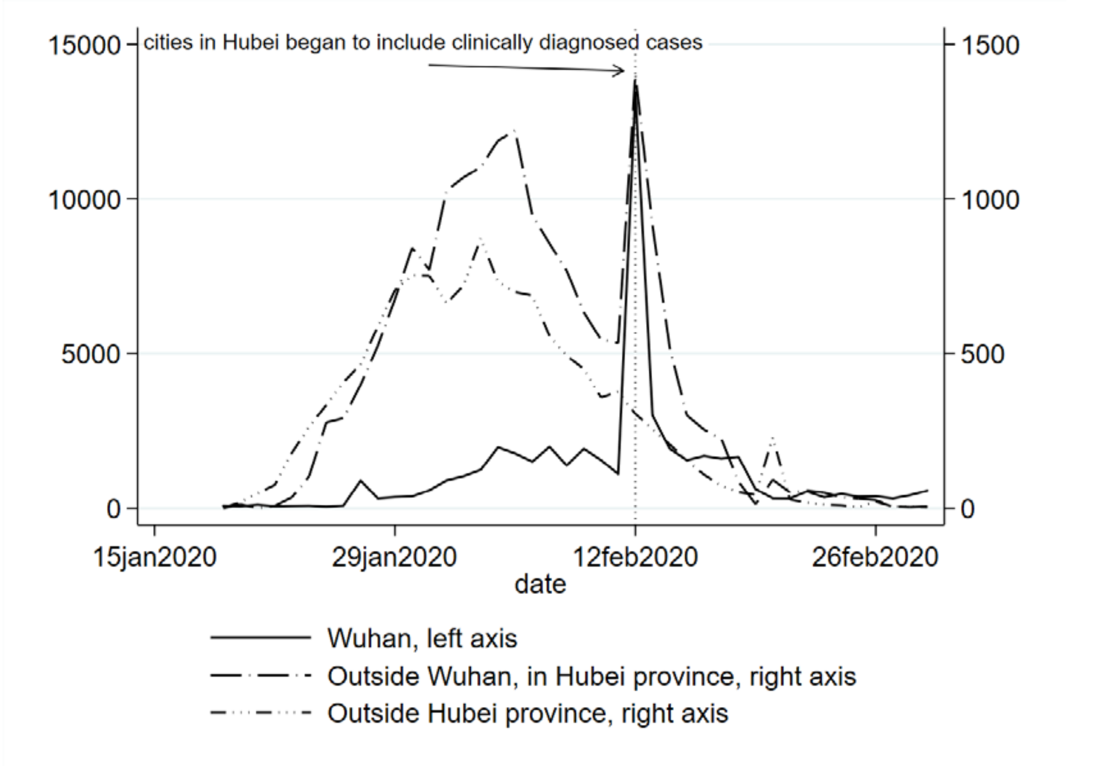
The primary assumption of the IVs is that weather conditions more than 2 weeks ago do not DIRECTLY affect the likelihood that a person susceptible to the virus contracts the disease, conditional on weather conditions within two weeks.

Data

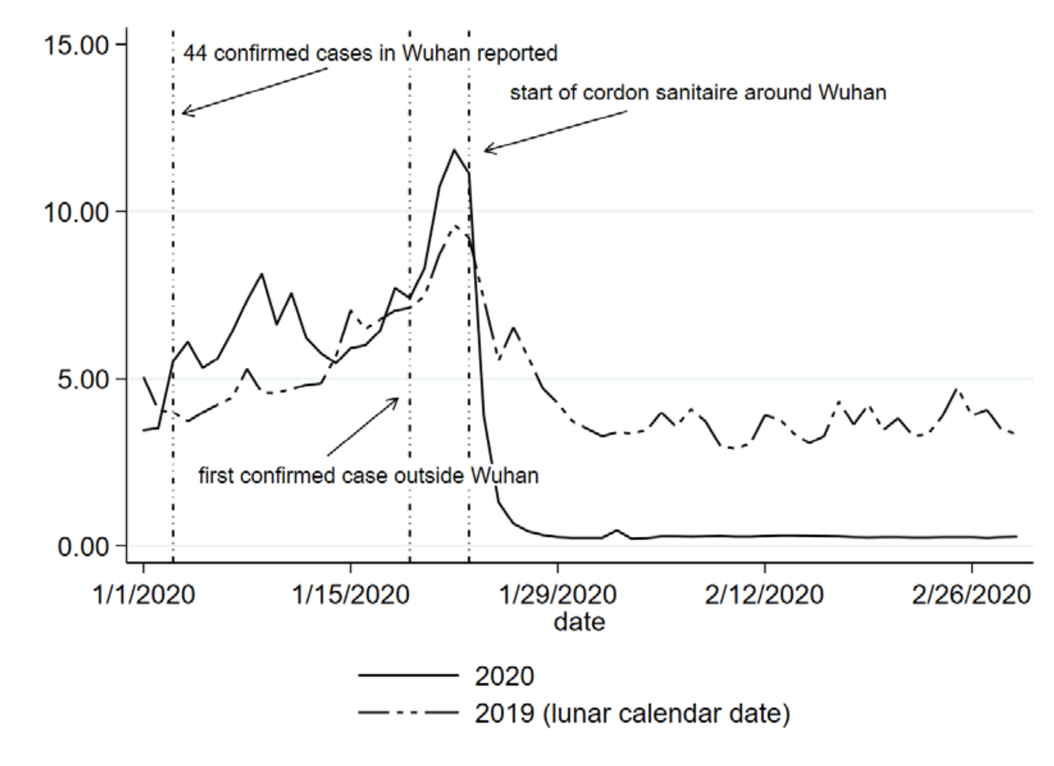
- Analytical sample: 304 prefecture-level cities in China
- Wuhan excluded from analysis because
  - The epidemic patterns in Wuhan are significantly different from those in other cities.
    - Some confirmed cases in Wuhan contracted the virus through exposure to Huanan Seafood Wholesale Market.
    - In other cities, infections arise from human to human transmissions.
  - The health care system in Wuhan faced the challenge of unknown virus infections in early January and became overwhelmed as # new cases increased exponentially from mid-January.
    - May cause severe delay and measurement error issues in the number of cases reported in Wuhan.

Data

COVID-19 cases

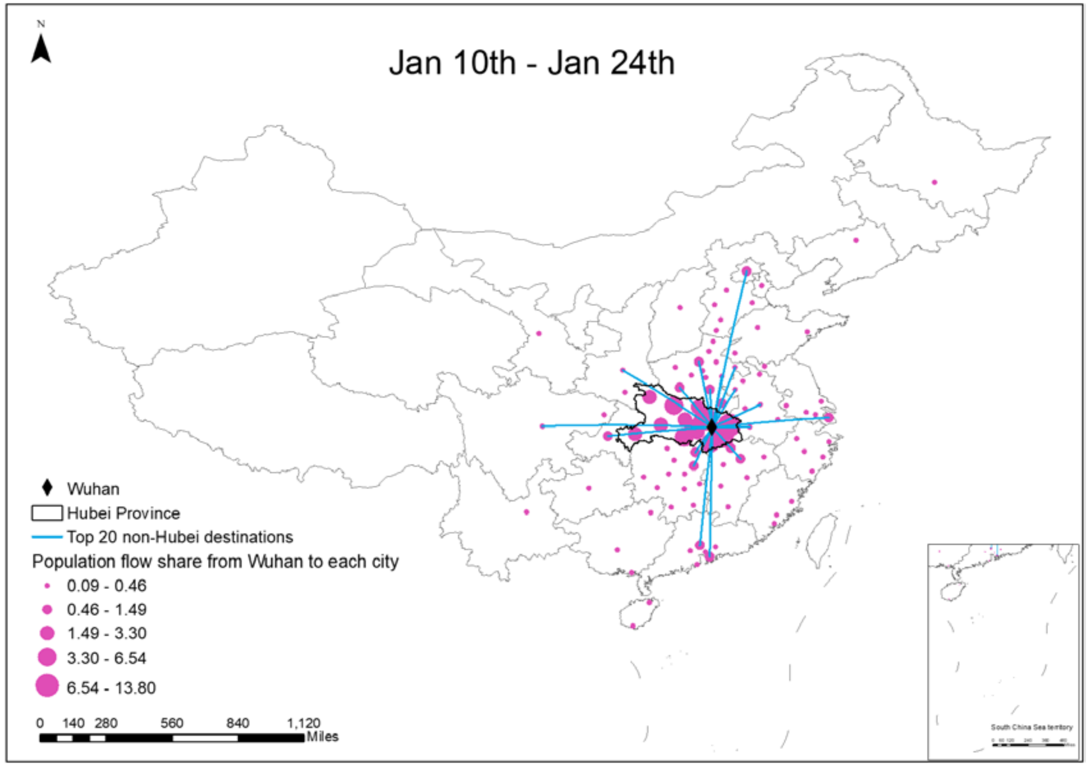


Baidu index of population flow from Wuhan

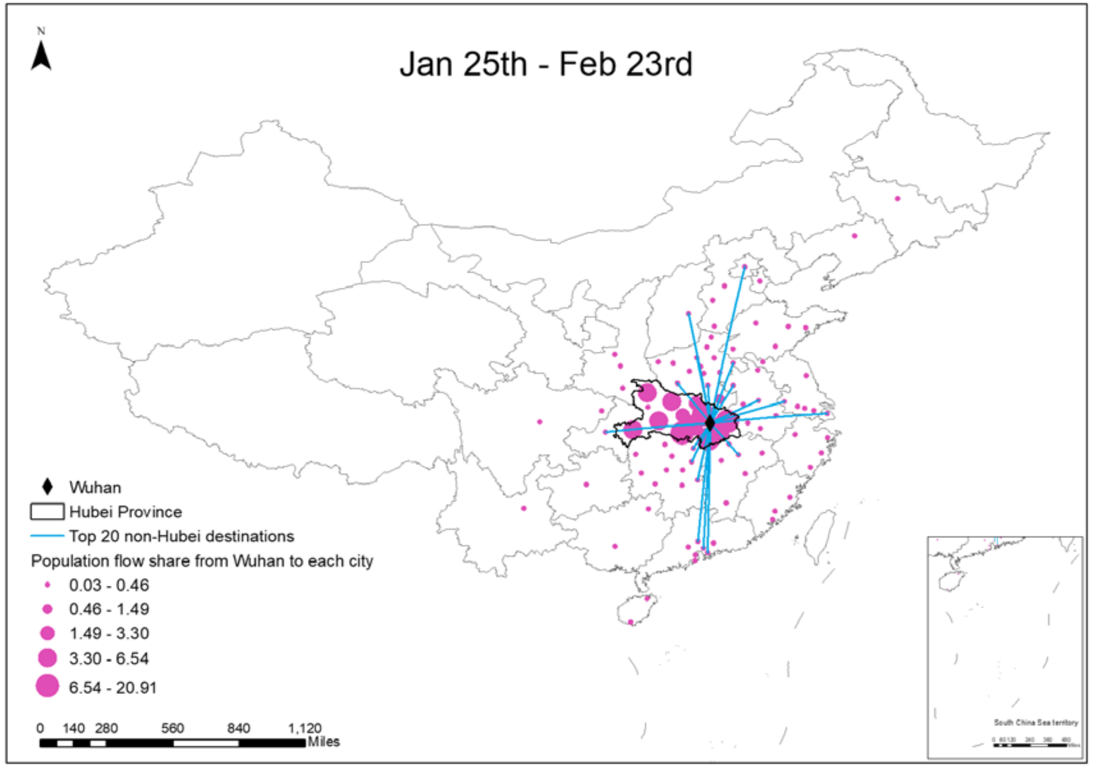


Data: Population flows from Wuhan, destination shares

January 10 – January 24



January 25 – February 23



Main results

- One can contract the virus from interacting with people who are infected and live in the same city or come from other cities.
- Severity of virus infections in other cities may influence the awareness of local public health authorities and residents. The spread rate of the virus can be reduced if more protective measures are taken.
- The lockdown in Wuhan on January 23 significantly reduced the population flow from Wuhan to other cities. We use a measure of the size of population flow from Wuhan to a destination city (constructed using the Migration Index of Baidu) and examine its mediating effect on virus transmission.

Overall R_0 reduced from 2.992 (Jan 19 - Feb 1) to 1.243 (Feb 2 – Feb 29)

	Jan 19 - Feb 29		Jan 19 - Feb 1		Feb 2 - Feb 29	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Model A: lagged variables are averages over the preceding first and second week separately						
Average # of new cases, 1 week lag						
Own city	0.862***	1.387***	0.939***	2.456***	0.786***	1.127***
	(0.0123)	(0.122)	(0.102)	(0.638)	(0.0196)	(0.0686)
Other cities	0.00266	-0.0248	0.0889	0.0412	-0.00316	-0.0212
wt. = inv. dist.	(0.00172)	(0.0208)	(0.0714)	(0.0787)	(0.00227)	(0.0137)
Wuhan	-0.0141	0.0303	-0.879	-0.957	-0.00788	0.0236
wt. = inv. dist.	(0.0115)	(0.0318)	(0.745)	(0.955)	(0.00782)	(0.0200)
Wuhan	3.74e-05	0.00151***	0.00462***	0.00471***	-0.00211***	-0.00238**
wt. = pop. flow	(0.000163)	(0.000391)	(0.000326)	(0.000696)	(4.01e-05)	(0.00113)
Average # of new cases, 2 week lag						
Own city	-0.425***	-0.795***	2.558	-1.633	-0.205***	-0.171
	(0.0318)	(0.0643)	(2.350)	(2.951)	(0.0491)	(0.224)
Other cities	-0.00451**	-0.00766	-0.361	-0.0404	-0.00912**	-0.0230
wt. = inv. dist.	(0.00213)	(0.00814)	(0.371)	(0.496)	(0.00426)	(0.0194)
Wuhan	-0.0410*	0.0438	3.053	3.031	-0.0603	-0.00725
wt. = inv. dist.	(0.0240)	(0.0286)	(2.834)	(3.559)	(0.0384)	(0.0137)
Wuhan	0.00261***	0.00333***	0.00711***	-0.00632	0.00167**	0.00368***
wt. = pop. flow	(0.000290)	(0.000165)	(0.00213)	(0.00741)	(0.000626)	(0.000576)

To interpret the magnitude of the effect, notice that the reproduction number of SARS-CoV-2 is estimated to be around 1.4 ~ 6.5 with median 2.79 as of January 28, 2020 (Liu et al., 2020).

Basic Reproduction Number (R_0)

Main results

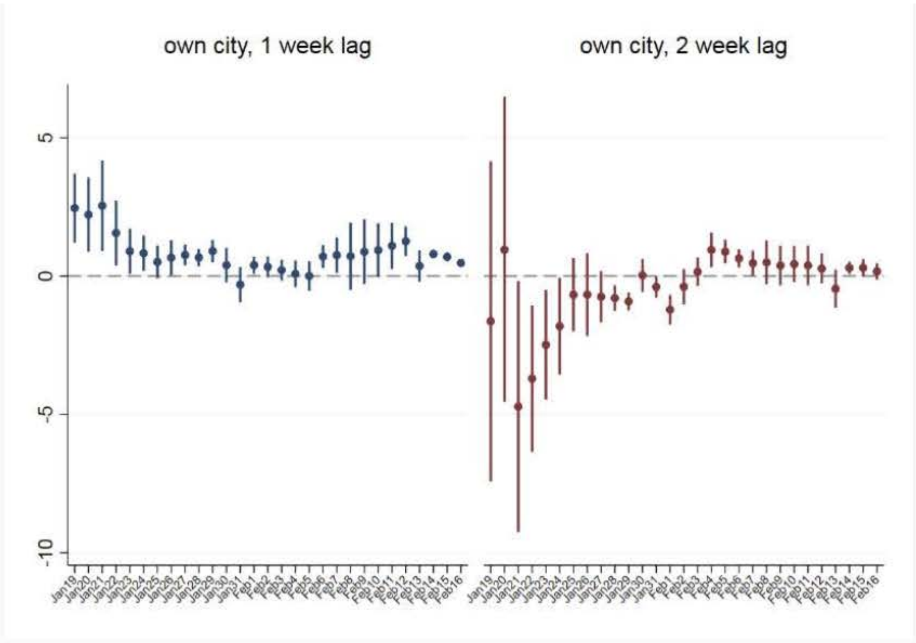
Overall R0 (excluding Hubei) reduced from 1.876 (Jan 19 - Feb 1) to 0.614 (Feb 2 – Feb 29)

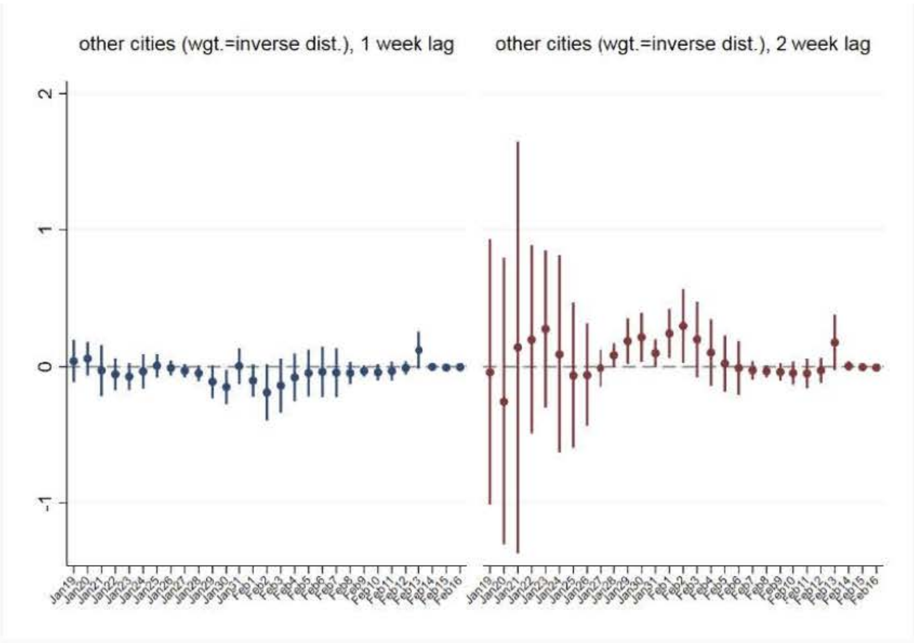
	Jan 19 - Feb 29		Jan 19 - Feb 1		Feb 2 - Feb 29	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Model A: lagged variables are averages over the preceding first and second week separately						
Average # of new cases, 1 week lag						
Own city	0.656***	1.117***	0.792***	1.194***	0.567***	0.899***
	(0.153)	(0.112)	(0.0862)	(0.302)	(0.172)	(0.0924)
Other cities	0.00114	-0.00213	-0.0160	-0.0734	0.000221	-0.00526**
wt. = inv. dist.	(0.000741)	(0.00367)	(0.0212)	(0.0803)	(0.000626)	(0.00244)
Wuhan	-0.000482	0.00420	0.104	0.233	5.89e-05	0.00769**
wt. = inv. dist.	(0.00173)	(0.00649)	(0.128)	(0.156)	(0.00194)	(0.00379)
Wuhan	0.00668***	0.00616***	0.00641***	0.00375	-0.000251	0.00390
wt. = pop. flow	(0.00159)	(0.00194)	(0.00202)	(0.00256)	(0.00245)	(0.00393)
Average # of new cases, 2 week lag						
Own city	-0.350***	-0.580***	0.230	-1.541	-0.157**	-0.250**
	(0.0667)	(0.109)	(0.572)	(1.448)	(0.0636)	(0.119)
Other cities	-0.000869	0.00139	0.172	0.584	-0.00266*	-0.00399
wt. = inv. dist.	(0.00102)	(0.00311)	(0.122)	(0.595)	(0.00154)	(0.00276)
Wuhan	-0.00461	0.000894	-0.447	-0.970	-0.00456	0.00478*
wt. = inv. dist.	(0.00304)	(0.00592)	(0.829)	(0.808)	(0.00368)	(0.00280)
Wuhan	0.00803***	0.00203	0.00973***	0.00734	0.00759***	0.00466***
wt. = pop. flow	(0.00201)	(0.00192)	(0.00317)	(0.00680)	(0.00177)	(0.00140)

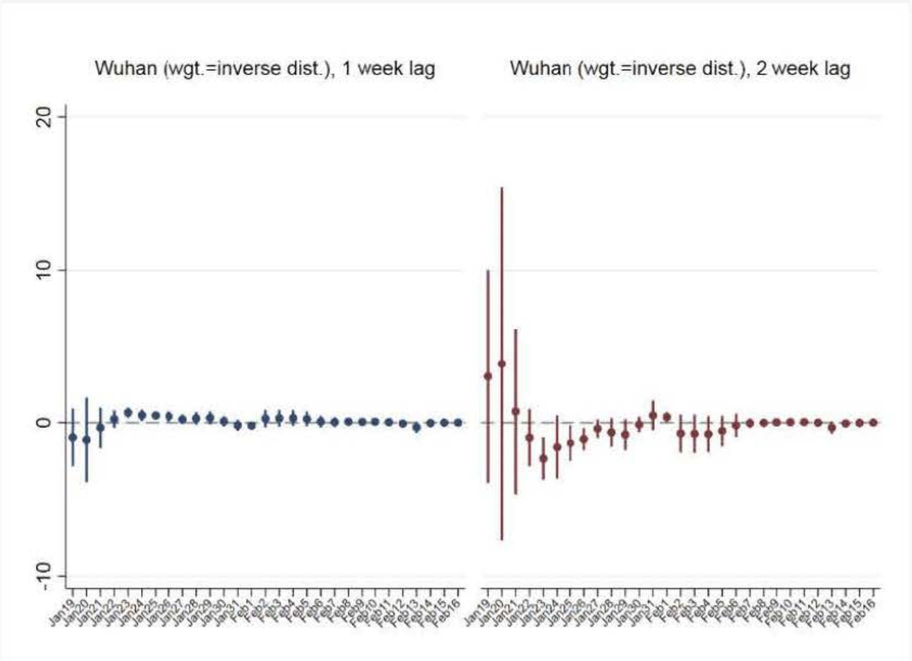
Basic Reproduction Number (R_0)

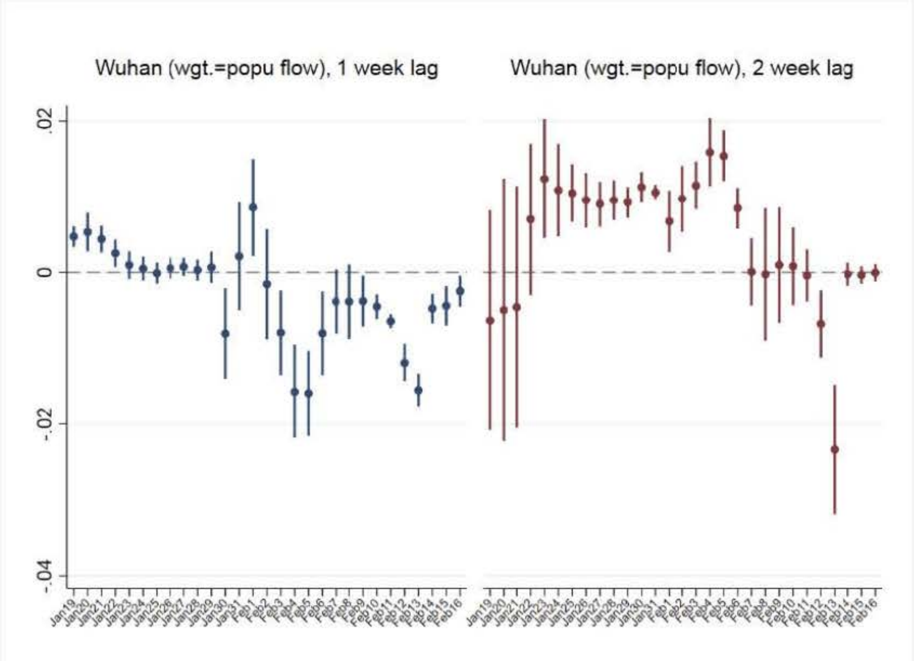
Main results, excluding cities in Hubei

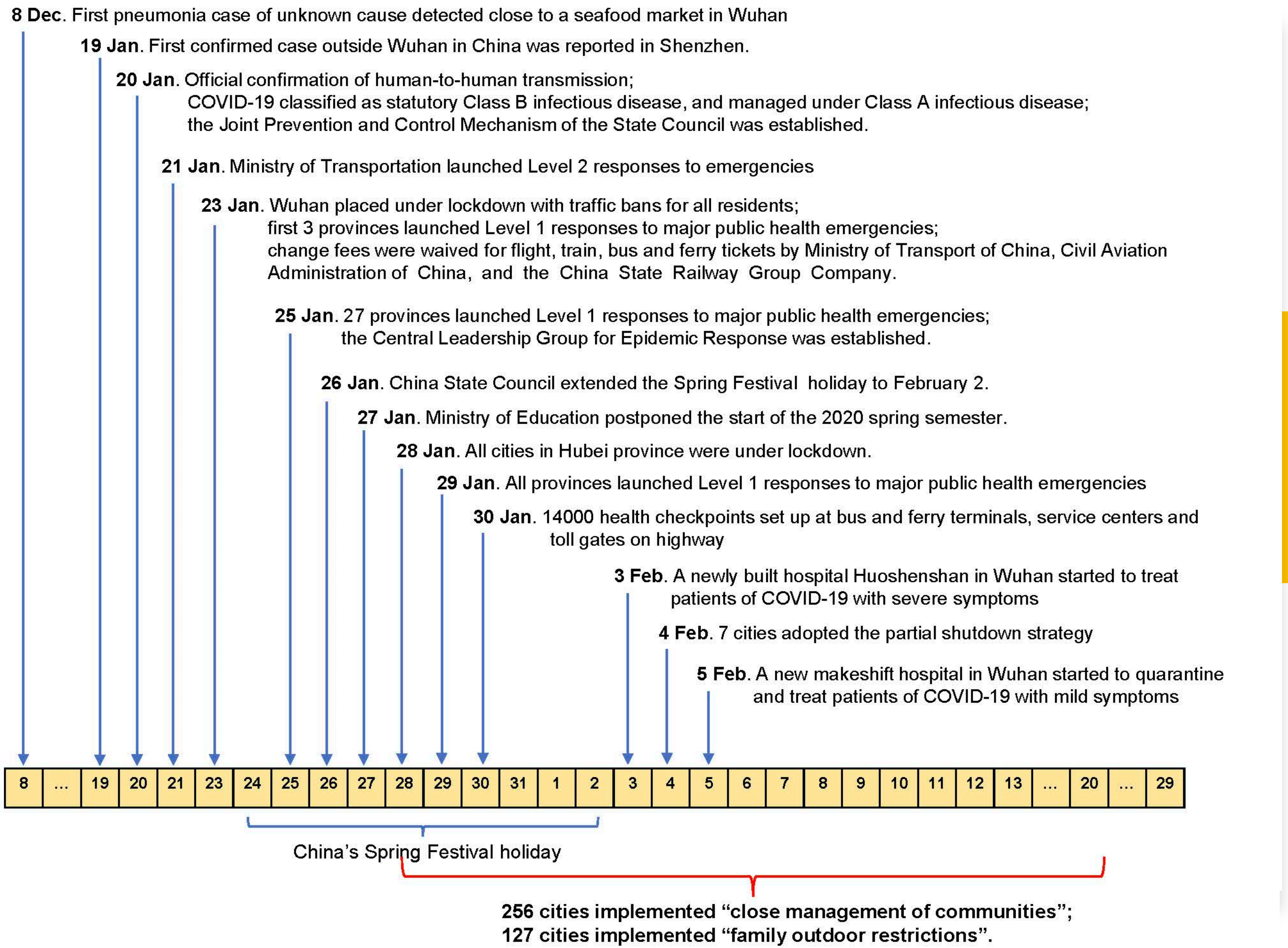
Rolling Window Analysis











Policy responses to the COVID-19 outbreak in China

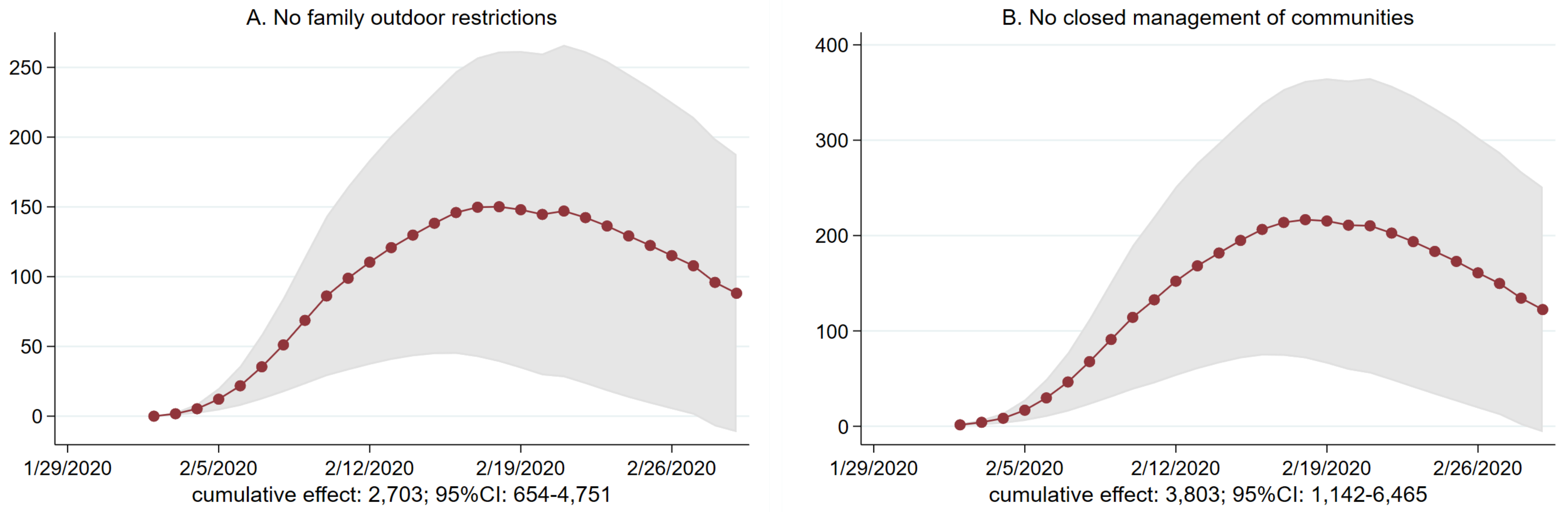
Assessment of the effects of non-pharmaceutical interventions

- Non-pharmaceutical interventions (NPIs) may decrease or effectively stop the transmission of COVID-19 even without vaccines.
- Spatial variations in the adoption of *closed management of communities* and *family outdoor restrictions*, allowing us to quantify the effect of these NPIs.
- We conduct a set of counterfactual analysis to assess the effects of the NPIs.
  - Estimating the model by 2SLS, obtain the residuals.
  - The changes in y_{ct} are predicted for counterfactual changes in the transmission dynamics (i.e., coefficients $\alpha^{k}_{within,\tau}$) and the impositions of specific NPIs.

Effects of local non-pharmaceutical interventions

- *closed management*: one infection will generate 0.244 (95% CI, -0.366 ~ -0.123) fewer new infections in the first week. The effect in the second week is also negative though not statistically significant.
- *family outdoor restrictions (stay at home)*: one infection will generate 0.278 (95% CI, -0.435 ~ -0.121$) fewer new infections in the first week. The effect in the second week is not statistically significant.

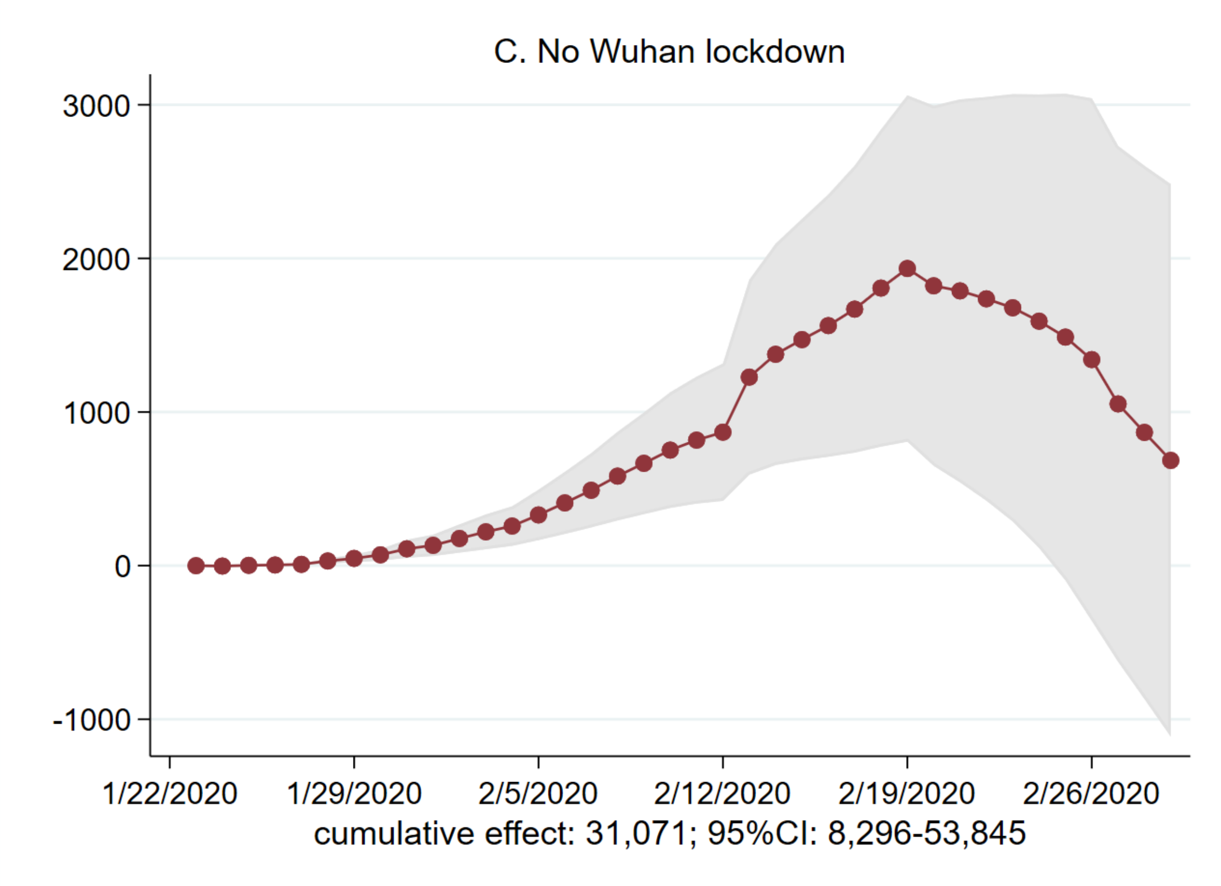
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
	Average # of new cases, 1 week lag					
Own city	0.642***	0.780***	0.684***	0.805***	0.654***	0.805***
	(0.0644)	(0.0432)	(0.0496)	(0.0324)	(0.0566)	(0.0439)
× *closed management*	-0.593***	-0.244***			-0.547***	-0.193*
	(0.162)	(0.0619)			(0.135)	(0.111)
× *stay at home*			-0.597***	-0.278***	-0.0688	-0.110
			(0.186)	(0.0800)	(0.121)	(0.143)
Other cities	0.00121	-0.00159	0.00167	-0.00108	0.00129	-0.00142
wt. = inv. dist.	(0.000852)	(0.00167)	(0.00114)	(0.00160)	(0.000946)	(0.00183)
Wuhan	0.00184	0.00382	0.00325*	0.00443	0.00211	0.00418
wt. = inv. dist.	(0.00178)	(0.00302)	(0.00179)	(0.00314)	(0.00170)	(0.00305)
Wuhan	0.00298	0.00110	-0.00187	-0.000887	0.00224	-3.26e-07
wt. = pop. flow	(0.00264)	(0.00252)	(0.00304)	(0.00239)	(0.00254)	(0.00260)



This figure displays the daily differences between the total predicted number in the counterfactual scenario and the actual number of daily new COVID-19 for cities outside Hubei province in mainland China. Shaded areas are 95% CI.

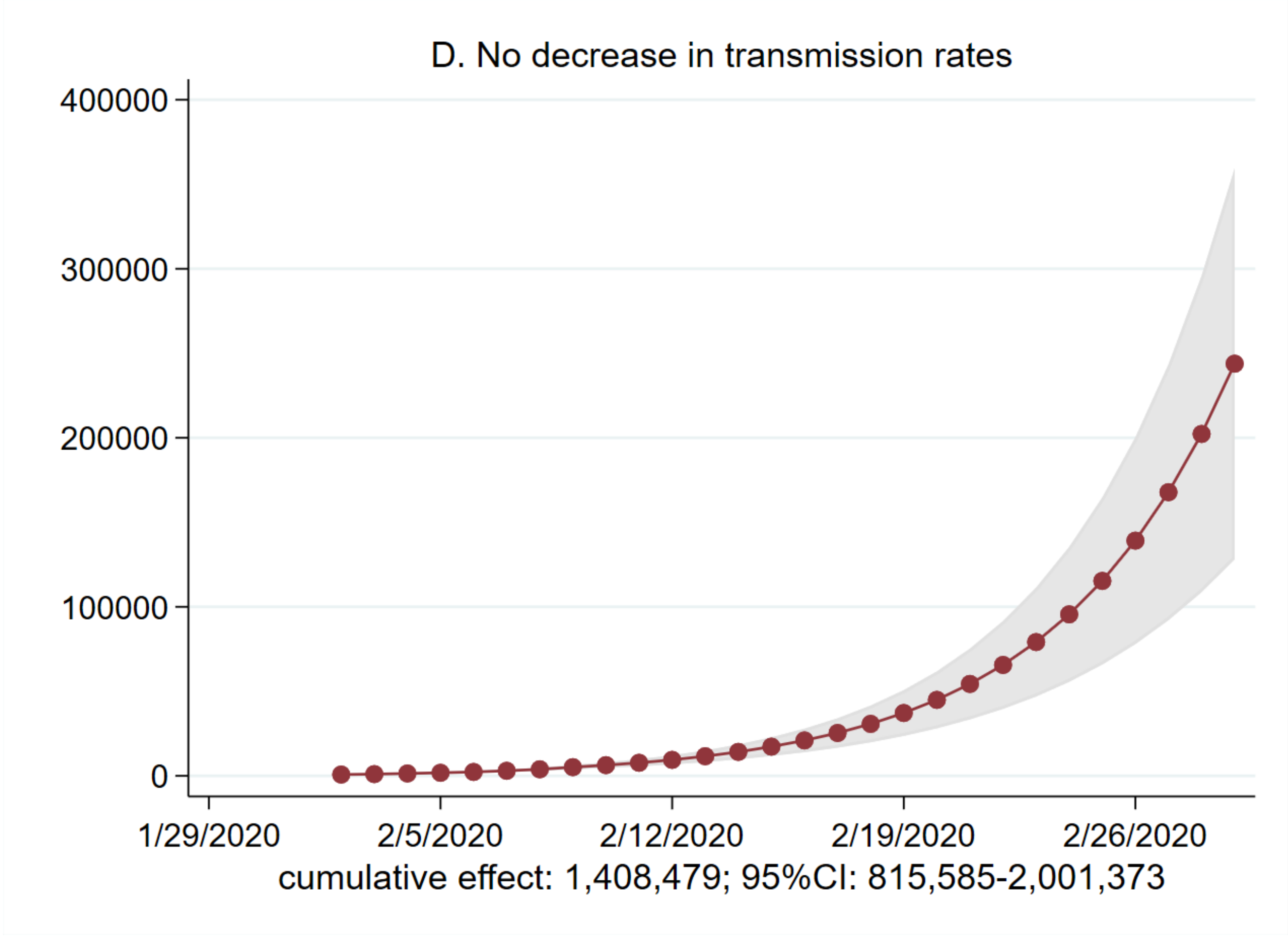
Counterfactual policy simulations

Counterfactual policy simulation: no Wuhan lockdown



- We assume the index of population flows out of Wuhan after the Wuhan lockdown (January 23) took the value observed in 2019 for the same lunar calendar date, which would be plausible had there been no lockdown around Wuhan.
- It is also likely that in the absence of lockdown but with the epidemic, more people would leave Wuhan compared with last year (Fang, Wang and Yang, 2020), and the effect would then be larger.

Counterfactual policy simulation: no decline in transmission rates



- Assume that the within city transmission dynamics were the same as those observed during January 19 ~ February 1
- By Feb 29, would be 1,408,479 (95% CI,815,585~2,001,373) more cases.
- Assuming a fatality rate of 4%, there would be 56,339 more deaths.
- Cost-benefit analysis

Assessment of the effects of NPIs

- Suppressing local virus transmissions to keep transmission rates well below those observed in Hubei in late January is crucial in forestalling large numbers of infections for cities outside Hubei.
  - Our retrospective analysis complements the simulation study of Ferguson et al. (2020).
- Keeping local transmission rates at low levels might have avoided one million or more infections in China. The public health policies announced by the national and provincial authorities in the last two weeks in January may have played a determinant role (Tian et al., 2020).
  - Chinazzi et al. (2020) also find that reducing local transmission rates is necessary for effective containment of COVID-19.
  - Among the measures implemented following provincial Level I responses, Shen et al. (2020) highlight the importance of contact tracing and isolation of close contacts before onset of symptoms in preventing a resurgence of infections once the COVID-19 suppression measures are relaxed.
- We also find that travel restrictions on high risk areas (the lockdown in Wuhan), and to a lesser extent, closed management of communities and family outdoor restrictions, further reduce the number of cases.
- **Caveats**:
  - These factors may overlap in the real world. In the absence of the lockdown in Wuhan, the health care systems in cities outside Hubei could face much more pressure, and local transmissions may have been much higher.
  - In China, the arrival of the COVID-19 epidemic in many cities coincided with the Lunar New Year. Had the outbreak started at a different time, the effects and costs of these policies would likely be different.

Summary

- COVID-19 infections have been reported in more than 200 countries or territories and more than 90,000 people have died. More and more national and local governments are implementing countermeasures, such as cross border travel restrictions, stringent social distancing, mandatory quarantine, city lockdown, etc.
- Based on the experience in China, preventing sustained community transmissions in the first place has the largest impact.
  - Restricting population flows from areas with high risks of infections can help achieve this goal.
  - Local public health measures such as closed management of communities and family outdoor restrictions can further reduce the number of infections.

Thank you!

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