## Social Connections and the Spatial Spread of COVID-19

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# How well can social connections be used to study the spread of infectious diseases?

- KNOWN: network data on human social interactions are more informative than geographic proximity
- UNCLEAR: which type of social interactions matters more for early stage spread and later-on local transmission

## Setting: the Spread of COVID-19 in China in Early 2020

- Jan 23rd-March 23rd for all Chinese cities
- Combine social media network and travel network to measure social connections
- Three steps
  - 1. When did the first COVID-19 case show up?
  - 2. How wide spread was the subsequent local transmission?
  - 3. How does the interplay of travel and information driven by social connections matter for local transmission?

## Data and Measurements

#### Social Connections (cross-sectional)

- Social Media Connection: 2013 snapshot of Weibo network created by Qin et al. (2021) •
- Baidu Travel Connection: aggregated average value at city-to-city level from Baidu Migration during Jan 1st-Jan 23rd 2020
- Cellphone Travel from Wuhan: estimated population movement from Wuhan during Jan 1st-Jan 23rd 2020

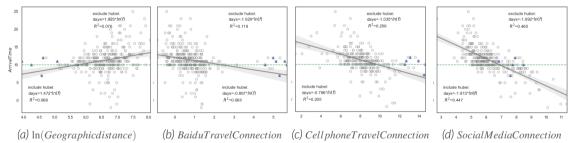
### Infection and social distancing (city daily panel)

- Daily infections outside Wuhan (from DXY)
- Social Distance index computed using Baidu Within-City Traffic Index

• distribution of connection to wuhan by network • PCA decomposition of connections

## Predicting the Arrival Time

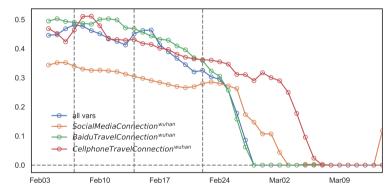
• Social media connections to Wuhan outperforms travel connections in predicting the arrival (higher R2)



• It also implies stronger transmission of COVID-19 (1.6  $\sim$  2 days faster per SD) (bigger slope)  $\checkmark$  table

## Predicting the Accumulated Number of Infections

Travel connection to Wuhan is a better predictor than social media connections (higher R2)



*Figure:* R-squared of prediction on number of infection using random forest regression

## The Dual Effects of Infection Import Exposure (1/4) To decompose by interacting the connection measures with travel restrictions

$$TravelExposure_{n,t}^{k} := \sum_{m \neq n} p_{nm}^{k} (1 - Lockdown_{m,t-1}) Infections_{m,t-1}$$
(1)

$$CommunicationExposure_{n,t}^{k} := \sum_{m \neq n} p_{nm}^{k} Infections_{m,t-1}$$
(2)

 $\Delta y_{c,t} = \alpha Infections_{n,t-1} + \gamma^k TravelExposure_{n,t-1}^k + \theta^k CommunicationExposure_{n,t-1}^k + X_{n,t} \Phi + FEs + \varepsilon_{n,t} + \delta^k CommunicationExposure_{n,t-1}^k + \delta^k Communic$ 

- $\theta^k Communication Exposure_{n,t-1}^k$ : effect under lock-down (no travel outflow from export cities)
- $\gamma^k TravelExposure_{n,t-1}^k$ : additional effect when there is no travel restrictions  $\bullet$  example

#### <u>Results</u>

• Travel speeds up spread while communication slows down spread

## Conclusion and Take away

To conclude

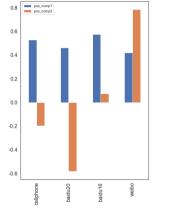
- Construct a Social Media Connection index between Chinese cities using Weibo data
- Nott only a measure of social contact proximity but also a conduit of information
  - outperform travel connections in predicting when and where
  - can both speed up (travel) and slow down (communication) the spread

Take Away

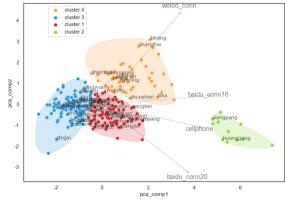
• Quick identification of high-risk regions upon initial outbreak



## PCA Decomposition • Dack

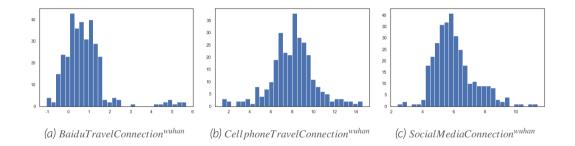


(a) factor loading

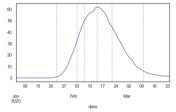


(b) K-means clustering on PCA components

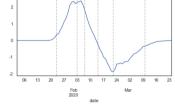
## Distribution of Connections to Wuhan by Network



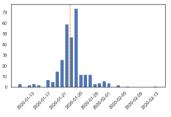




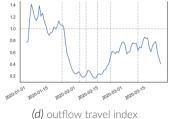
(a) avg current daily infection

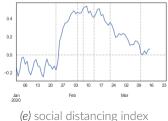


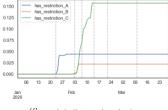
(b) avg change in daily infection



(c) Distribution of arrival date





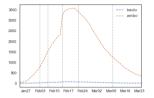


(f) social distancing index

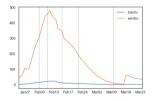
## Predicting the Arrival Time • back

VARIABLES	(1)	(2)	(3)	(4)	(5)
SocialMediaConnection <sup>wuhan</sup>	-2.6039***			-2.1878***	-2.0373***
	(0.187)			(0.238)	(0.265)
$BaiduTravelConnection^{wuhan}$		-1.2324***		-0.0738	-0.2329
		(0.234)		(0.257)	(0.284)
$Cell phone Travel Connection^{wuhan}$			-2.0960***	-0.6656**	-0.3316
			(0.219)	(0.321)	(0.414)
Observations	244	243	244	243	243
R-squared	0.446	0.103	0.275	0.468	0.473
Mean	11.209	11.210	11.209	11.210	11.210
Control	NO	NO	NO	NO	YES

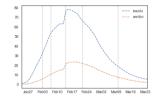
## Two Examples on Infection Import Exposure



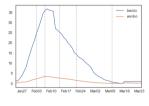
(a) CommunicationExposure, Guangzhou



(c) TravelExposure, Guangzhou



(b) CommunicationExposure, Yongzhou



(d) TraveExposure, Yongzhou

# The Dual Effects of Infection Import Exposure on Newly Infections •••••

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	early	early	early	later	later	later
$Communication Exposure^{weibo}$	-1.4404***		-1.4032***	-0.2937***		-0.2479***
	(0.447)		(0.470)	(0.062)		(0.053)
TravelExposure <sup>weibo</sup>	1.3883***		1.2727***	0.3376***		0.2914***
	(0.366)		(0.375)	(0.088)		(0.085)
$Communication Exposure^{baidu}$		-0.7115***	-0.5829***		-0.2593***	-0.2261***
		(0.170)	(0.127)		(0.050)	(0.045)
$Travel Exposure^{baidu}$		0.5336***	0.4284***		0.2892***	0.2281***
		(0.130)	(0.120)		(0.073)	(0.067)
Observations	6,224	6,224	6,224	8,475	8,475	8,475
R-squared	0.340	0.299	0.351	0.195	0.194	0.205
Mean	-0.029	-0.029	-0.029	-0.099	-0.099	-0.099
Controls	Х	Х	Х	Х	Х	Х
dateFE	Х	Х	Х	Х	Х	Х
SEcluster	City+date	City+date	City+date	City+date	City+date	City+date

## The Dual Effects of Infection Import Exposure on Social Distancing

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	early	early	early	later	later	later
$Communication Exposure^{weibo}$	0.0897***		0.0900***	0.0095		0.0307
	(0.030)		(0.030)	(0.030)		(0.028)
TravelExposure <sup>weibo</sup>	0.1129***		0.1157***	0.0055		-0.0137
	(0.030)		(0.031)	(0.028)		(0.028)
$Communication Exposure^{baidu}$		-0.0267	-0.0360		-0.0872**	-0.0925**
		(0.035)	(0.033)		(0.038)	(0.038)
TravelExposure <sup>baidu</sup>		-0.0310	-0.0334		0.0852***	0.0932***
		(0.033)	(0.030)		(0.030)	(0.032)
Observations	5,669	5,669	5,669	7,633	7,633	7,633
R-squared	0.887	0.882	0.888	0.912	0.913	0.913
Mean	0.006	0.006	0.006	0.002	0.002	0.002
Controls	Х	Х	Х	Х	Х	Х
CityFE	Х	Х	Х	Х	Х	Х
dateFE	Х	Х	Х	Х	Х	Х
SEcluster	City+date	City+date	City+date	City+date	City+date	City+date