Healthcare Crowd-out and Resource Allocation: Evidence from COVID-19 Pandemic*

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Abstract

Efficient resource allocation, during a possible new wave of the COVID-19 pandemic and similar public health crisis, requires understanding whether (and to which extent) COVID-related healthcare demand may displace or *crowd-out* non-COVID care. We study this crowd-out hypothesis using a large sample of online drug retailing transactions in Mainland China which covers the height of the pandemic's first wave (January-February 2020). Since an interaction with healthcare providers is required to purchase prescription drugs (Rx) but not for over-the-counter drugs (OTC), crowd-out can be inferred based on relative Rx/OTC demand changes. Built on a triple-differences (DDD) identification framework, our results are consistent with the presence of crowd-out, estimating it equivalent to a 10% healthcare capacity decrease for non-COVID care at peak. Such a crowd-out effect also varies across different therapeutic classes. This variation is consistent with medically-guided healthcare prioritization. Based on these results, we propose and evaluate an α-reserve healthcare capacity reallocation policy, which could be implemented at large scale using tele-health infrastructure. Significant crowd-out reduction could be achieved with limited capacity reallocation.

*The usual disclaimer applies.

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1 Introduction

One of the most troubling aspects of a public health crisis is that a large amount of medical needs may be left unmet, especially for these not directly related to the virus. For example, the COVID-19 (hereafter "C19") pandemic has fueled large demand for medical care. This demand is beyond infected patients: medical care is also required by patients fearing infection, those requiring more active management of their chronic conditions, among others. This alarm has been raised, among others, by reports from the pandemic's hotspots (cities like Wuhan and New York), where medical resources and personnel have been massively reassigned to the C19 "front line" (Sengupta, 2020; Bloomberg, 2020; Arnold, 2020). Despite the additional resources made available, reports leave little doubt that frontline care has significantly displaced or *crowded-out* non-C19 care.

Given increased awareness, testing, and adoption of social and public health protocols, it is unlikely that hotspot-like emergencies will occur again during the pandemic's predicted second wave. However, it is still crucial to understand the extent and mechanics by which a potential resurgence of C19 could reduce access to non-C19 care. Further, efficient healthcare resource allocation (Ailawadi et al., 2020; Yoon, 2020) during such a critical period calls for understanding the extent healthcare demand may be shifted and can be rearranged. We address two questions emanating from this imperative: how strong may crowd-out effects be during a potential C19 second wave? How could these effects be lessened?

Our analysis is much needed because it is not a priori certain that crowd-out effects unfolded outside hotspots during C19's first wave. Crowd-out is supported by the reportedly widespread demand surge for C19-related care outside the frontline (Goldberg, 2020). Part of this surge has come from "at risk" patients demanding access to testing and/or inquiring about potential treatments. Individuals suffering chronic conditions associated to more likely severe C19 complications (e.g., diabetes) also expect more medical care. Yet another part may have been spurred from increased C19-fueled morbidity, e.g., mental health impacts of disruptions to normal life. These effects may have led to a reduction of routine (non-C19) care even among physicians that remain outside of the frontline. From the surface, the large reductions in overall healthcare utilization observed during the pandemic (Maddipatla and Humer, 2020) seem inconsistent with crowd-out: crowd-out should induce a substitution among types of care rather than an overall reduction thereof. However, this observation does not fully negate crowd-out effects, as these could stem from system bottlenecks.

The natural approach to study healthcare crowd-out effects would rely on insurer claims data. However, systematic claims data only become available with significant time lags,

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especially during a public health crisis like C19. Moreover, in many emerging countries, claims data may be restricted and of poor quality. To surmount this practical challenge, we leverage a large dataset of online drug retailing transactions across 31 Chinese provinces during January-February of 2020.[1] By exploiting the novel insight that marketing-related outcomes can be informative of healthcare utilization, our approach provides a timely alternative for healthcare providers and policymakers. Our analysis empirically tests the hypothesis of C19-fueled crowd-out during the pandemic's first wave in Mainland China. Since this period includes the peak of C19's first wave in China, the dataset provides us with a unique opportunity to produce a timely assessment of the questions at hand. The key data aspect that allows us to infer crowd-out regards demand differences between prescription (Rx) and over-the-counter (OTC) drugs. Specifically, because a provider-written prescription is required for Rx but not for OTC purchases, relative Rx/OTC demand changes reflect changes in the amount of used medical consultations. Since most sample drugs target non-C19 symptoms, changes in the amount of used non-C19 care can be inferred from this variation.

We embed this insight in a differences-in-differences-in-differences (DDD) identification framework (Gruber, 1994). The first difference cancels baseline Rx/OTC demand disparities; the second, differences unfolding temporally and in direct relationship to C19's spread in each province (e.g., via social distancing). Combining these differences into a differences-in-differences estimate (DD), we find that C19's spread was associated to larger OTC demand increases. But since C19 symptoms are disproportionally targeted by OTC drugs, this effect cannot be interpreted as crowd-out. The framework's third difference tackles the issue exploiting DD variation across provinces with different healthcare capacity levels (i.e., per-capita physicians). If present, crowd-out effects should have been stronger in lower-capacity provinces (fewer C19 cases per physician). We can thus declare the presence of crowd-out if DD effects vary consistently with the idea that access to non-C19 medical care was reduced relatively more in lower-capacity provinces. Put differently, identification is possible by using OTC demand to proxy Rx demand in the no-crowd-out counterfactual. This strategy is empirically supported: pre-trends are parallel and OTC demand is capacity-independent.

The DDD result reveals a C19-fueled relative surge of online Rx/OTC demand in lower-capacity provinces. Given that the Chinese system implicitly bundles utilization with offline Rx demand, this result suggests that patients from lower-capacity provinces were less likely to receive care as demand for C19-related care strained the system. At the pandemic's peak, estimated effects suggest crowd-out equivalent to an aggregate 10% decrease of non-C19 care. This result is robust to a series of checks. Some external validity is provided by

[1]For simplicity, municipalities and autonomous regions are also referred to as provinces.

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the heterogeneity across therapeutic classes: larger effects are inferred for conditions that, according to medical guidelines, would have been de-prioritized given scarce resources.

Based on these findings, we then propose and evaluate an "α-reserve" capacity reallocation policy. Relying on tele-health infrastructure, this policy would reallocate healthcare supply across provinces on a spot (weekly) basis, aiming to minimize aggregate crowd-out. Specifically, a fraction α of each province's physician population would be reserved for serving in-province patients, while the complement (1-α) would be allocated to provinces according to C19-fueled need. Significant crowd-out reduction (about 11%) is possible without drastically undercutting any province's healthcare capacity (i.e., high reserves). Efficiencies like these would still arise if the second wave is characterized by a more uniform geographical spread and/or smaller overall case count.

2 Data

2.1 COVID-19 epidemiology

We utilize province-level epidemiological series available from Johns Hopkins University's Center for Systems Science and Engineering.[2] The dataset contains series for the cumulative number of confirmed C19 cases, associated deaths, and recoveries. We utilize this information to construct series of active C19 cases (confirmed minus deaths minus recovered), which provide a sensible proxy for the burden placed by C19-related care on the system. Figure 1 presents the resulting figures across provinces and weeks. Active cases in the epicenter Hubei province (secondary axis) were orders of magnitude larger than in the average other province (main axis). Indeed, outside Hubei, there were about 0.6 cases per thousand residents at the crisis' peak Hubei had almost 80. Nevertheless, the overall surge and decline were broadly similar.

Figure 1 also displays a series of milestones related to the outbreak (vertical dotted lines). Each of these milestones may have triggered containment measures that conditioned outcomes moving forward.[3] We also note on analyses suggesting many active C19 cases may have gone undetected due to scarce testing (Li et al., 2020). In our econometric analysis we will employ a series of fixed effects as means to control for these types of unobserved heterogeneity.

[2]The dataset is described by Dong et al. (2020). Kaiser (2020) labels this as "the most authoritative source for COVID-19 case data."

[3]E.g., the Wuhan lockdown may have reduced contagion across provinces (Fang et al., 2020).

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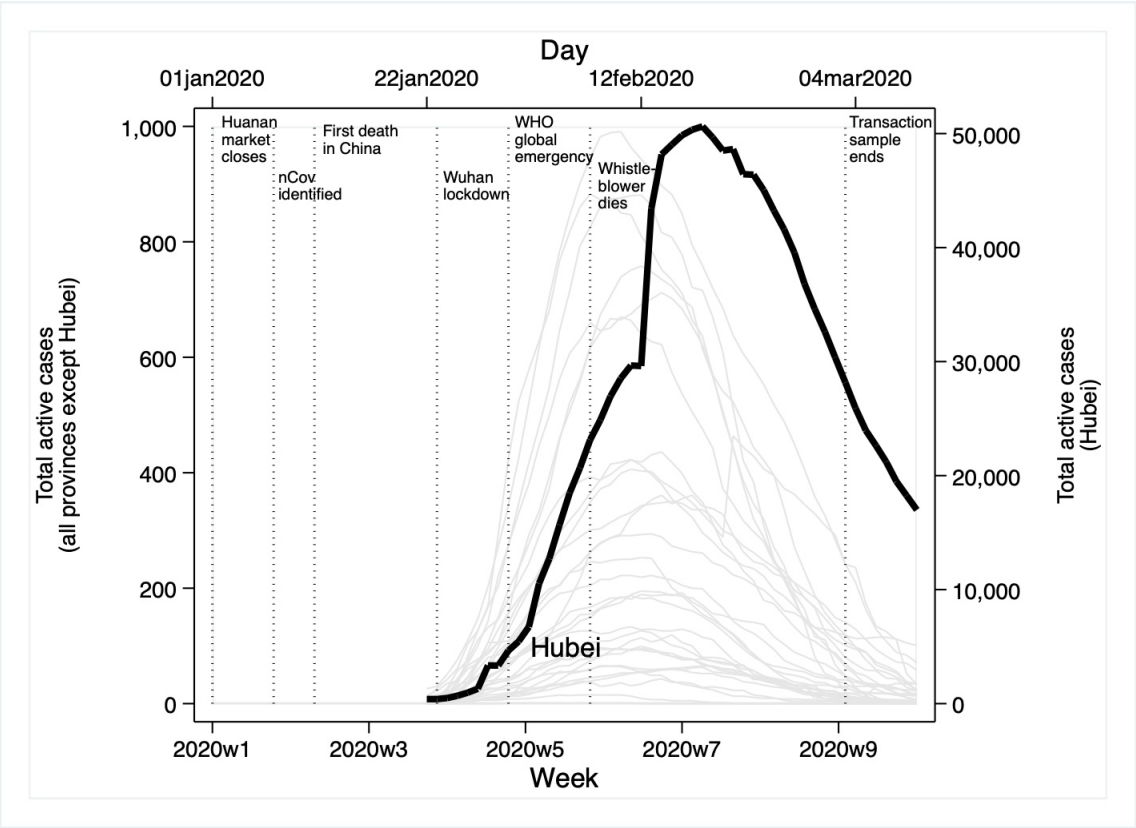
Figure 1: Active C19 cases by province/week.



For each day, active cases are computed as the difference between total confirmed minus the sum of recovered and dead patients. Data were obtained from Johns Hopkins University's Center for Systems Science and Engineering (Dong et al., 2020).

2.2 Online drug retailing transactions

The dataset spans the first 9 weeks of 2020 (2020w1-2020w9) and covers about 7,400 drug products—64% are Rx, 36% OTC. Records list hundreds of thousands of transactions originated from all 31 Chinese provinces. Per our data non-disclosure agreement, descriptives and estimation results mask some data moments (original series are used for estimation).

The firm partitions products into 15 therapeutic classes and over 60 subclasses.[4] Table 1 shows the former partition, along with three demand proxies: volumes of transactions, product units and implied daily doses. Since the scales of these proxies may vary across products, one of our analysis includes product-specific fixed effects. Demand activity is led by "daily medications," which includes Rx-antibiotics. In turn, this class' OTC demand is significantly

[4]This company is the top player in the Chinese online pharmaceutical market and has significant market share from Mid-2000s when it was founded.

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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).

reliant on products targeting C19 symptoms (primarily cough, fever, respiratory difficulties), e.g., Ganmaoling granules.[5] Several classes have either no or very few OTC alternatives, e.g., Diabetes, HIV.

The dataset also includes pricing information. While the retailer does not engage in geographic price discrimination, discounts are available and applied to total order value. For each product, our measure of price corresponds to the average discounted price paid by all customers (nation-wide) each week. The price of competitor products is computed as the average price of other products within subclass/week.

2.3 Healthcare capacity

From the 2018 China Health Statistics Yearbook (National Health Commission, 2018), we retrieved each province's number of practicing physicians and nurses. Both series reflect healthcare *capacity*, i.e., the system's ability to meet a large demand for healthcare. In the Chinese context, however, nurses are known to play more of a supporting role in healthcare provision (Zhan et al., 2019). For this reason, we will primarily measure each province's healthcare capacity through physicians per-capita. Using the sum of physicians and nurses does not substantially change results.

Figure 2 presents retrieved values per thousand residents (sorted by the physician num-

[5] A leading use of this product is fever reduction.

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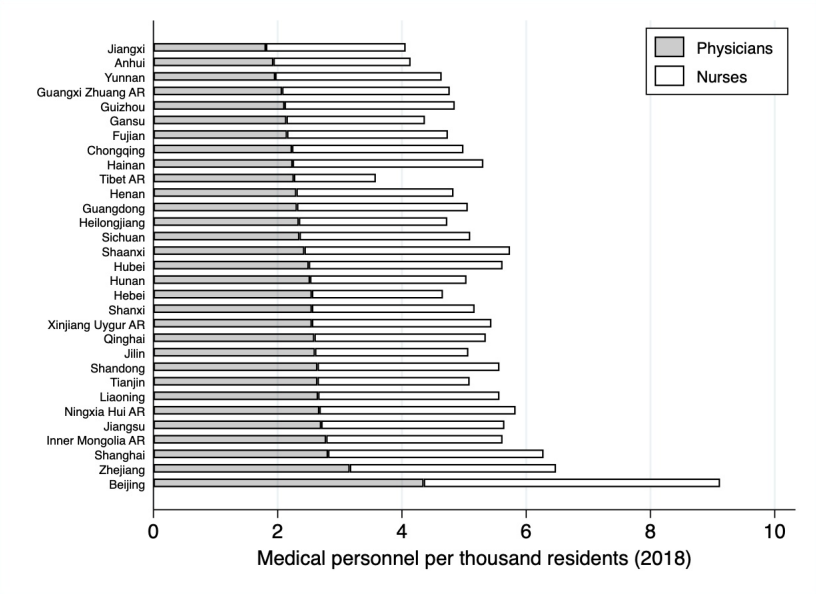
Figure 2: Healthcare capacity across provinces: physicians and nurses per thousand residents.



ber). Averages across provinces are about 2.5 for physicians and 2.8 for nurses. Beijing ranks top in both dimensions, by a margin. Hubei ranks median (16/31) in the physician ranking. Consistent with previous research (e.g., Tang et al., 2008), these statistics showcase wide gaps across provinces. Notice that, while these differences are endogenous to local healthcare demand in the long-run, they are fixed in the short-run that we analyze.

3 Empirical strategy

3.1 Capacity-independent C19 spread

A first important question is whether the spread of C19 was mediated by provinces' healthcare capacity levels. Such an effect could have occurred, e.g., if higher-capacity provinces were better able to identify and isolate early cases. Our analysis fails to detect these effects in the data—the virus' spread seems to have been capacity-independent.

We first provide graphical evidence from one of the peak weeks (2020w6). The hollow markers of Figure 3 illustrate the correlation between per-capita cases and physicians across provinces. The correlation is weak (about 0.2) and the coefficient of variation about four times larger for cases. This ample variation of per-capita cases combined with the relative compression of capacity further is telling—it suggests broad cross-province disparities in

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

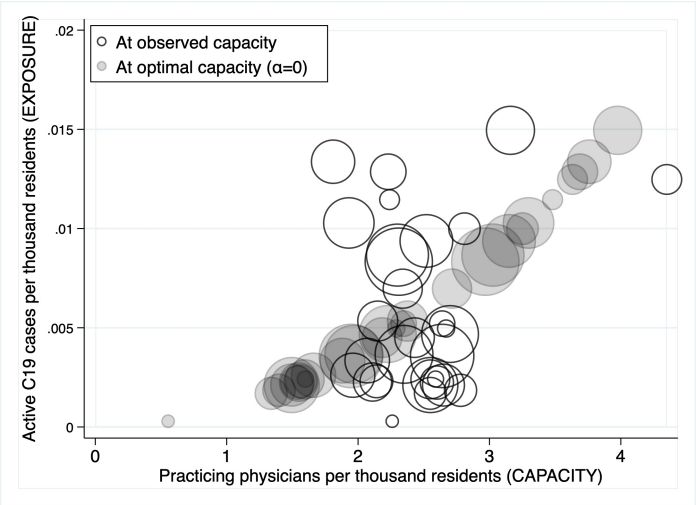

Table 2: Healthcare capacity and COVID-19 case flows.

	(1) Confirmed	(2) Recovered	(3) Deaths
CAPACITY	0.341	0.144	0.478
	(0.229)	(0.203)	(0.595)
N	279	279	279

Negative binomial estimates in Columns 1 and 2, zero-inflated negative binomial estimate in Column 3. All models include logged province population and the one-week lag number of active cases. Standard errors are clustered at the province level and presented in parentheses. Legend: $^{*}p < .1$,$^{**}p < .05$,$^{***}p < .01$.

cases-per-physician. This statistic (cases-per-physician) is pivotal in our regressions and simulations—estimated crowd-out effects will linearly depend on it.

Results from a more systematic analysis are presented in Table 2. The estimate of Column 1 is obtained by regressing the number of new C19 cases (province/week level) on capacity (negative binomial regression that also includes logged population and lagged number of active cases). The effect is not statistically significant. Columns 2 and 3 repeat the analysis but focusing on the number of recoveries and deaths. The capacity coefficients are again estimated too imprecisely for statistical significance. Based on these results, we will hereafter treat series of active C19 cases as capacity-exogenous.

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Table 3: Healthcare capacity and online drug demand. Negative binomial estimates from January 2020 data.

	(1)	(2)	(3)	(4)
CAPACITY×Rx	-0.886***	-0.784***	-0.269***	-0.267***
	(0.123)	(0.116)	(0.077)	(0.071)
CAPACITY×OTC	-0.711***	-0.617***	-0.188**	-0.188***
	(0.133)	(0.127)	(0.076)	(0.070)
Rx	1.708***	1.667***	1.711***	1.674***
	(0.308)	(0.303)	(0.336)	(0.320)
GDP	1.006***	0.717***	0.792***	0.515***
	(0.152)	(0.149)	(0.156)	(0.152)
MOBILE USERS	1.400***	1.725***	1.250***	1.711***
	(0.354)	(0.351)	(0.408)	(0.402)
INSURED	0.634***	0.508***	0.601***	0.462***
	(0.083)	(0.079)	(0.085)	(0.080)
DELIVERY TIME	-0.879***	-1.661***	-1.053***	-1.908***
	(0.262)	(0.328)	(0.285)	(0.339)
	Sample			
Provinces	All	All but Hubei	All	All but Hubei
Definition of CAPACITY	Physicians	Physicians	Physicians +Nurses	Physicians +Nurses
N	868	840	868	840

Robust standard errors in parentheses. Legend: $^{*}p < .1$,$^{**}p < .05$,$^{***}p < .01$.

3.2 How online drug demand reflects healthcare utilization

We noted that relative Rx/OTC demand changes can be informative about healthcare utilization because Rx transactions require an interaction with healthcare providers but OTC ones do not. Here we describe how Chinese institutional characteristics shape the interpretation of this variation. The key observation is that, given that most medical care and Rx drugs are distributed through public hospitals in China, the two products can be seen as implicitly bundled. Indeed, an estimate suggests that over 70% of outpatients fill their prescriptions in hospitals' pharmacies (Zhang, 2003). The reasons span beyond convenience: greater assurance of quality, physicians' recommendations, and ease at handling nonstandardized prescriptions (Sun et al., 2008). As a result, by the mid-2000s, public hospitals' pharmacies accounted for about 80% of Rx sales in China (Wang, 2006). Due to the sub-

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Table 4: DDD identification from weekly transaction volumes.

	Hubei		Other 30 provinces			
			Below-median capacity		Above-median capacity	
	Jan	Feb	Jan	Feb	Jan	Feb
Rx	1	2.26	1	1.53	1	1.38
OTC	1	4.04	1	2.57	1	2.56
DD		-1.78		-1.04		-1.18
		[0.56]		[0.59]		[0.54]
DDD					0.14	
					[1.09]	

stitutability of online and offline drug demand, this means that higher levels of online Rx demand will correlate with lower levels of healthcare utilization.

Table 3 presents econometric results supporting this interpretation. Using January data (few C19 cases), we estimated a negative binomial regression of Rx and OTC demand (transactions aggregated at province/class) on a series of determinants of online drug demand: GDP, mobile users, insured residents (all per-capita and logged), average delivery times to each province (logged hours), and an Rx indicator. Healthcare capacity was also included, while allowing for differentiated Rx/OTC slopes.

Consistent with the proposed interpretation, estimates of Column 1 indicate that capacity negatively correlates with online Rx demand. Our interpretation: more per-capita physicians means that more patients are getting care and thus going to hospitals, which increases offline Rx demand and in turn decreases online Rx demand (channel substitution). Notice that the effect's estimate is more pronounced for Rx than OTC given the former's higher reliance on healthcare utilization. Other coefficients have the expected signs and the results are robust to different specifications (Columns 2-4). The estimated elasticity of Rx transaction volume to capacity is -1.18 (Column 1).

3.3 DDD identification

The C19 spread spurred online drug demand for important reasons besides crowd-out. For example, because social distancing and mobility restrictions dissuade offline transactions. Table 4 illustrates how crowd-out effects are identified by DDD despite the presence of effects like these. Values in this table represent weekly Rx and OTC transaction volumes from above- and below-median capacity provinces, averaged within each month in the sample. Hubei data

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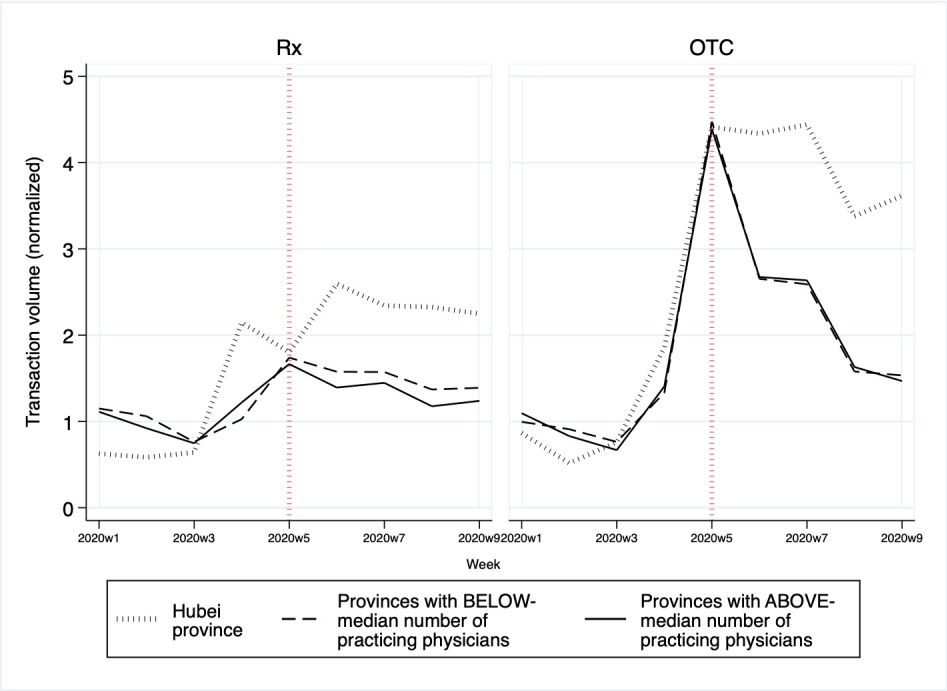
Figure 4: Average weekly online Rx/OTC transaction volumes and healthcare capacity.



The vertical line denotes the end of January data. Each series is normalized by its January average.

are presented separately due to their peculiarity. Given our agreement with the data provider, scales are hidden by a January normalization. Baseline Rx/OTC gaps (first difference) are purged by this normalization.

Since most C19 cases arose in February, the first-order impacts of the virus' spread (through social distancing, etc.) are reflected by January/February gaps. The impact of social distancing and related effects is reflected by the larger February values. A differences-in-differences estimate (DD) is obtained by subtracting the OTC increase from the Rx increase. (Bracketed values replace subtraction for division.) The negative DD estimates indicate that, across all provinces, online demand rose more in OTC than Rx products. This result is not surprising given that (i) OTC products disproportionally target flu symptoms (closely related to C19 symptoms), and (ii) OTC drugs are "easier" to acquire (no prescription needed). Per se, these effects do not reflect C19-fueled crowd-out.

Crowd-out is inferred exploiting healthcare capacity variation. Specifically, the inference is drawn by comparing DD effects in above- and below-median capacity provinces. Given the January normalization, February statistics are enough to conclude that the relative Rx/OTC surge was larger in lower-capacity provinces. The DDD estimate based on subtractions suggests C19-fueled crowd-out led to a 14% relative Rx demand increase. The figure based

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on divisions (bracketed values), estimates the effect at 9%.

Even though it is conceivable that crowd-out may also impact OTC demand, notice that February OTC surges are almost the same across the two types of provinces. That is, in our sample, OTC demand does not appear to be capacity-mediated. This result provides some validity for our identification assumption, namely, that OTC series are a valid approximation for Rx demand in the no-crowd-out counterfactual. Finer evidence for this assertion is shown by Figure 4, which presents weekly demand series. Throughout the sample, OTC series (right panel) display starkly similar trends between province types. Had C19-fueled crowd-out impacted OTC demand, these trends would have been separated in February. For Rx, in turn, transactions from below-median capacity provinces systematically overtake those from above-median provinces in February after displaying similar January pre-trends. These pre-trends are formally tested for (and rejected) below, after introducing the econometric framework.

3.4 Econometric specification

Our specification makes more efficient data use relative to the above analysis, by exploiting continuous (rather than dichotomous) variation, and by controlling for a host of unobservables. Data are formatted at the product (j)/province (p)/week (t) level.[6] The variable EXPOSURE proxies for virus' longitudinal spread:

$$\text{EXPOSURE}_{pt} = \frac{\text{Average number of active cases in province } p \text{ during week } t}{\text{Population of province } p}$$

The normalization is introduced to account for the large population differences across provinces. Population figures are for 2018 and in thousands. RX is an indicator for Rx products and CAPACITY is physicians per thousand residents. Thus, EXPOSURE/CAPACITY equals cases per physician.

The DDD specification (Gruber, 1994) includes two-way interactions of the three differ-

[6]We prefer product/province/week over product/province/day aggregation because it minimizes the percentage of zero-sales observations.

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encing variables plus their three-way interaction (which gives the DDD estimate):

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

Since demand proxies y (transactions, units, doses) are counts, f is implemented as negative binomial regression. As noted, the parameter of interest is obtained from the three-way interaction. A positive DDD estimate ($\hat{\beta}_8 > 0$) would suggest that C19's spread led to larger relative Rx/OTC demand surges in lower-capacity provinces. By previous arguments, this would be interpreted as evidence of C19-fueled crowd-out.

Variable interactions use the inverse of CAPACITY for intuitive and analytical reasons. Assuming a statistically significant $\hat{\beta}_8 > 0$, estimated crowd-out is increasing in $\hat{\beta}_8 \cdot$EXPOSURE/CAPACITY. That is, estimated crowd-out directly depends on the intuitive quantity of C19 cases-per-physician. Estimated crowd-out also has the following properties: (i) null at zero exposure, (ii) additional capacity lowers crowd-out in a marginally decreasing way, and (iii) additional capacity has infinite marginal return at the zero limit. Beyond describing a reasonable structure, these properties allow us to propose and evaluate an optimal capacity reallocation policy (section 5).

Note that estimated crowd-out would not only operate on top of first order (β_3, β_4) and two-way interaction effects ($\beta_5, \beta_6, \beta_7$), but also on top of various forms of observed and unobserved heterogeneity. These include the effects of products' own (logged) prices and those of competitors. Regional time-invariant online drug demand determinants (internet access, demographics, CAPACITY, etc.) are subsumed into province-specific fixed effects (μ). The impacts of attitudes and policies of national reach and captured by week-specific effects (τ). Lastly, baseline demand differences across product classes, e.g., due to a varying chronic/acute-targeted product mixes, are controlled for by product class fixed effects (λ).

Although count data frameworks are the natural choice to analyze the available outcomes, their likelihood functions are relatively intolerant of highly-saturated specifications. This is limiting in our context, e.g., because we would ideally include a large number of fixed effects to control for baseline demand differences across products. We lessen this problem by clustering standard errors at the product level. Nevertheless, for reassurance, we also estimate an analog

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although much more saturated log-linear specification. This specification better controls for unobserved heterogeneity by: (i) replacing class-specific effects for product-specific ones, and (ii) replacing separate week and province fixed effect for week/province ones.[7]

3.5 Pre-trend analysis

The DDD identifying assumption is that OTC demand is not impacted by crowd-out, which makes it a valid proxy for Rx demand in the no-crowd-out counterfactual. Although we cannot observe this directly, we can examine the trends of Rx and OTC demand in the period just prior to C19 spread. Identification would be challenged if these trends suggested that effects giving rise to $\hat{\beta}_8 > 0$ where brewing in the data during this period. We test the existence of such pre-trends with the following analysis.

Our specification is a modified version of Equation 1, specifically:

$$\begin{aligned} y_{jpt} \quad = f\Big(\quad & \mu_p + \tau_t + \lambda_{\text{class}(j)} + \phi_1 \cdot \text{PRICE}_{jt} + \phi_2 \cdot \text{COMPPRICE}_{jt} + \\ & \phi_3 \cdot \text{RX}_j + \phi_4 \cdot t \times \text{RX}_j \times \text{EXP}\bar{\text{O}}\text{SURE}_p \times \tfrac{1}{\text{CAPACITY}_p} \quad \Big), \end{aligned} \tag{2}$$

where $t = 1, 2, 3$ indexes weeks (2020w1-2020w3). One key difference with respect to Equation 1 is that we use average exposure levels during 2020w4-2020w9 (EXP$\bar{\text{O}}$SURE) instead of EXPOSURE itself (which is zero during 2020w1-2020w3). Parameter ϕ_4 captures Rx/OTC demand differentials unfolding in anticipation of DDD effects. In particular, $\hat{\phi}_4 > 0$ would lead us to attribute potential crowd-out to pre-trends.[8] Hubei data are dropped but results are robust to their inclusion.

Table 5.a presents estimation results. Coefficients for ϕ_4 are imprecisely estimated across demand proxies—associated p-values are larger than required by standard confidence levels. This result suggests that confounding pre-trends were not present in the data. Table 5.b presents the results of the corresponding log-linear specification. Except for the daily doses outcome, estimates are again statistically non-significant. The negative estimate for daily doses indicates the existence of a pre-trend moving in opposite direction to crowd-out effects. Thus, DDD results for daily doses may underestimate crowd-out.

[7] The introduction of these more granular controls means that product-invariant variables (RX) and week/province-invariant variables (EXPOSURE, EXPOSURE/CAPACITY) become redundant and need to be dropped. Note that week/province fixed effects would absorb effects such as gradual province-specific adoption of mitigation policies. These effects would also capture effects derived from inter-provincial migration (Jia et al., 2020).

[8] Stand-alone CAPACITY and EXP$\bar{\text{O}}$SURE/CAPACITY by the inclusion of μ effects; stand-alone t, by the inclusion of τ effects.

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Table 5: Econometric evaluation of pre-trends.

	(1) Transactions	(2) Units	(3) Doses
	(a) Negative binomial.		
ϕ_4	0.019	0.010	-0.009
	(0.717)	(0.541)	(0.152)
	(b) Log-linear.		
ϕ_4	0.000	0.001	-0.005**
	(0.969)	(0.788)	(0.031)
N	664470	664470	664470

Presented estimates have been standardized. Negative binomial regressions include week, province and product class fixed effects. Log linear regressions include product and week/province fixed effects. Standard errors are clustered at the product level and p-values are presented in parentheses. Legend: $^{*}p < .1$,$^{**}p < .05$,$^{***}p < .01$.

4 Results

4.1 Main estimates

The first three columns of Table 6.a show negative binomial DDD estimates.[9] Column 1 uses the number of transactions as outcome; Columns 2 and 3 respectively use units and daily doses. Consistent with C19-fueled crowd-out, all estimates are positive. However, except for transactions, parameters are estimated imprecisely. Log-linear results (Columns 4-6) are qualitatively similar. Results are replicated in Panel (b) excluding Hubei data. While Hubei's demand surge was comparable to other provinces' (Table 4), C19 cases were orders of magnitude larger (Figure 1). This suggests that Hubei's data-generating process may have fundamentally differed from that of other provinces. Accordingly, Panel (b) estimates (which continue to reflect crowd-out) are much more precise. Results again support crowd-out in Panel (c), where capacity is measured by the sum of (per-capita) physicians and nurses. Since a second wave is unlikely to reflect Hubei's first wave scenario, Panel (b) estimates are preferred. Hubei data are excluded from the remainder of our analysis.

As noted earlier, implied crowd-out effects can be assessed by computing the Rx demand

[9]Given that parameter estimates contain information on data levels, we present standardized as means to safeguard data privacy.

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lift operating exclusively through the DDD estimate. Results will allow us to characterize temporal changes in crowd-out rather than its absolute levels. To characterize absolute levels we require an estimate that allows us to translate the scale of Rx demand changes into the scale of implied healthcare utilization changes. Given that capacity measures are time-invariant in our data, an estimate that accurately reflects this relationship during the pandemic is not available. We thus turn to a second-best alternative, namely, the cross-sectional estimate of subsection 3.2, which associated a 10% larger Rx transaction volume to 8.5% fewer practicing physicians. Due to the estimates' limitations we promote a careful interpretation of absolute crowd-out estimates (temporal changes are not subject to this limitation).

The resulting series are presented in Figure 5. Solid lines represent individual provinces (darker tonalities for higher-capacity provinces). Beyond capacity differences, the wide variation across provinces is explained by C19 exposure levels. The dashed line represents a national population-weighted average. This average indicates that the peak-week Rx demand surge attributable to crowd-out channel was equivalent to an about 10% capacity reduction. Considering that there were about 2.5 active cases per thousand physicians at peak (nationwide excluding Hubei), these results would suggest that an additional active case per thousand physicians yielded an about 4% capacity reduction. This statistic suggests that, outside Hubei, the bulk of C19-related care demands may have not come from infected patients, but rather, from C19-related care outside the frontline.

4.2 Robustness checks

We perform the following robustness checks on the definition of EXPOSURE: (i) replacing it for its first lag, (ii) measuring cases at each week's first day, and (iii) relying on total confirmed (rather than active) cases. DDD estimates (in Table 7) are always positive and statistically significant in their majority, thus continue to support the crowd-out hypothesis.

Evidence from unreported analyses suggests that prices may increased with C19's spread. The effect appears small, however: for every 10% increase in the total C19 case count, average prices increase by about 0.01% (possibly through shallower discounting). Assuming that offline prices remained constant (likely given widespread price controls), this result would suggest that our DDD estimates include a moderate attenuation bias.

An additional concern is if provinces with fewer physicians tend to also have healthcare facilities of lower square footage. In this case, to respect social distancing, lower-capacity provinces may have tried harder to contain the number of patients accessing healthcare

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premises. If so, the DDD estimate could be upward-biased. Although the China Healthcare Statistics Yearbook does not contain floorspace information, it reports the total number of beds available from medical institutions. After a per-capita normalization, we use this variable as a proxy for healthcare-facility floorspace. The stated concern would be supported by a positive slope linking the floorspace proxy to per-capita physicians. While we estimate a positive slope, the effect is minimal (0.08 correlation) and quite imprecise ($p = 0.68$).

We also note on reports indicating that physicians "were sent" from across provinces to Hubei (Bloomberg, 2020). This information suggests that the *effective* healthcare capacities may have dwindled in provinces other than Hubei. Since the reported number of re-allocated physicians was small percentage-wise (23 thousand out of 3.6 million nationwide, or 0.6%), we do not regard this as a major concern.

Additional concerns stem from possible short-term endogenous capacity adjustments. For example, capacity may have been endogenously adjusted because some providers became C19-infected and therefore withdrawn from service. Working in opposite direction, patient/physician ratios may have increased. Although these effects should be captured by the two-way interaction of EXPOSURE and CAPACITY, there may be a bias-inducing remainder built into the error. The sign of the associated DDD bias will depend on which of the two effects dominates and cannot be directly assessed. Our analysis of the following subsection suggests that, even if these effects introduce some bias, DDD estimates still exhibit a measure of external validity by virtue of their variation across product classes.

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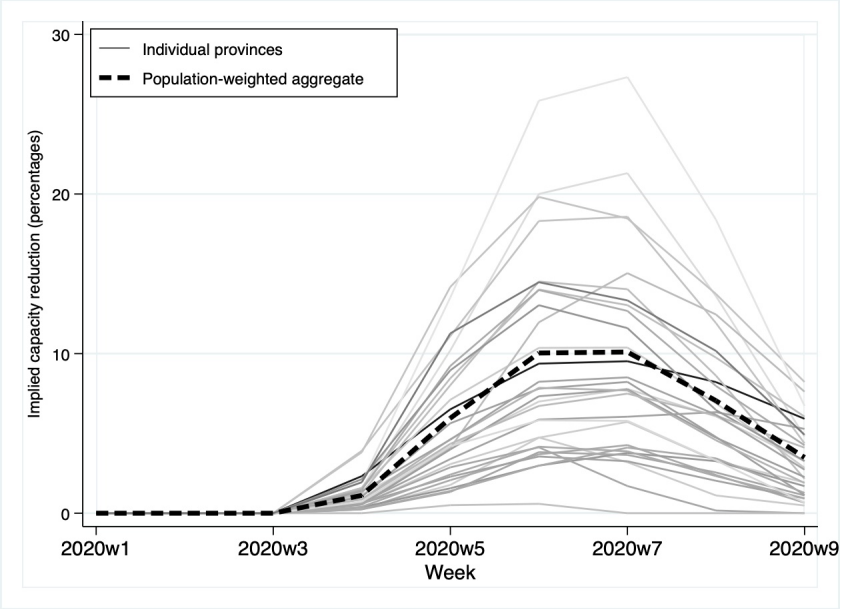
Figure 5: Implied crowd-out effects.



Based on the results of Column 1, Table 6 (excludes Hubei data). Tonality reflects CAPACITY values (darker tones for higher CAPACITY).

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Table 6: 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)

Presented estimates have been standardized. Negative binomial regressions include week, province and product class fixed effects. Log linear regressions include product and week/province fixed effects. Standard errors are clustered at the product level and p-values are presented in parentheses. Legend: $^{*}p < .1$,$^{**}p < .05$,$^{***}p < .01$.

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Table 7: Robustness checks.

	(1)	(2)	(3)	(4)	(5)	(6)
	Negative binomial			Log linear		
	Transactions	Units	Doses	Transactions	Units	Doses
(a) EXPOSURE replaced for its first lag.						
EXPOSURE × Rx / CAPACITY	0.094**	0.029**	0.006**	0.016***	0.017***	0.015***
	(0.016)	(0.043)	(0.033)	(0.001)	(0.002)	(0.008)
(b) EXPOSURE measured on each week's first day.						
EXPOSURE × Rx / CAPACITY	0.085**	0.019	0.005	0.015***	0.017***	0.013**
	(.013)	(0.152)	(0.109)	(0.001)	(0.001)	(0.013)
(c) EXPOSURE constructed from the number of total recorded cases.						
EXPOSURE × Rx / CAPACITY	0.112***	0.038**	0.007**	0.019***	0.019***	0.019***
	(0.009)	(0.014)	(0.046)	(0.001)	(0.001)	(0.002)

All estimates are (i) obtained without using Hubei data (N=1,993,410), (ii) employ the baseline CAPACITY measured, and (iii) are standardized. Negative binomial regressions include week, province and product class fixed effects. Log linear regressions include product and week/province fixed effects. Standard errors are clustered at the product level and p-values are presented in parentheses. Legend: $^{*}p < .1$,$^{**}p < .05$,$^{***}p < .01$.

4.3 Heterogeneity of DDD estimates across product classes

Here we examine how DDD estimates vary across product classes. The purpose is twofold. First, since crowd-out refers to a C19-fueled reduction of non-C19 care, DDD effects should primarily arise for products which do not target C19 symptoms. Second crowd-out would imply that some types of care are de-prioritized in practice. Estimated crowd-out effects should therefore be larger for products targeting conditions which, according to medical guidelines, would be deemed as less deserving of (scarce) medical care during the pandemic.

The fair and compassionate allocation of scarce medical resources in the C19 pandemic has been intensively debated (e.g., Emanuel et al., 2020; Truog et al., 2020; Pathak et al., 2020). Overwhelmingly, the focus of this debate has been on how to allocate resources needed to care for C19-infected patients and who are in critical condition (e.g., allocation of ventilators). Although with dissent, proposed mechanisms align along the principles of saving the most lives or life-years. For our analysis, we must consider how these criteria would be applied for determining the prioritization of non-critical care. We would expect C19-related care to be favored given that it represents a more imminent threat to lives lost. Recipients of this type of care would include potentially infected patients as well as patients whose chronic conditions outline more severe profiles of C19 complications (e.g., diabetes). In turn, patients with chronic conditions which do not interact with the virus (e.g., skin-related conditions) may be associated to lower mortality risks, hence be de-prioritized.

For our analysis we employ a modified version of Equation 1, which allows us to estimate class-specific DDD effects with a smaller sacrifice of statistical power compared to estimating class-specific regressions. Specifically, we define an indicator CLASS_j^c (activated if product j belongs to class c) and estimate the following negative binomial equation:

$$\begin{aligned} y_{jpt} \quad = f\Big(\quad & \Delta^c \cdot X_{jpt} + \theta^c \cdot \text{EXPOSURE}_{pt} \times \text{RX}_j \times \tfrac{1}{\text{CAPACITY}_p} \times (1 - \text{CLASS}_j^c) + \\ & \beta_8^c \cdot \text{EXPOSURE}_{pt} \times \text{RX}_j \times \tfrac{1}{\text{CAPACITY}_p} \times \text{CLASS}_j^c \quad \Big). \end{aligned} \tag{3}$$

X is a vector containing all the independent variables of Equation 1 (including fixed effects), except for the triple interaction. Class-specific DDD coefficients β_8^c are obtained separately estimating Equation 3 for each product class. Figure 6 presents the results in the form of implied capacity reductions (population-weighted national averages). Solid lines are used for product classes for which the DDD estimate was significant with 95% confidence; dashed lines, when significance at 90% confidence was not met (no intermediate cases). Estimates are presented only for classes with enough Rx/OTC variation.

Recall that larger implied capacity reductions (vertical axis) would indicate stronger de-

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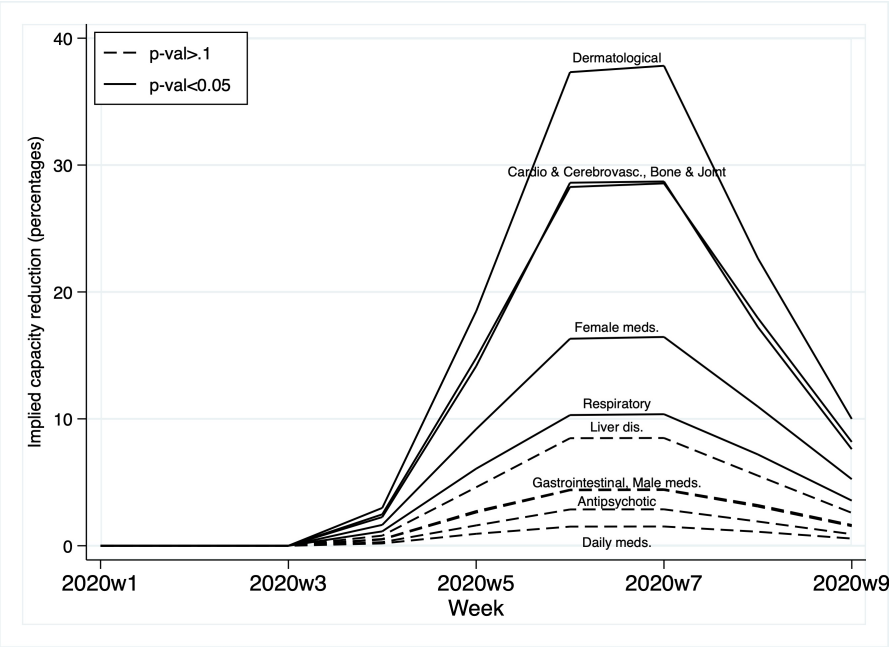
Figure 6: Class-specific implied crowd-out effects.



Series correspond to population-weighted national aggregates.

prioritization. The largest estimated effects are found for dermatological, bone & joint, and cardio & cerebrovascular. Dermatological and bone & joint care is generally oriented at the management of chronic conditions which do not pose significant mortality risks. The large effect for cardiovascular drugs is counterintuitive given that cardiovascular conditions cause many deaths. One factor that may explain our result is that a significant amount of cardiovascular care regards routine follow-up checkups, which may be expendable in the short term. Importantly, none of these classes includes products targeting C19-related symptoms. That is, DDD estimates are consistent with a C19-fueled reduction of non-C19 care.

In turn, the smallest effects are observed for the antipsychotic and daily medication classes. About 65% of Rx transactions in the antipsychotic class are for drugs targeting anxiety & depression, headache and insomnia, and epilepsy. For individuals suffering these conditions, the events triggered by the outbreak may have increased the risk of acute episodes. In turn, antibiotics command about 60% of Rx transactions in the daily medications class. That is, Rx demand in this class is driven by individuals deemed at risk of infectious disease, which makes them unlikely candidates for down-prioritization given the above criteria. These results are consistent with medically-guided prioritization of medical care during the pandemic.

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5 α-reserve capacity reallocation

Results above highlight that physician scarcity (relative to C19 cases) may be costly by reducing non-C19 healthcare provision. Here we propose a capacity reallocation policy to better meet C19-fueled healthcare demands. While we model the geographical allocation of medical care supply, we simplify the language by interchangeably referring to this object as *physician* or *capacity reallocation*. It is also important to note that, rather than a system of traveling physicians (costly and difficult at large scale), we envision the policy's deployment through tele-health. This approach is well-suited for countries where tele-health has gained attention and seen ramped-up investments in response to C19, such as in China (Campbell, 2020). Our results cap required tele-health investments: no more than 15% of medical consultations would need to be provided via tele-health for optimal crowd-out reduction.

To motivate the policy we return to Figure 3, which showed ample cross-province variation in cases-per-physician during 2020w6. Given that capacity has marginally decreasing crowd-out-reducing returns, this variation suggests that overall crowd-out could be lowered. Specifically, by transferring capacity from provinces in which the cases-per-physician ratio is small into others where the ratio is large. Scale differences may also drive reallocation gains: moving physicians away from large province A into small province B will disproportionally improve the situation on the latter.

The natural starting point to determine reallocations is by minimizing the aggregate loss function $\sum_p \text{POPULATION}_p \cdot \text{EXPOSURE}_{pt}/\text{CAPACITY}_{pt}$. Solid markers in Figure 3 illustrate the result: cases-per-physician with the new allocation are about constant—marginal returns are equalized. Nationwide crowd-out in 2020w6 would have been reduced by 15% with this allocation. However, this policy has the problem that it may prescribe unreasonably large capacity contractions. For example, since Tibet had few active cases during 2020w6, the policy allocated a number of physicians that would have left this region with about 0.5 physicians per thousand residents (see Figure 3). This would be a 75% capacity reduction. While this problem could be lessened by incorporating a capacity-displacement shadow cost, the solution would be imperfect: (i) sharp contractions would not be fully prevented, and (ii) credible shadow cost estimation may be difficult.

We therefore propose an *α-reserve* policy whereby each province reserves a fraction $\alpha \in [0,1]$ of its physicians to continue to care for local patients while contributing the complement (1-α) to a national pool. Physicians in the national pool are then allocated to provinces, with the objective of minimizing aggregate crowd-out. Since nationwide capacity is always fully deployed, *effective capacity* (i.e., after reallocation) would increase for some

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provinces and decrease for others (depending on cases-per-physician), but never drop below α the original value. Thus, low effective capacities are avoided through the choice of the reserve parameter α. Results indicate that most gains can be materialized with relatively large reserve levels.

Figure 7.a summarizes the policy's performance, had it been used during the first wave. (Hubei data excluded from all analyses herein.) Aggregate crowd-out levels are presented for α=1 (no reallocation), 0.9, 0 (no reserves). Gains are illustrated by the gap between the former and latter two series—there is less crowd-out when pool contributions are larger. The similarity between the two α<1 series expresses that much of potential gains are materialized with small pool contributions (i.e., large reserves). This point is further illustrated by the solid line of Panel (b), which shows percentage crowd-out reductions (averaged 2020w4-2020w9) across the α domain. Pool contribution of 25% (α=0.75) reduce aggregate crowd-out by about 11%. Larger contributions levels make little difference.

Given increased awareness and mitigation protocols, less geographical variation in C19 rates may be expected in a second wave. The dashed line of Figure 7.b illustrates gains in the extreme "uniform wave" scenario: cases-per-capita are the same across provinces while maintaining the national weekly case counts of the first wave. Given the large reduction of cross-province variation in cases-per-physician, potential gains shrink at all contribution levels. A second wave may also be milder. We thus consider a "uniform half-wave" and display associated results with the dotted line. In this scenario, cases-per-capita remain constant across provinces but the national case count is cut in half. Pool contributions reduce crowd-out in about the same way as in the uniform wave. This similarity suggests that the policy's benefits will primarily depend on the second wave's cases-per-physician disparities rather than on its overall case count.

The amount of implied reallocation may be an important statistic to evaluate the financial and logistical challenges of the policy's implementation. We measure reallocation through the share of physicians providing care for patients from a different province. Figure 8.a shows weekly reallocation series.[10] Even when all physicians are contributed to the pool (α=0), the reallocation share is relatively minor (about 15%). In addition, because reallocation is primarily fueled by cross-province variation in cases-per-physician, the amount of reallocation is largely independent of the total case count. Figure 8.b shows reallocation figures predicted throughout the α domain. Reallocation volumes would increase rapidly at small contribution levels but soon stabilize. The irrelevance of total case counts is again manifest by the almost

[10]Note that for α=1 there is no reallocation. Also note that reallocation shares are smaller than corresponding 1-α values because some pool physicians care for same-province patients.

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identical series of uniform waves.

6 Conclusions

While researchers across different fields have produced a large amount of studies on the impacts of the COVID-19 pandemic, to the best of our knowledge, we are the first to address the issue of healthcare crowd-out in such a public health crisis. Given the importance of healthcare resource allocation, understanding and addressing this effect and providing sensible policy remedy becomes critically important. We see our analysis, which relies on online drug retailing data, as a timely first take on the issue. Crowd-out inference based on drug demand data is possible based on the changes in relative Rx/OTC demand activities since Rx purchases require interactions with the healthcare system while OTC ones do not. Our results suggest that crowd-out may have been significant (equivalent to 10% capacity reduction at peak), and that it could be contained through a policy of spot capacity reallocation. This policy could be deployed at large scale using tele-health infrastructure.

In attempting to transfer these insights to other settings, however, there are several questions to consider. One leading question concerns the measurement of healthcare capacity. Whereas in China nurses play a fundamentally supporting role in healthcare provision, in other countries (e.g., U.S.) they play a more significant role. Another question regards our findings on relative crowd-out effects across different therapeutic areas. The specific mechanics behind this heterogeneity hinge on the criteria used to prioritize care. To the extent that these are based on universal medical practice, our findings should transfer to other countries (at least partially). Our analysis would then suggest that, as the system normalizes, follow-up priorities may be given to patients who were neglected the most at the height of the crisis, e.g., those suffering of dermatological- or bone-related conditions.

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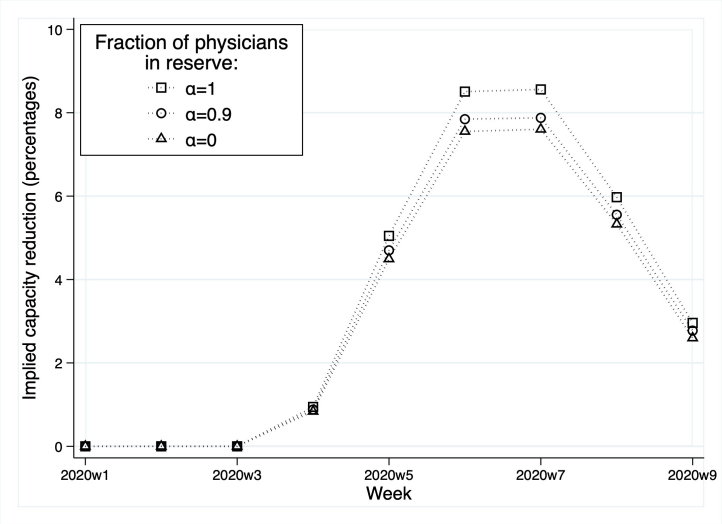
Figure 7: Crowd-out reductions from capacity rellocation.

(a) Implied crowd-out effects (population-weighted national aggregates).



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

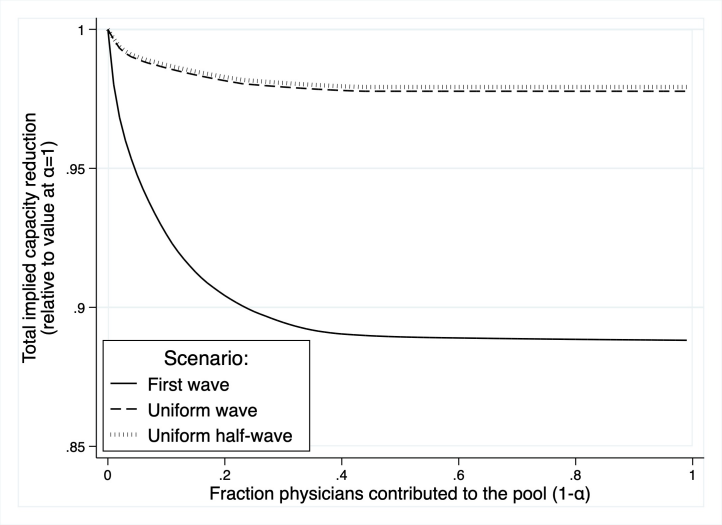


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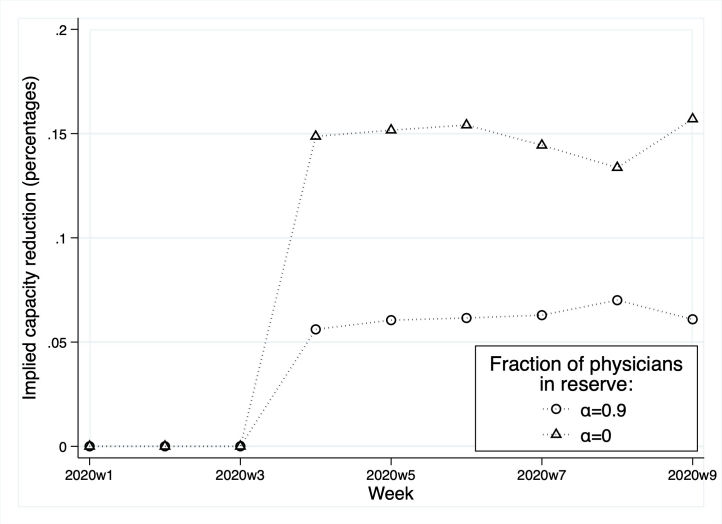
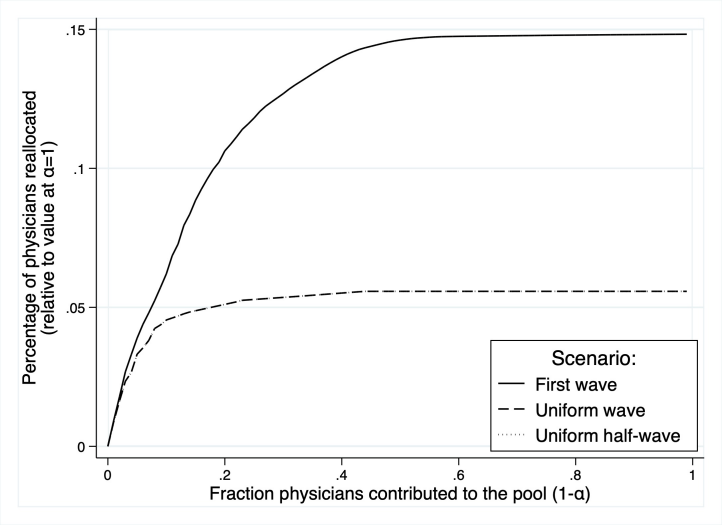
Figure 8: Amount of reallocation.

(a) Implied crowd-out effects (population-weighted national aggregates).



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



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