Neighborhood-Level Public Facilities and COVID-19 Transmission: A Nationwide Geospatial Study In China

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Abstract

Background: Individual-level studies on the coronavirus disease 2019 (COVID-19) have proliferated, however, research on neighborhood-level factors associated with COVID-19 is limited. Our study aim at examining the assocaiton between having COVID-19 cases in the neighborhood and public facilities.

Methods: We gathered the geographic data of all publically released COVID-19 cases in China and the point-of-interests data from *Gaode* map including restaurant, shopping center, hotels, living facilities, recreational facilities, public transit, reducation and health services. We used a case-control design (1:4 ratio; 4,329 cases vs. 17,316 controls) to investigate the association between having COVID-19 cases in the neighborhood and the number and types of public facilities nearby.

Results: In the multivariable logistics regression model, having more restaurants (high vs. low, OR: 2.09, 95% CI: 1.95, 2.25), shopping centers (OR: 2.27, 95% CI: 2.12, 2.43), hotels (OR: 2.32, 95% CI: 2.16, 2.48), living facilities (OR: 1.82, 95% CI: 1.70, 1.95), recreational facilities (OR: 2.27, 95% CI: 2.11, 2.43), public transit (OR: 1.32, 95% CI: 1.23, 1.41), educational institutions (OR: 1.96, 95% CI: 1.83, 2.10), and health service facilities (OR: 4.12, 95% CI: 3.83, 4.44) was associated with significantly higher odds of having COVID-19 cases in a neighborhood. The associations for restaurants, hotels, reactional and education facilities were more pronounced in cities with fewer than six million people than those in larger cities ($Ps_{\text{interaction}} < 0.05$).

Conclusions: Our results have implications for designing targeted prevention strategies at the neighborhood level to reduce the burden of COVID-19.

Introduction

Coronavirus disease (COVID-19) caused by the SARS-CoV-2 virus has claimed over ten million cases reported in 185 countries or regions by July 30, 2020 [1]. Through massive societal efforts including a city-wide lock-down in Wuhan and nation-wide social distancing, the outbreak in China from January to April, 2020 has been contained [2]. Studies on COVID-19 have proliferated since early 2020, with the majority focusing on individual-level risk factors for COVID-19 transmission and clinical management of COVID-19 patients. [3–6]. However, neighborhood-level factors have been relatively understudied, despite contributing to infectious risk and being potential targets for disease prevention and management. For instance, prior studies have demonstrated that neighborhood-level public facilities, such as surrounding gyms and restaurant, are associated with infectious disease transmission, particularly in diseases transmitted by contact, aerosols, or droplets [7–10]. However, little is known about the potential role of these types of public facilities in COVID-19 transmission.

Since the early stage of the COVID-19 pandemic, Chinese local governments and Centers for Disease Control and Prevention (CDC) regularly released online the names of neighborhoods with confirmed cases of COVID-19. This was done primarily to increase outbreak transparency and risk awareness for nearby residents, but it also provided a valuable data source for neighborhood-level geospatial studies.

One of the defining features of neighborhoods is the number of public facilities surrounding the living areas. These facilities include gyms, restaurants, and parks, where residents, particularly older adults, spend most of their time when not at home [11, 12], and are thus highly relevant for potential susceptibility to COVID-19 [13].

In the present study, we aimed to examine the associations of the numbers and types of neighborhood-level public facilities with COVID-19 risk. Such information can be important for urban planners, policymakers, and public health professionals to try and reduce neighborhood transmission of COVID-19. Details of the study methods are given in supplementary materials. A condensed version is provided here.

Methods

Geographical data

We collected addresses of the COVID-19 cases form two Application programming interfaces (API) from from January 18th to April 30th, 2020, and one of the Application Programming Interfaces (APIs) was based on the Tencent location-based service (https://ncov.html5.qq.com/api/getCommunity). The other was built by *vuejs* (JAVA SE 8, available in Github: https://github.com/hack-fang/ncov-map) from 510 Chinese Centers for Disease Control and Prevention (CDC) local website, local health commission website and WeChat public accounts. Only laboratory-confirmed cases of COVID-19 were reported in those websites or public accounts and data from the official reports of the health commission, CDC report or WeChat public accounts of 162 city-level administrative units was collected by the two APIs. We extracted the latitude and longitude coordinates, reported time and reported city of the COVID-19 cases from those two POIs using.

We collected the points-of-interest (POIs) dataset extracted from Autonavi (Gaode) by *Tencent*, a Chinese desktop web mapping service application that provides information on the names, locations, and types of various facilities [14]. Following previous studies and the classification of POI data itself [14], eight types of facilities were extracted from the POI dataset including restaurant (e.g. food restaurant, tea house and bakery), shopping center (e.g. supermarket, sports store, commercial street and clothing store), hotels, living facilities (e.g. travel agency, ticket office and job center), recreational facilities (e.g. sports stadium, theatre and cinema, park and square), public transit (railway station, coach station and subway station), education (e.g. museum, library and school) and health services (e.g. hospital, clinic and pharmacy) (Table S1). A total of 986,363 POIs were gathered in 162 cities. All the geocodes were coded using the geocoding GPS co-ordinates (Esri, ArcGIS 10.4)

Case-control design

We defined the case group as those communities with COVID-19 cases. We excluded Wuhan city due to its exceptionally high incidence of COVID-19 that made it difficult to find control neighborhoods and may bias the results. We also excluded neighborhoods with no or few nearby public facilities (total number

across eight types < 8) because the results on public facilities may not apply to these neighborhoods. A total of 4,329 communities in 26 provinces were defined as cases. A radius of 1500-meter (approximately 1 mile) from the reported geocodes and the resulting circular areawas used to capture information on nearby public facilities. Although there is no consensus on “proximity,” this cut-off point has been widely used in research [15-17]. To determine the control neighborhood, we collected the latitude and longitude coordinates of all the neighborhood (N=127,995) in those regions first. Then, we moved the coordinates of the case communities 4.5 km (for 1.5 km buffer) to its north, south, east and west respectively and calculated the coordinates of the new points. We applied K-nearest-neighbor algorithm (Python3, Scikit-learn 0.23.2) to find the communities with nearest distance to each control coordinates but higher than 4.5 km from the case neighborhood. Those neighborhoods were selected as the control communities (Figure S1). If there is another case neighborhood in 4.5 km from the control neighborhood, we selected another control neighborhood farther than 4.5 km from the two case communities. We counted the number of each type of facilities in the 1.5 km buffers around both the case and control communities. We use Python3 to calculate the numbers of each types of facilities. For sensitivity analysis, we counted the number of the eight types of facilities in 800 m (Figure S1: R=800 m) and 1.2 km (Figure S1: R=1.2 km) buffer using the same methods as the 1.5 km buffer.

Co-variates

Population sizes, gross domestic product (GDP), unemployment rate, Government Budget Balance (GBB) for each city in 2018 were obtained from the China City Statistical Yearbook (http://olap.epsnet.com.cn/). Resident mobility (outflow and influx population flow in each city) were tracked with mobile phone data, through location-based services (LBS) employed by popular Tencent applications such as WeChat and QQ. Movement outflows from Wuhan City to other cities (i.e. records of the number of people leaving each day) by air, train and road, were obtained from the migration flows database (https://heat.qq.com/) (*19*). We use the average outflow and influx population flow (resident mobility) in each city from 18th January 2017 to 30th April as co-variates.

Statistical analysis

The eight types of facilities were compared according to the case-control neighborhood. Means and standard deviations (SD) were calculated for each types of facilities. Paired T-test and Mann-Whitney U test were applied to examine the difference in each types of facilities.

We fit mutivariable logistic regression models adjusted for city-level covariates including population size, Gross Domestic Product (GDP), unemployment rate, Government Budget Balance, and resident mobility recorded by Tencet applications (WeChat and QQ). Due to the high correlations between the eight types of facilities with Pearson’s correlation coefficients ranging from 0.62 to 0.92 (Table S2), we ran separate multivariable models for each of the eight types. As we had eight variables of interest, we applied the

Bonferroni method to control for multiple comparisons and used the p-value of <0.006 to indicate statistical significance [18]. We also used multivariable logistic regression with penalized splines to evaluate the potentially non-linear associations of public facilities with having COVID-19 cases in the neighborhoods [19].

In subgroup analyses and interaction analyses, we dichotomized the public facilities by the median cutoffs and examined whether the associations between public facilities and having COVID-19 cases in the neighborhood differed by city population (<6 million versus ≥6 million, approximately the median value for city population size in our sample). We also conducted the sensitivity analyses using the 800 m and 1.2 km buffer in the case-control design to exam the robustness of our results.

Results

Neighborhood Characters

Our sample included 4,329 case and 17,316 control neighborhoods. The case neighborhoods had 7,631 COVID-19 cases accounting for 23.0% of the total number of cases outside of Wuhan City. The time (Figure S2) and geographical distributions (Fig. 1) of the analyzed cases were consistent with the trends of the COVID-19 pandemic in China. Over 50% of publicly released COVID-19 cases were reported from Feb 1st 2020 to Feb 10th 2020 during the peak period of the outbreak. The provinces near the epicenter of Hubei Province had larger numbers of cases and higher proportions of cities reporting COVID-19 cases (Fig. 1) than other provinces.

Associations of Eight Types of Public Facilities with Having COVID-19 Cases in Neighborhood

Case neighborhoods had greater quantity of each of the eight types of public facilities compared to control neighborhoods (Table 1). However, the specific relationship between public facilities and reported cases of COVID-19 differed by facility type (Fig. 2). The relationship between six types of public facilities — shopping, restaurant, education, health service, hotel, and living facilities —and having COVID-19 cases in the community was nearly linear when the number of facilities was smaller than 10 and flattened thereafter (Fig. 2, A,B, E-H). The association between recreational facilities and having COVID-19 cases in the community was nearly linear (Fig. 1, C).The association of public transit with having COVID-19 cases in the community was J-shaped (Fig. 2D).

Table 1
Mean and median of the eight types of facilities

Facilities	Control Neighborhoods	COVID-19 Neighborhoods	*P*-value [b]
N[a]	17,316	4,329	
Restaurant			
Mean (SD)	14.9 (42.2)	17.6 (27.5)	< 0.001
Median (IQR)	2.0 (0.0, 10.0)	5.0 (1.0, 20.0)	< 0.001
Shopping			
Mean (SD)	14.9 (42.9)	17.4 (24.7)	< 0.001
Median (IQR)	3.0 (0.0, 10.0)	7.0 (2.0, 21.0)	< 0.001
Hotel			
Mean (SD)	13.1 (26.9)	19.4 (25.5)	< 0.001
Median (IQR)	4.0 (1.0, 13.0)	10.0 (3.0, 26.0)	< 0.001
Living			
Mean (SD)	14.7 (35.6)	19.1 (28.0)	< 0.001
Median (IQR)	3.0 (0.0, 12.0)	6.0 (2.0, 25.0)	< 0.001
Recreation			
Mean (SD)	16.6 (29.6)	23.9 (28.6)	< 0.001
Median (IQR)	7.0 (2.0, 17.0)	13.0 (5.0, 31.0)	< 0.001
Public transit			
Mean (SD)	2.0 (0.8)	2.1 (0.8)	< 0.001
Median (IQR)	2.0 (1.0, 3.0)	2.0 (1.0, 3.0)	< 0.001
Education			
Mean (SD)	12.5 (26.5)	15.7 (21.4)	< 0.001
Median (IQR)	4.0 (1.0, 11.0)	7.0 (3.0, 20.0)	< 0.001
Health service			
Mean (SD)	7.0 (17.2)	19.3 (27.2)	< 0.001
Median (IQR)	1.0 (0.0, 6.0)	7.0 (2.0, 25.0)	< 0.001
All facilities [C]			

Facilities	Control Neighborhoods	COVID-19 Neighborhoods	*P*-value [b]
Mean (SD)	104.9 (220.1)	146.8 (169.7)	< 0.001
Median (IQR)	34.0 (14.0, 92.0)	68.0 (27.0, 206.0)	< 0.001

[a] Numbers shown are mean (standard deviation-SD) and median (inter-quartile range – IQR).

[b] P-value was calculated by paired t-test (for mean) and Mann–Whitney U test (for median).

[c] Sum of all eight types of facilities.

For each types of facilities, the number equal to ten (demonstrated by the vertical dashed lines) was used as reference (odds ratio of 1 demonstrated by horizontal dashed lines).

In logistic regression models adjusting for city-level variables, having a larger number of facilities was associated with higher odds of community with COVID-19 cases (ORs ranged from 1.32 for public transit to 4.12 for health service; Fig. 3).

Subgroup and Sensitivity Analyses

We explored whether the association between each type of public facillity and having COVID-19 cases in the neighborhood differed by city's population size. We used a cut-off point of 6 million (representing approximately the median value in our sample) to classify larger versus smaller cities. The associations for restaurants, hotels, and recreational and education facilities were more pronounced in smaller cities than larger ones (*P-values* for interaction < 0.006, Fig. 3).

All sensitivity analyses, using the 800-meter and 1200-meter instead of 1500-meter radius (Table S3), and excluding neighborhoods with total number of facilities smaller than one, three or five (Table S4) showed that the associations between public facilities and having COVID-19 cases in the neighborhoods were consistent with results from the main analyses.

Discussion

Our study is novel and has several strengths. First, unlike previous studies only analyzing provincial or city-level data, our study utilized the addresses of reported COVID-19 cases linked with POI data to investigate the associations between neighborhood-level factors and COVID-19. Second, for neighborhoods that reported case locations, all confirmed cases were reported. Extensive testing and reporting of COVID-19 cases in China contributed to the reliability of our results. Third, control neighborhoods were systematically chosen to be compatible with case neighborhoods and our analyses also adjusted for city-level characteristics. More in-depth modelling with stratitication by city population size uncovered significant effect modification that may shed light on future disease containment strategies.

Our primary finding was that having COVID-19 cases in the neighborhood was associated with having larger numbers of neighborhood-level public facilities, particularly in cities with fewer than six million population. One plausible explanation is that residents living in neighborhoods with more surrounding facilities might be attracted to go out and use these facilities more, leading to greater exposure to the SARS-CoV-2 virus that increases the risk of infection. Also, in some facilities such as restaurants, hotels, recreation, education and health service, people are more likely to take off their masks to communicate or dine. In subgroup analyses, we found that the associations of COVID-19 transmission with restaurants, hotels, recreation and education facilities were more prounouced in cities with population sizes smaller than six million compared to larger cities. In the early stage of the outbreak in China, before social-distancing and lock-down measures were not strictly implemented, the geographical scopes of the activities of asymptomatic individuals in larger cities were likely to be wider and more disperse than smaller cities; thus infection may occur far from its residential neighborhood, which was beyond the scope of our study. The tracking of cases in Beijing, China in June 2020 partially confirmed this hypothesis.

While findings from our study may seem intuitive, they have not been previously demonstrated. Empirical data-driven evidence from our study helps to address the controversies around different disease containment measures. To be more specific, in the neighborhood with more public facilities, more extensive preventative measures such as educational or behavioral enhancements for mask-wearing and social distancing are needed. Additionally, innovative facility-level measures besides complete shutdowns may be useful. For example, partially shut down or restricted hours, staggered appointments/reservations, different hours for different subpopulations of the neighborhoods, specific reminders for social distancing inside the facilities may be useful for prevention during the pandamic. With these targeted interventions, policy makers and social forces can optimize resource allocations in settings with limited medical and personnel resources.

Our study is relevant for COVID-19 control in the long term because it sheds lights on neighborhood-level factors associated with transmission. Up to now, there is still no effective vaccine or drug treatments for COVID-19, and the primary intervention is non-pharmaceutical and mostly preventive through public health approaches. A recent modelling studies indicated that without the non-pharmaceutical interventions in China, COVID-19 cases in China would likely have shown a 67-fold increase by February 29, 2020 [20]. Given the current trends in the COVID-19 pandemic, active surveillance and social distancing may be needed for longer periods than previously anticipated, which might pose substantial social and economic burdens. Hence, neighborhood-based facility-targeted prevention at relevantly lower costs to hinder COVID-19 transmission is desired.

Different countries and even different regions within one country have adopted various disease control strategies with vastly different results and socio-economic consequences. Our study findings have implications for other low-and middle-income countries such as India and Brazil with similar population density and city infrastructures but limited human and economic resources to fight the surging epidemic.

If validated in other countries and by further research, targeted prevention strategies by city size is warranted and may lead to better disease control through facility-based containment approaches.

Our study has limitations. First, we did not have location data for all cases in China as not all cities chose to publicly disclose case locations. Nevertheless, we collected data on *all* publicly reported cases for four months covering the major epidemic period in China. Second, the POI data may not be exhaustive either and may miss information on some facilities. However, we used the most comprehensive data source available to date and results from multiple sensitivity analyses were consistent. Lastly, we did not have detailed information on routes of COVID-19 transmission. Our cross-sectional study can not make causal inferences regarding the relationship between neighborhood features and disease transmission. More studies are needed, especially epidemiological case tracking data with extensively recorded geo-information and longitudinal research.

Conclusion

In summary, having COVID-19 cases in residential neighborhoods was associated with the numbers and many types of surrounding public facilities. The associations of COVID-19 transmission with restraurants, hotels, recreation and education facilities were more pronounced in Chinese cities with a population size fewer than six million. COVID-19 has caused millions of cases and claimed hundreds of thousands of lives, and it is very likely that our battle against it will not be over soon. Large-scale disease control strategies such as social distancing and lock-downs have been shown to be effective, but achieved at enormous social and economic costs. Targeted interventions taking into account neighborhood characteristics which can decrease the costs and improve the efficiencies of disease containment measures are warranted. We expect our findings to shed light on improving the COVID-19 prevention strategies at the neighborhood level for China and potentially other countries.

Declarations

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Author contributions

X.J., L.L.Y., and C.W. designed the study. X.J. and Y.L. collected and processed the API and POI data. X.J. and Y.L. conducted the analyses. X.J. and Y.L. wrote the manuscript. E.G., S.X., Y.Y., K.C., R.V., L.L.Y. and C.W. assisted with interpretation of the results and edited the manuscript. All authors critically reviewed and approved the manuscript.

Competing interests

All authors declare no competing interests.

Availability of data and materials

The datasets analyzed in this study are available from the corresponding author Lijing L. Yan (lijing.yan@dukekunshan.edu.cn) on reasonable request

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Figures

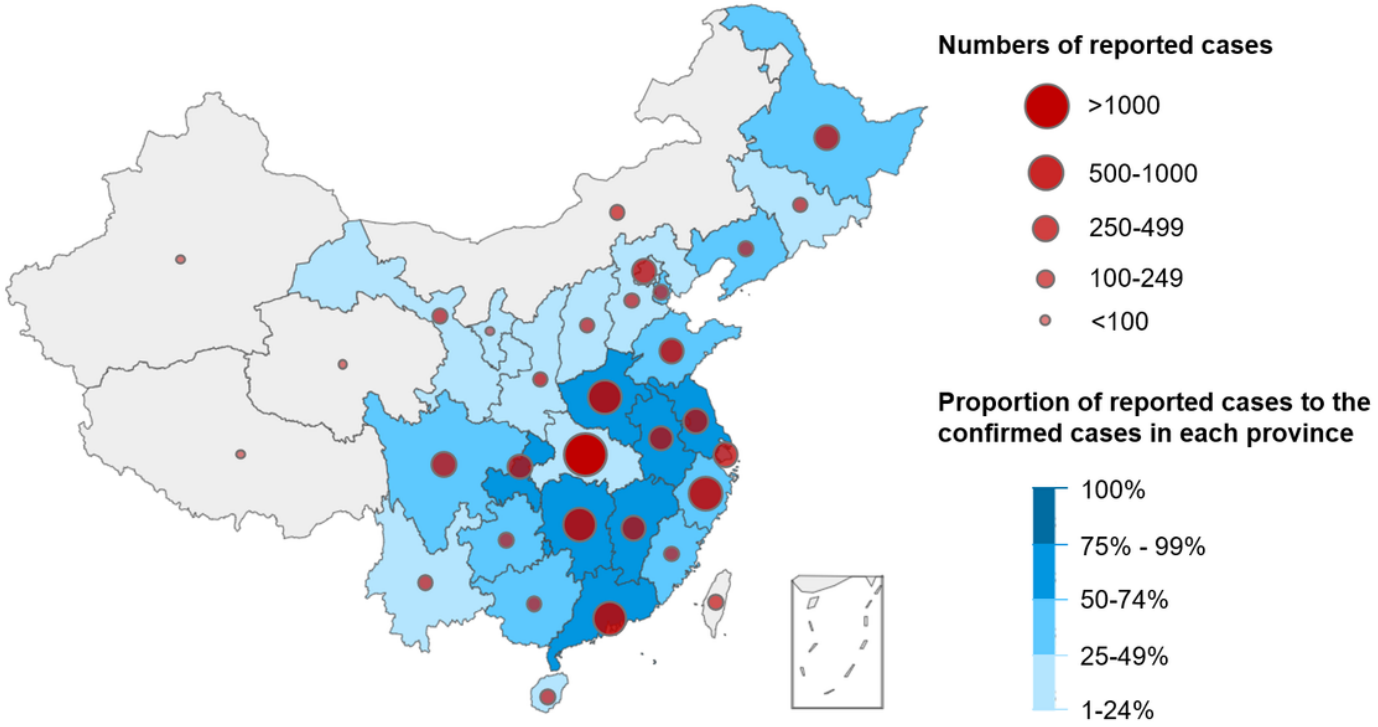

Figure 1

Geographic Distribution of Reported and Confirmed COVID-19 Cases in China Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

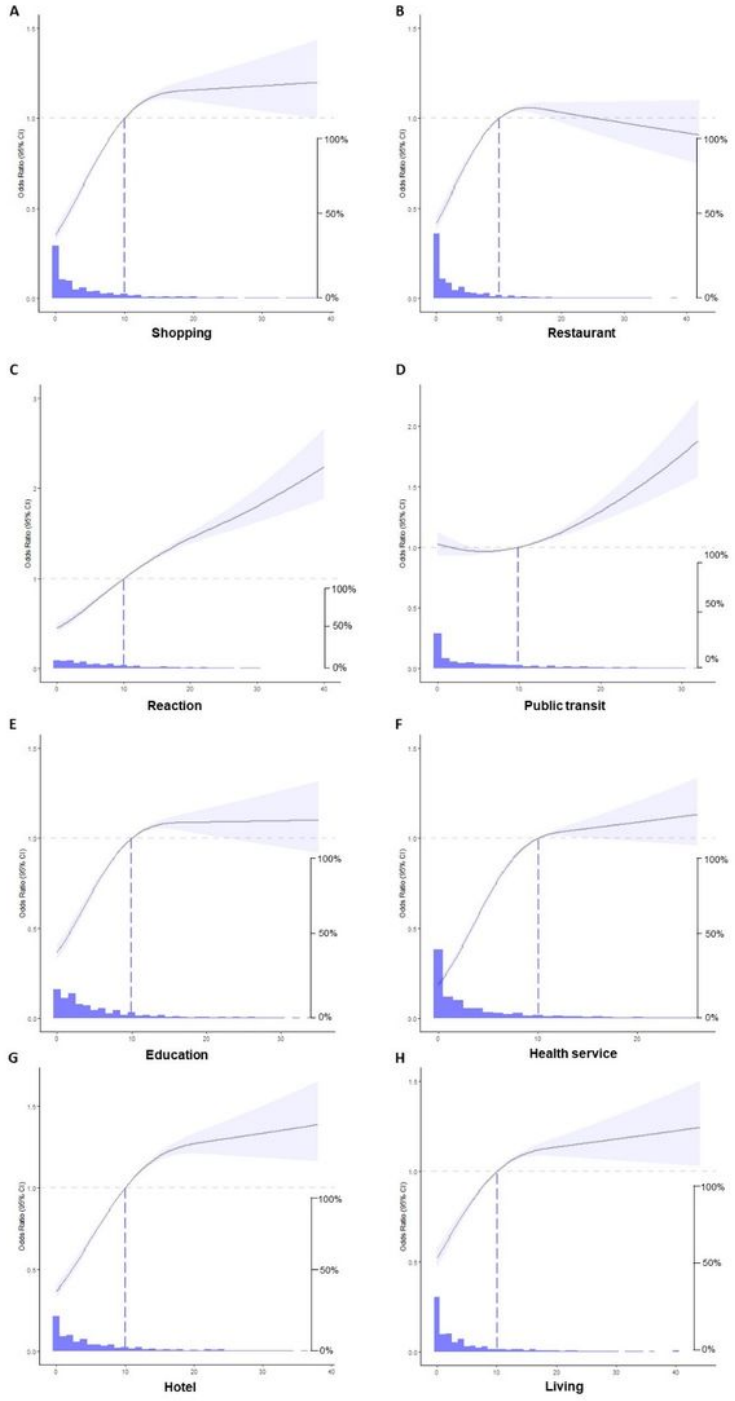

Figure 2

Distribution a and Association b of eight types of public facilities with having COVID cases in the communities a Histogram with y-axis on the right-hand side. b Model adjusted for city-level variables including population size, Gross Domestic Product, unemployment rate, Government Budget Balance, and resident mobility. Odds ratios from logistic regressions are shown on the left-hand side. For each types of

facilities, the number equal to ten (demonstrated by the vertical dashed lines) was used as reference (odds ratio of 1 demonstrated by horizontal dashed lines).

	Total	≥6 million N=11,030	<6 million N= 10,615		*P* for interaction
	Odds ratio [b] (95% Confidence Interval)	Odds ratio [b] (95% Confidence Interval)	Odds ratio (95% Confidence Interval)	≥6 million <6 million	
Restaurant [a]	2.09 (1.95, 2.25)	2.00 (1.91, 2.29)	2.45 (2.14, 2.81)		0.023
Shopping	2.27 (2.12, 2.43)	2.28 (2.10, 2.51)	2.27 (2.07, 2.52)		0.82
Hotel	2.32 (2.16, 2.48)	2.04 (1.87, 2.23)	2.69 (2.44, 2.98)		<0.001
Living	1.82 (1.70, 1.95)	1.81 (1.65, 1.98)	1.87 (1.69, 2.06)		0.78
Recreation	2.27 (2.11, 2.43)	2.08 (1.90, 2.28)	2.50 (2.26, 2.75)		0.005
Public transit	1.32 (1.23, 1.41)	1.30 (1.19, 1.43)	1.38 (1.25, 1.53)		0.49
Education	1.96 (1.83, 2.10)	1.79 (1.64, 1.96)	2.22 (2.01, 2.45)		0.001
Health service	4.12 (3.83, 4.44)	4.22 (3.84, 4.64)	4.11 (3.70, 4.57)		0.59

Figure 3

Sub-Group Analysis by City Population above and below 6 million: Odds Ratio and 95% CI of Having COVID-19 Cases in the Community with Eight Types of Surrounding Facilities * The reference group was the “lower than the median” for each public facility. ** Model adjusted for population size, Gross Domestic Product (GDP), unemployment rate, Government Budget Balance, and resident mobility.

Supplementary Files

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- 03Supplementary.docx