Healthcare Utilization during COVID-19 Pandemic

Jian Ni (Johns Hopkins University)

新冠疫情模型论坛

July 16, 2020

Policy Analysis for COVID-19

- …. (maybe too many)

- Epidemiologists: herd immunity, timing, tracking, effect of mitigation, etc.
  - Develop guidelines to slow the spread of the disease and lessen its impact

- (Applied) economists: costs of lockdowns, tradeoff of opening, optimal policy, etc.
  - costs of lockdowns, optimal policy, etc.

Policy Analysis for COVID-19

- Timely and implementable to meet the needs of intervention
- Granularity
  - Macro-level policy (long term) and/or 宏大叙事
  - Micro-level (based on the empirical data)
- Very asymmetric impact
  - Age groups
  - Different medical specialty (needs)

Unmet Needs: Healthcare Crowd-out During the COVID-19 Pandemic

Based on joint work with

M. Hermosilla (JHU), H. Wang (Sun Yat-sen University), J. Zhang (Jinan University)

The New York Times | https://nyti.ms/2xPO8uU

With Virus Surge, Dermatologists and Orthopedists Are Drafted for the E.R.

Specialists who haven't worked an intensive care shift in years are being pressed into duty as coronavirus cases overwhelm New York's hospitals.

美国外科医师学会（American College of Surgeons, ACS）表示，由于医院不得不将医疗资源分配给数量激增的COVID-19患者，癌症手术可能需要推迟，并针对此次疫情发布了一套新的建议。

新华社北京2月17日: 新冠肺炎流行，医院不免成为很多人心中“危险等级最高的地方”。特殊时期，其他病还要不要去医院？有轻微发热或呼吸道症状就要去发热门诊吗？

The New York Times | https://nyti.ms/3afAgIL

These Doctors Have Specialties. Fighting Coronavirus Wasn't One of Them.

The pandemic's spread is creating new challenges for doctors who usually care primarily for patients with particular medical needs.

COVID-related care spans beyond infected patients

- Infected patients
  - Critical care
- Patients at risk
  - Testing
  - Pre-emptive management of chronic conditions
- Not infected patients
  - Accelerated morbidity (e.g., mental health)

COVID's healthcare toll: more than just the frontline

Has COVID care *crowded-out* non-COVID care?

- Focus on non-hotspots

- Online drug demand data & JHU CSSE data
  - Several hundred thousand transactions, from all 31 provinces
  - Jan-Feb 2020

- Indirect approach
  - Direct approach: leverage medical claims data (where??? If any)
  - Advantage: timeliness
  - Direct use: resource allocation in "2nd wave"
  - Broad contribution: healthcare utilization inference from drug demand data

How drug demand data reflect healthcare utilization

- Targeted inference on healthcare utilization (medical consultations)

- Two types of drugs
  - **Rx:** requires interaction with healthcare system
  - **OTC:** interaction not required

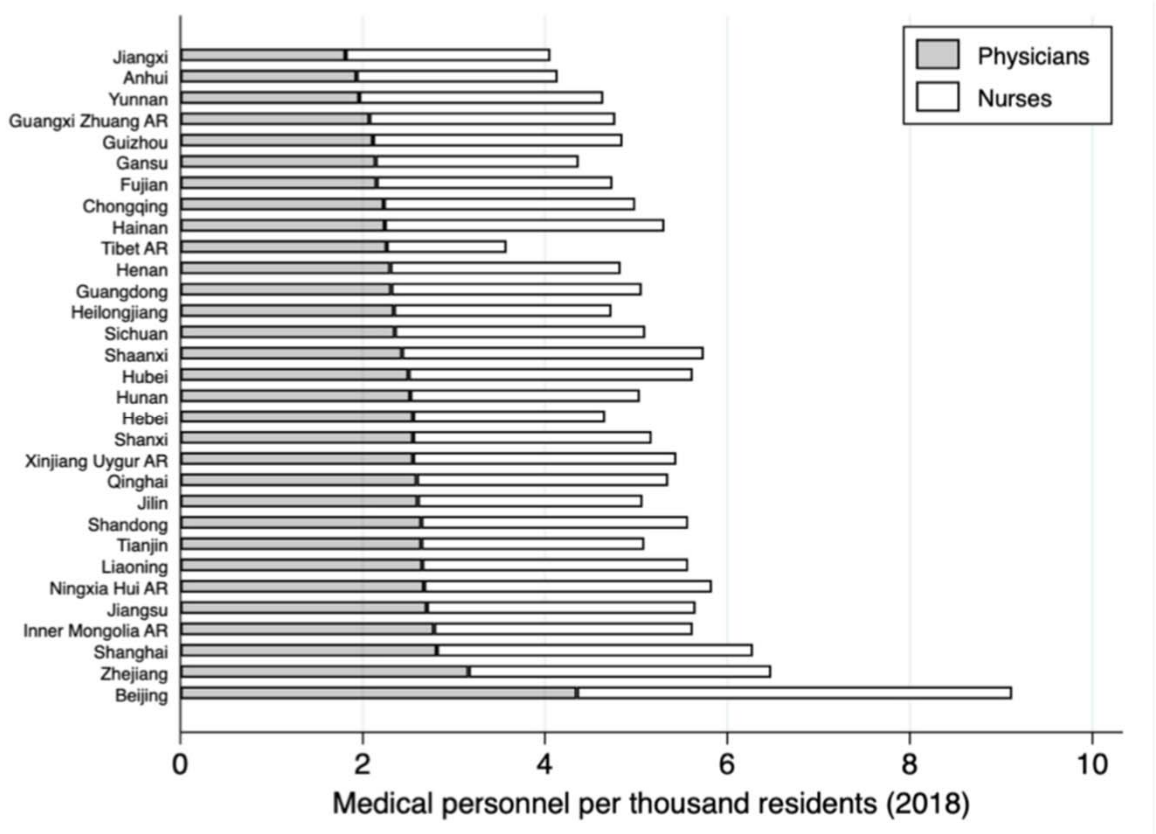
- China: more utilization -> more offline Rx -> less online Rx

△ utilization -> △ Rx/OTC demand

Crowd-out: ~10% healthcare capacity reduction at peak

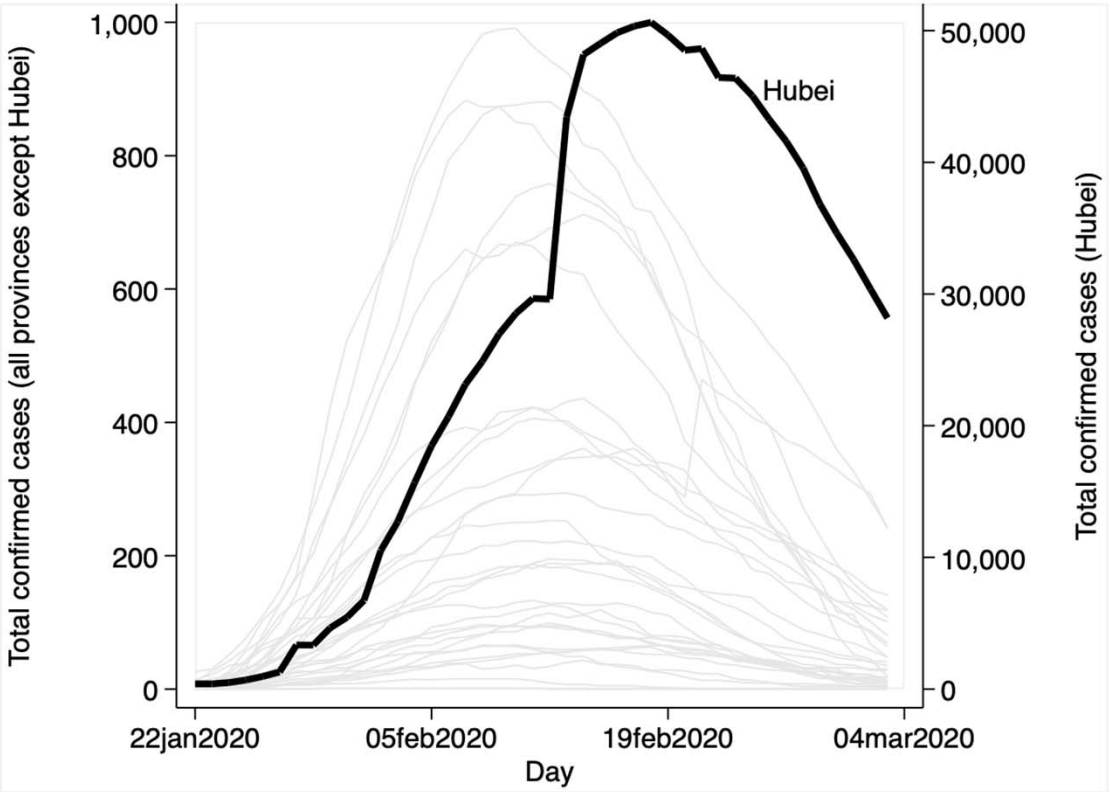
- Accounts for "secular" COVID-19 online drug demand impacts
  - Social distancing, mobility restrictions, etc.
- Robust to leading inferential concerns
- Some degree of external consistency
- Simple capacity reallocation policy can meaningfully reduce crowd-out

Healthcare capacity in China: a function of per-capita doctors



Wide cross-province variation

Wide cross-province variation in COVID-19 exposure

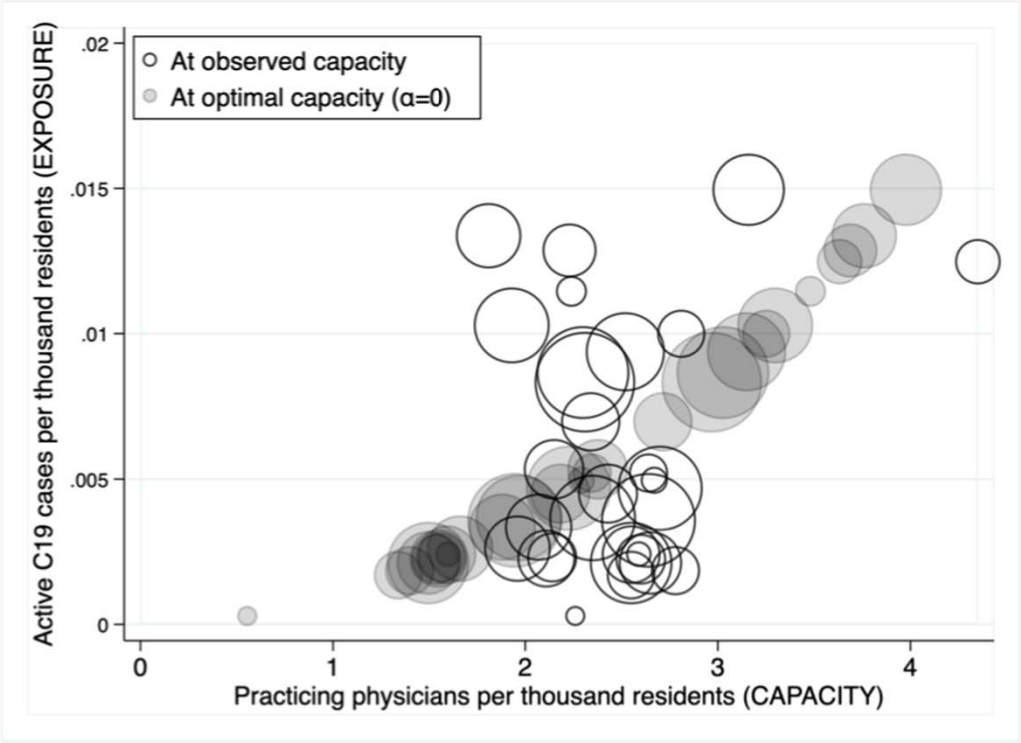


$$EXPOSURE_{prov,week} = \frac{COVID\ CASES_{prov,week}}{POPULATION_{prov}}$$

Hubei's first wave scenario unlikely in second wave

CASES/DOCTORS ratio also varied widely

Figure 3: Active C19 cases and physicians per capita in 2020w6.



COVID-19 did not "choose" best-prepared provinces

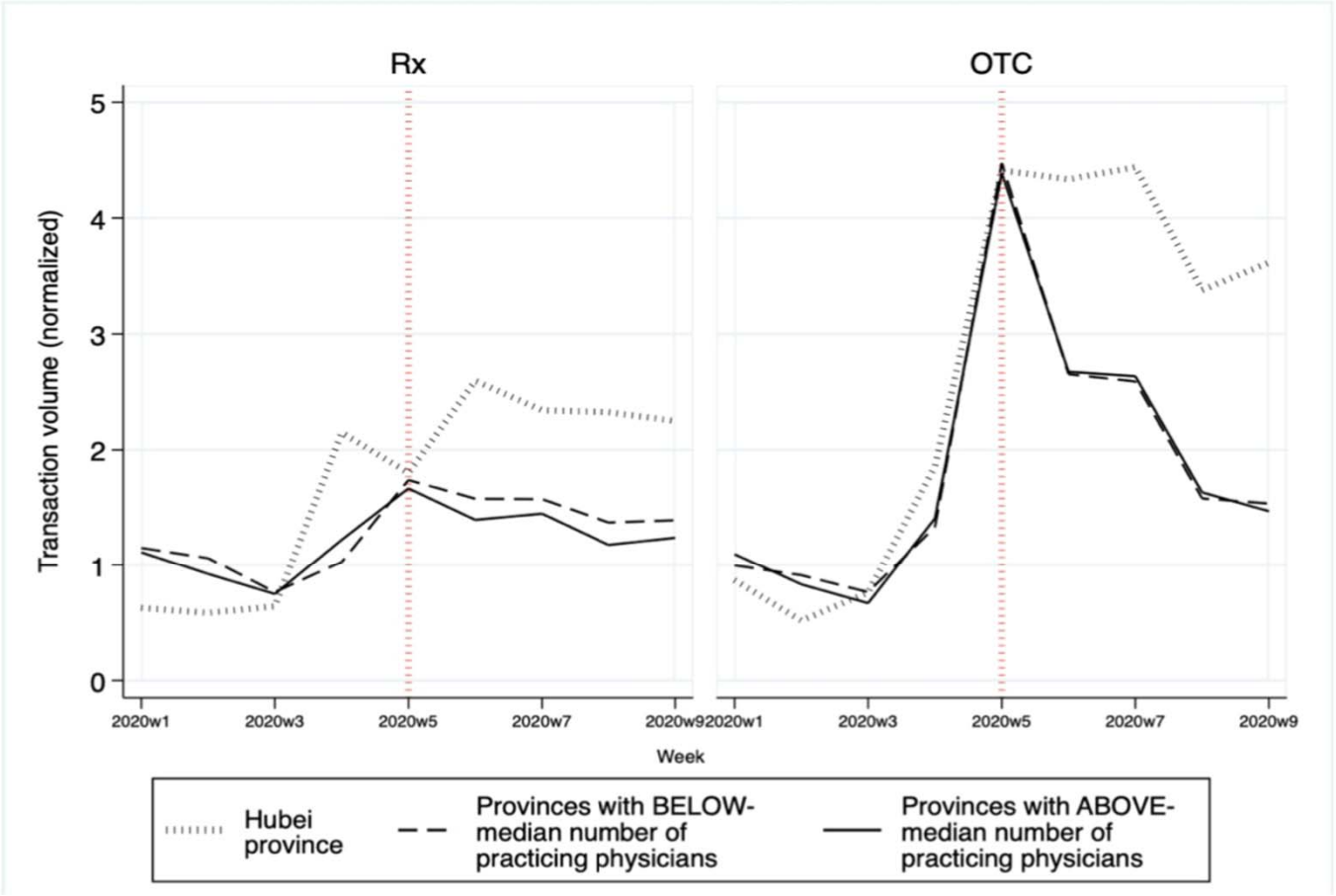
Table 1: Transactions and doses by therapeutic class.

	Rx			OTC		
	Transactions	Units	Doses	Transactions	Units	Doses
Antipsychotic	10.3	16.1	9.6	0.7	0.5	0.1
Bone & Joint	11.6	12.5	9.8	3	1.9	1.1
Cardio & Cerebrovasc.	17.1	30.6	32.1	0.2	0.1	0.1
Daily Meds.	100	100	100	100	100	100
Dermatological	22.9	24.2	22	7.4	4.1	5.3
Diabetes	3.4	5.6	5.8	0	0	0
Dietary Supplements	1	1.1	15	18	17	26.2
Female Meds.	5.8	9.4	5.6	3.2	2.6	1.2
Gastrointestinal	10.4	11.9	17.3	11.6	9.8	6.5
HIV	0.3	0.3	0.2	0	0	0
Liver Disease	6.3	10.8	8.1	0.4	0.4	0.1
Male Meds.	7.3	7	7.2	2.2	1.9	1
Oncology	3.1	4.3	5.5	0	0	0
Respiratory Tract	14	13	15.8	13.7	8.8	4.4
Trad. Chinese Med.	1.3	0.9	0.6	0	0	0

Values are normalized by each column's maximum (set to 100).

DDD Identification & Estimation

Figure 4: Average weekly online Rx/OTC transaction volumes and healthcare capacity.



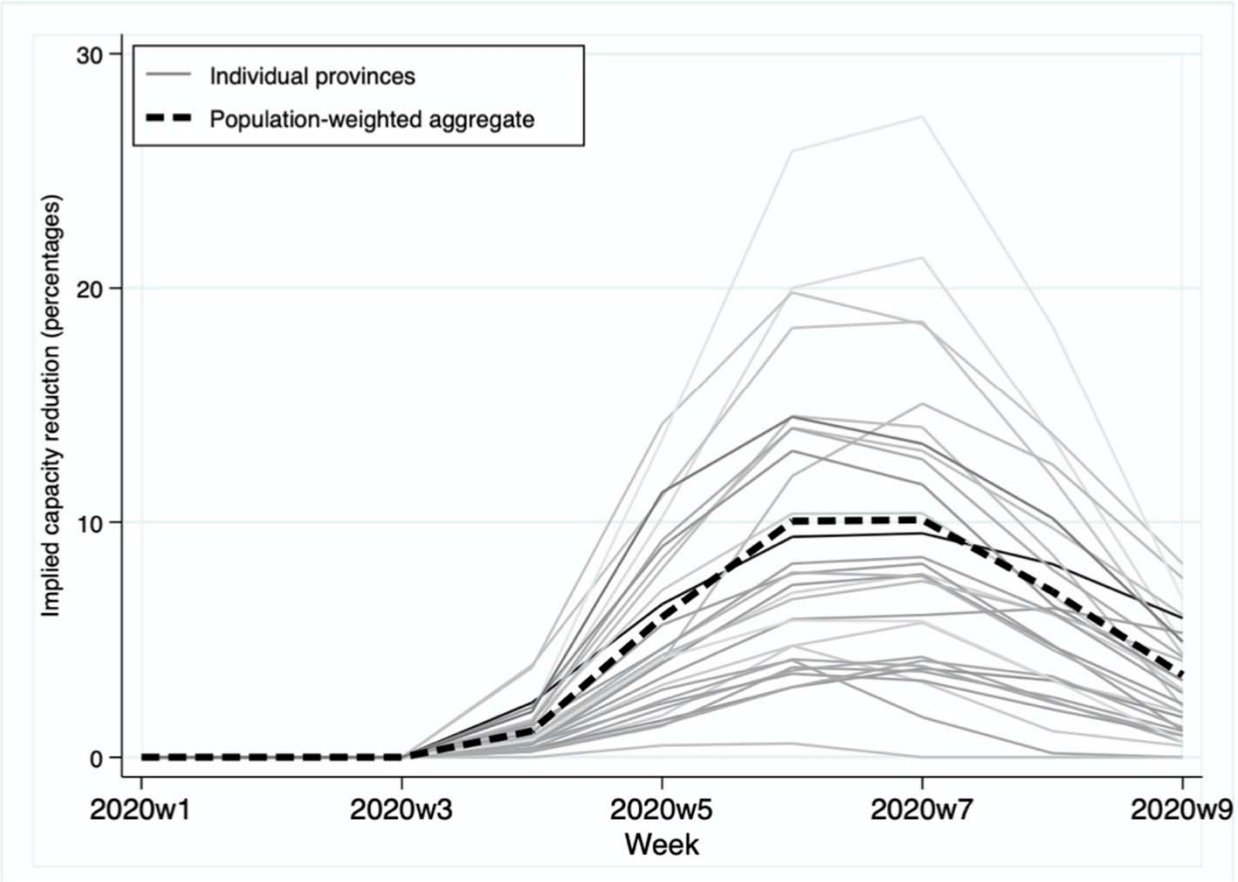
$$
\begin{aligned}
y_{jpt} = f\Big(& \mu_p + \tau_t + \lambda_{\text{class}(j)} + \beta_1 \cdot \text{PRICE}_{jt} + \beta_2 \cdot \text{COMPPRICE}_{jt} + \\
& \beta_3 \cdot \text{RX}_j + \beta_4 \text{EXPOSURE}_{pt} + \beta_5 \cdot \text{EXPOSURE}_{pt} \times \text{RX}_j + \\
& \beta_6 \cdot \text{RX}_j \times \frac{1}{\text{CAPACITY}_p} + \beta_7 \cdot \text{EXPOSURE}_{pt} \times \frac{1}{\text{CAPACITY}_p} + \\
& \boxed{\beta_8 \cdot \text{EXPOSURE}_{pt} \times \text{RX}_j \times \frac{1}{\text{CAPACITY}_p}} \Big)
\end{aligned}
$$

- Aggregation: product j / province p / week t
- $\beta_8 > 0$ consistent with crowd-out
- Estimated crowd-out proportional to β_8 x CASES/DOCS

Table 4: DDD estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
	Negative binomial			Log linear		
	Transactions	Units	Doses	Transactions	Units	Doses
A. All provinces; baseline capacity measure (N=2,059,857).						
EXPOSURE × Rx / CAPACITY	1.728**	0.171	0.096	0.171	0.239**	0.134
	(0.036)	(0.564)	(0.200)	(0.112)	(0.029)	(0.257)
B. Hubei data excluded; baseline capacity measure (N=1,993,410).						
EXPOSURE × Rx / CAPACITY	0.102***	0.023*	0.006	0.020***	0.019***	0.017***
	(0.007)	(0.091)	(0.103)	(0.000)	(0.000)	(0.003)
C. Hubei data excluded; capacity measured by the sum of per-capita physicians and nurses (N=1,993,410)						
EXPOSURE × Rx / CAPACITY	0.128***	0.037**	0.016***	0.017***	0.020***	0.010*
	(0.003)	(0.026)	(0.000)	(0.003)	(0.000)	(0.086)

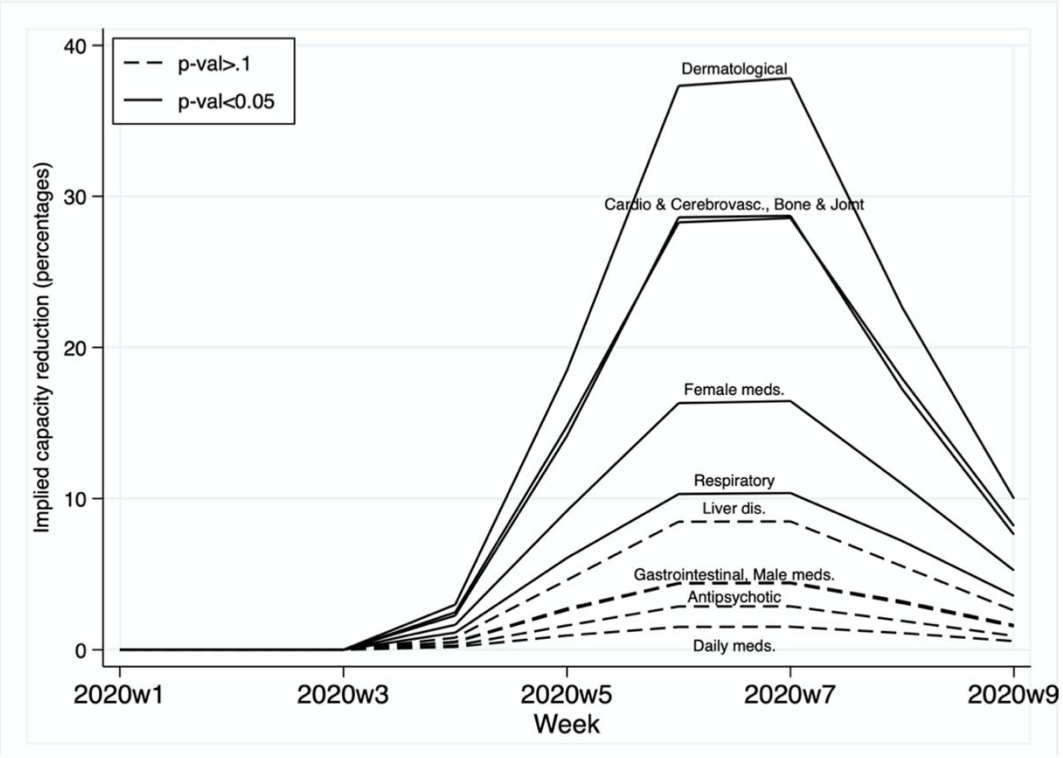
Figure 4: Implied crowd-out effects.



1 additional case per 1k physicians -> 4% reduction non-COVID care

DDD effects fueled by COVID-unrelated product classes

Figure 5: Class-specific implied crowd-out effects.



Variation consistent with medically-guided prioritization

Policy simulation:

α-Reserve Capacity Reallocation

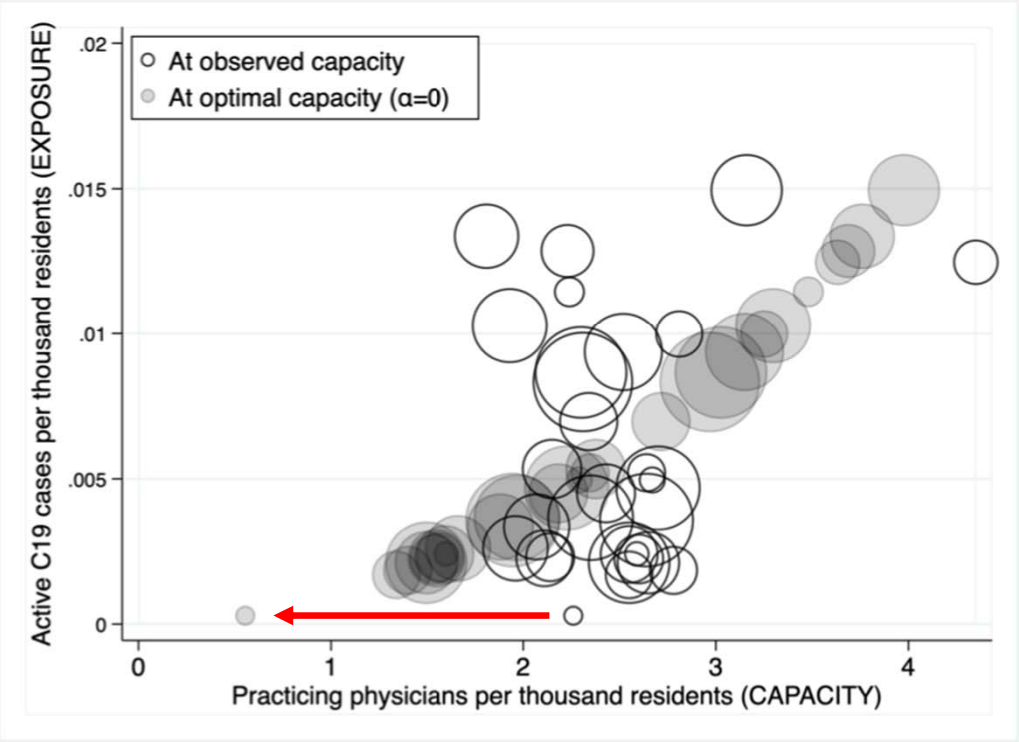
(via tele-health or similar)

$$
\begin{aligned}
y_{jpt} = f\Big(& \mu_p + \tau_t + \lambda_{\text{class}(j)} + \beta_1 \cdot \text{PRICE}_{jt} + \beta_2 \cdot \text{COMPPRICE}_{jt} + \\
& \beta_3 \cdot \text{RX}_j + \beta_4 \text{EXPOSURE}_{pt} + \beta_5 \cdot \text{EXPOSURE}_{pt} \times \text{RX}_j + \\
& \beta_6 \cdot \text{RX}_j \times \frac{1}{\text{CAPACITY}_p} + \beta_7 \cdot \text{EXPOSURE}_{pt} \times \frac{1}{\text{CAPACITY}_p} + \\
& \boxed{\beta_8 \cdot \text{EXPOSURE}_{pt} \times \text{RX}_j \times \frac{1}{\text{CAPACITY}_p}} \Big)
\end{aligned}
$$

- Aggregation: product j / province p / week t
- $\beta_8 > 0$ consistent with crowd-out
- Estimated crowd-out proportional to β_8 x CASES/DOCS

Equalizing marginal productivity of doctors across provinces reduces crowd-out by ~12%

Figure 3: Active C19 cases and physicians per capita in 2020w6.



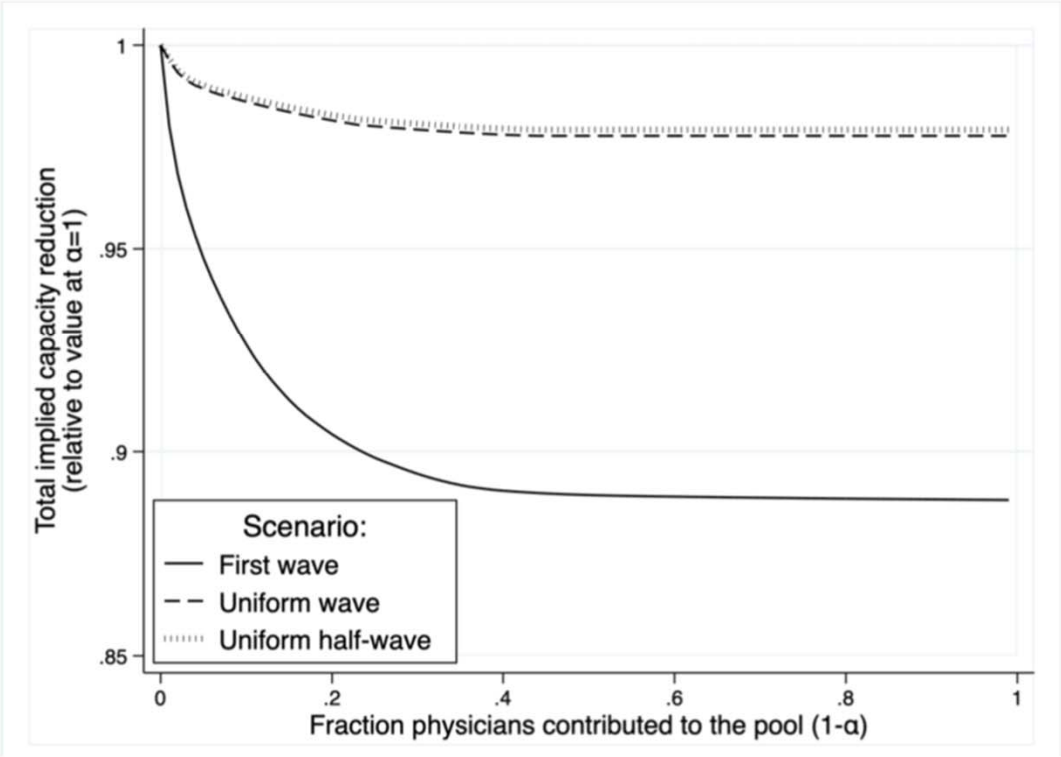
Problem: unreasonably low effective capacities

α-reserve capacity allocation

- Each province reserves $\alpha \in [0,1]$ of doctors for in-province care
- Complement 1-α contributed to national pool
- National pool allocated based on marginal conditions
  - Larger cases/doctors on given week -> province gets more doctors
  - Effective capacity does not drop below α

Most gains materialized with high reserves

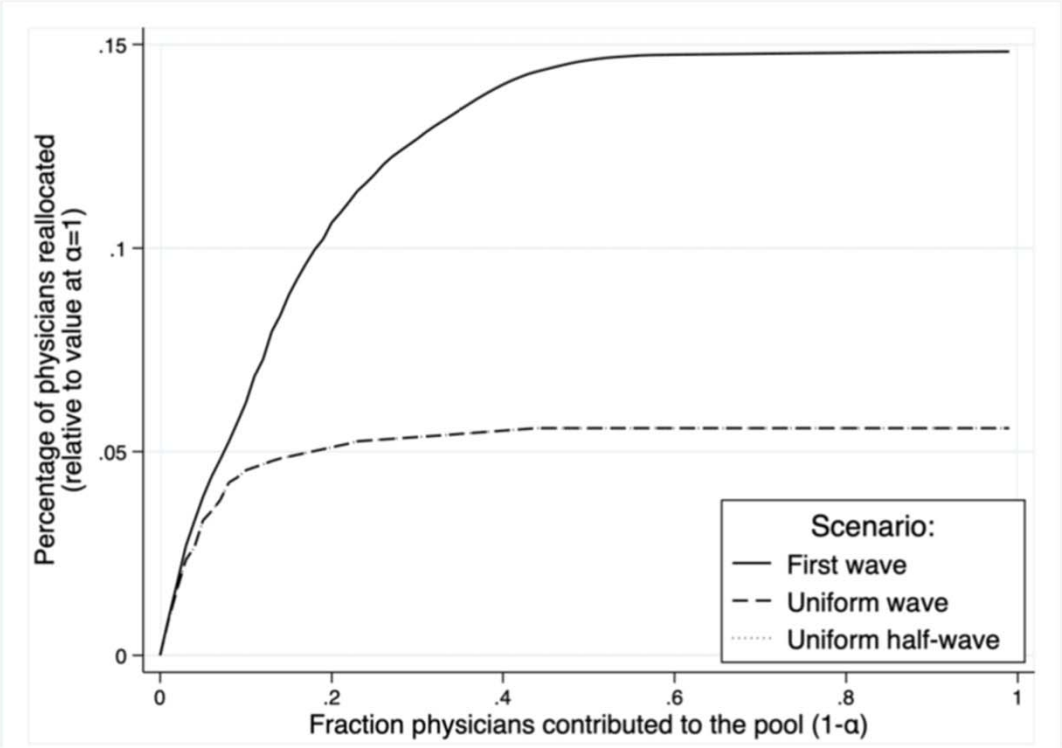
(b) Reallocation-fueled crowd-out reduction in potential second waves.



Gains to also be materialized in "uniform" second waves

Not a lot of reallocation needed

(b) Reallocation (physicians caring for patients from other provinces).



Summary

- Evidence of COVID-fueled healthcare crowd-out in China
  - Inference from online Rx/OTC demand activity
  - Clean of secular COVID impacts (eg, social distancing)
  - Peak crowd-out ~10% capacity reduction

- Simple healthcare capacity reallocation policy
  - Via telehealth
  - Reduce crowd-out impacts by 12\%
  - Requires participation of <=15% of physician population

Thanks!

Questions?