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Association of time to diagnosis with socioeconomic position and geographical accessibility to healthcare among symptomatic COVID-19 patients: A retrospective study in Hong Kong

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ABSTRACT

Early diagnosis is important to control COVID-19 outbreaks. This study aimed to assess how individual and area socioeconomic position and geographical accessibility to healthcare services were associated with the time to diagnosis among symptomatic COVID-19 patients in Hong Kong. Multivariable generalized linear regression was used to estimate the associations while adjusting for sociodemographic characteristics and case classification. This study found living in public rental housing and living in an area with low education were associated with longer time to diagnosis in the first wave of infections. Specifically, the risk of delayed diagnosis for public rental housing residents was mitigated by the higher density of public clinics/hospitals but was slightly increased by the higher density of private medical practitioners nearby. No such relations were found in the second wave of infections when the surveillance measures were enhanced. Given the grave impact of pandemics around the world, our findings call on taking inequalities into account when public health policies are being devised.

1. Introduction

An atypical form of pneumonia, coronavirus disease 2019 (COVID-19), caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is spreading throughout the world at an alarming rate. Up to 16 October, 2020, there have been 39,023,292 confirmed cases of COVID-19 and 1,099,586 deaths worldwide (World Health Organization, 2020). Characterized by high transmissibility (Zhao et al., 2020), long incubation period (Backer et al., 2020), and high mortality rate (Huang et al., 2020), COVID-19 affected people in unprecedented ways.

In the absence of an efficacious vaccine and pharmaceutical measures, early diagnosis of COVID-19 cases is critical to prevent infections and save lives (Bedford et al., 2020). Rapid diagnosis, followed by immediate isolation of cases and rigorous contact tracing, may help break the transmission chains (Rong et al., 2020). It also provides a clear picture of the epidemiology situation to guide hospital resources preparation, including the requirements of ICU beds and ventilators (Marcel et al., 2020).

As many concerns over the impact of COVID-19 on equality (Bambra et al., 2020; Chung et al., 2020b; Wright et al., 2020), it is worried that the low socioeconomic position (SEP) groups might be at a disadvantage in getting timely testing and diagnosis (Berger et al., 2020). While there have been tons of research examining how socioeconomic position (either at individual or area level) determines the diagnostic delay of both infectious and non-infectious diseases (Storla et al., 2008; Mukolo et al., 2013), related research of emerging infectious disease like

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COVID-19 is strikingly scant. Nevertheless, some signs of the issue were observed in recent studies. A study on COVID-19 in New York, USA, revealed that people residing in poor neighbourhoods were less likely to be tested (Borjas, 2020). The cluster outbreak in some low SEP groups, such as the explosion of cases in Singapore's low-skilled migrant workers (Kim et al., 2020), also indicates insufficient testing and surveillance among them.

Furthermore, often overlapping with SEP, geographical accessibility to healthcare is also widely identified as a determinant of diagnostic delay (Wang, 2012), suggesting regions with fewer healthcare services deterring timely diagnosis. Nevertheless, some studies have also suggested that geographical accessibility to healthcare had no significant impact on the time to diagnosis of non-infectious diseases (Henry et al., 2013; Roll, 2012). However, research on the impact of geographical accessibility to healthcare services on time to diagnosis of emerging infectious disease during a pandemic is quite limited. Only one research in Canada found different hospitalization rates between people living in urban and rural area during the 2009 influenza A (H1N1) pandemic, which was explained by the difference in availability of healthcare and laboratory testing services (Morrison et al., 2014).

Given the high level of income inequality and the long battle against COVID-19, Hong Kong serves as an ideal setting to study the association of time to diagnosis of COVID-19 with SEP and geographical accessibility to care. Due to its proximity to Wuhan, China, and it being an international travel hub, Hong Kong has been combating COVID-19 outbreaks since January 2020 (Chan et al., 2020). Even before the first infected case was identified, various measures had been implemented in Hong Kong to control the transmission of COVID-19 (Wong et al., 2020; Cowling et al., 2020). Among them, testing and intense surveillance for infections, including enhancing surveillance in public hospitals/clinics, providing free testing to suspected cases in the private health sector, and increasing testing among inbound travelers, played important roles in slowing the increase of local cases (Wong et al., 2020; Cowling et al., 2020; Centre for Health Protection, 2020b). Once individuals were tested positive for COVID-19, their close contacts would also receive testing and be quarantined in special facilities.

Using the residential addresses of patients, we merged the publicly available information of each symptomatic COVID-19 patients in Hong Kong with the census tract data as well as the data of healthcare resources distribution. The aim of this study was to determine if individual and neighborhood SEP factors and geographical accessibility to public and private healthcare services were associated with time to diagnosis of COVID-19 in Hong Kong. We also examined the interaction between individual SEP and geographical accessibility to healthcare services. With a focus on the socioeconomic and health system factors, this study contributes to the equity dimension in the studies of the COVID-19 pandemic and aims to inform related policymaking.

2. Methods

2.1. Study setting

Hong Kong has one of the most densely populated areas in the world. About 7.5 million population live on the land of 1106 square kilometers, in which only 24% are built-up areas. Although with a GDP per capita ranking at the top in Asia, Hong Kong is one of the regions with the most severe income inequality as well as housing affordability issue in the world (Chung et al., 2020a).

Before the summer of 2020, Hong Kong experienced two "waves" of COVID-19 outbreaks. The first wave of infections occurred in January and February of 2020 alongside the outbreak in Wuhan and the second wave started after March and lasted till April with the surge of returned residents from epidemic regions worldwide (Fig. 1) (Chan et al., 2020). During the period of the second wave, government surveillance measures were much strengthened, including providing free tests to symptomatic patients of Private Medical Practitioners (PMPs) since 9 March and establishing a temporary test centre at Hong Kong International Airport to provide tests to returnees with symptoms from high-risk regions since 19 March.

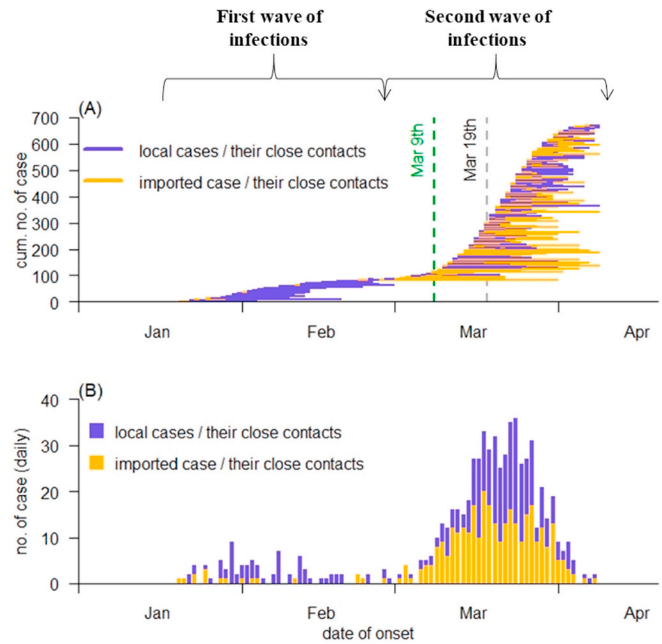

Fig. 1. COVID-19 patients in Hong Kong from 23 January to 9 April by date of symptom onset: (A) Cumulative number of cases and time from symptom onset to diagnosis; (B) Number of cases each day.
Note: The first wave of infections referred to patients with symptom onset before 1 March while the second wave of infections referred to those with symptom onset after 1 March. The first wave of infections was mainly incurred by patients infected in mainland China while the second wave was mainly driven by imported cases from epidemic regions worldwide. During the period of the second wave, government surveillance measures were much strengthened: 1) After 9 March, free RT-PCR tests for SARS-CoV-2 virus (the COVID-19 virus) are provided to the symptomatic patients of Private Medical Practitioners (PMPs) through accredited private microbiology laboratories. 2) After 19 March, returnees with upper respiratory symptoms or from high-risk regions will be sent to a temporary test centre at Hong Kong International Airport, where they will be tested for the SARS-CoV-2 virus and await the results. Other returnees will be given bottles to place their deep throat saliva specimens for COVID-19 testing and return the collected specimen to designated collection points of the Department of Health clinics.

Hong Kong has a public-private mixed healthcare system, where the tax-based public healthcare institutions are running in parallel with the privately funded private healthcare providers. The public system run by the Hospital Authority (HA) provides about 90% of inpatient bed days while the private sector provides 70% of all outpatient services (Yeoh et al., 2020). All healthcare settings have been recommended by the Hong Kong Government's Centre for Health Protection (CHP) to follow precautionary measures to minimize the risk of contracting and spreading COVID-19. They use epidemiological criteria – Fever, Travel, Occupation, Contact, and Cluster (FTOCC) – for risk assessment among patients (Centre for Health Protection, 2020a).

2.2. Data

Our study included a total of 974 laboratory-confirmed COVID-19 cases reported by the government from 23 January to 9 April, 2020. Data of each case was obtained from CHP, including the date of symptom onset, the date of the report, sex, age, Hong Kong resident status, case classification (i.e., local cases or imported cases). Patients who resided in Hong Kong during the incubation period were required to report their residential buildings and/or hotels to the government.

Using the residential address of each patient, we merged the patient data released by the CHP with the 2016 population census data (provided by the Hong Kong Census and Statistics Department) and the location information of public and private clinics and hospitals (respectively provided by the HA and the Hong Kong Medical Association). The merging allowed us to obtain SEP factors of the neighborhood of each patient and to measure patients' geographical accessibility to healthcare resources.

We restricted our sample to symptomatic patients and excluded those who only reported hotel addresses or did not report any residential addresses. This reduces the sample size from 974 to 670 cases (See Appendix Figure A1 for the flow chart of sample selection).

2.3. Measurements

2.3.1. Outcome: time to diagnosis of COVID-19

The time to diagnosis is calculated as the number of days between the date of symptom onset and the date of report. The timeline includes the time of 1) symptom onset, 2) accessing healthcare (optional), 3) specimen collection, 4) release of the reverse transcription-polymerase chain reaction (RT-PCR) test result, and 5) release of the report (See Appendix Figure A2 for the timeline). As Hong Kong has been using RT-PCR test for diagnosis (Centre for Health Protection, 2020b) and followed the WHO guidance on information release (World Health Organization, 2020), it is reasonable to assume that the time interval between specimen collection and report released by the government remained constant within our study period. Consequently, the variation in time to diagnosis was mainly driven by the variation in the time interval between symptom onset and time of accepting the PCR-testing, which is more related to individual factors, health system characteristics, and public health measures.

2.3.2. Sociodemographic characteristics

Age and sex of each patients were included in all the analyses.

2.3.3. Individual-level socioeconomic characteristics

Housing type has been widely used to proxy the socioeconomic position in local studies (Chung et al., 2015, 2020abib_Chung_et_al_2015bib_Chung_et_al_2020a). We obtained the housing type (i.e., public rental housing or non-public housing) based on the address of each patient to proxy individual-level socioeconomic characteristics. Patients were classified as public rental housing residents and non-public rental housing residents. Public rental housing apartments are rented at discounted rates for eligible low-income households who passed the means-test. The non-public rental housing residents include patients living in private permanent estates or patients living in public housing estates other than public rental housing estates.

2.3.4. Area-level socioeconomic characteristics

Area-level income and education data were extracted from the 2016 census survey and were compiled at the level of Tertiary Planning Unit (TPU, $n = 214$) and large street block groups (LSBG, $n = 1622$). TPU and LSBG unit are devised and used by the Planning Department for town planning purposes and widely used in local health equity research. Using the home addresses reported, we identified the TPU and LSBG where each patient was located. Information on whether the median household income is above the median household income of Hong Kong (HKD24900) and the percentage of population with low education (education attainment with primary school or below) in the TPU and LSBG were used to characterize the patients.

2.3.5. Geographical accessibility of public and private healthcare services

We measured the patients' geographical accessibility of public and private healthcare services, respectively. For public healthcare services, we included public hospital or general outpatient clinics which provided consultation services to patients with symptoms. The list and addresses of public hospitals and general outpatient clinics were obtained from the website of the HA (Hospital Authority, 2020). For private healthcare services, we included private medical practitioners (PMP) registered as family medicine practitioners and accident and emergency doctors. The registered addresses and the specialties were obtained from the website of the Hong Kong Medical Council. We mapped the distribution of public hospitals/clinics and PMP and calculated their density, respectively, using the kernel density method (Worton, 1989). Software package ArcGIS 10.3 was used.

2.3.6. Case classification

Following a previous local study (Chan et al., 2020), patients were classified as 1) imported cases or their close contacts and 2) local cases or their close contacts in the present study. Imported cases referred to infected patients with a history of travel to the affected areas 14 days before symptom onset. Local cases were cases with no identified source of infection, such as a recent overseas travel history or close contact with other known cases. Close contacts referred to cases with no history of travel to the affected areas 14 days before symptom onset but could be linked to either imported cases or local cases. Due to the surveillance measures, different types of cases might experience different timelines from symptom onset to government release of the test result (See Appendix Figure A2).

2.4. Statistical analysis

Descriptive statistics of the patients were reported. Considering the substantial changes in the context of the two waves of infections in Hong Kong, both on the policy and epidemiological perspectives, our research studied the patients with symptom onset before and after 1 March separately. To test for the significance of the differences in characteristics between the two waves of cases, we employed t-tests and chi-square tests for continuous variables and categorical variables, respectively.

Multivariable nonlinear regressions were applied to assess the independent associations of SEP factors and geographical accessibility of public and private healthcare services with time to diagnosis. Apart from adjusting for sex, age, and case classifications, the interaction term between individual SEP factor and the geographical accessibility to public and private healthcare services was also included in the multivariable regressions. Given the right-skewed non-negative nature, the outcome variable was modeled by generalized linear regression with Gamma distribution and log-transformation (De Jong and Heller, 2008). To quantify the effect size, excess risk (ER) was calculated as the exponentiated parameter estimates minus 1, i.e., $ER = [\exp(\text{parameter}) - 1] \times 100\%$, and it is interpreted as the percentage change in time to diagnosis for one unit increase in the independent variable.

For validation, we adopted the Cox proportional hazard models with the similar formulation and examined the consistency of estimates in terms of the positivity or negativity of the association and the level of statistical significance. Considering both individual-level and area-level characteristics we have, we also estimated the interclass correlation coefficient (ICC) in a mixed model to investigate the clustering effect. ICC was found close to zero, indicating no substantial clustering in the data.

Concerning the Modifiable Areal Unit Problem in geography that spatial analysis results can be affected by the zoning scheme or geographic scale of the areal units used, we conducted all analyses using area SEP factors on both TPU level and LSBG level, to check the robustness of our results. Model 1.1 (first wave) and Model 2.1 (second wave) used area SEP factors compiled at the level of TPU, while Model 1.2 (first wave) and Model 2.2 (second wave) used area SEP factors compiled at the level of LSBG. All statistical procedures were performed with Stata 15.

3. Results

Descriptive statistics of the 670 laboratory-confirmed cases of COVID-19 is presented in Table 1. The average time to diagnosis of the first wave of infections was 8.6 (SD = 5.5) days and that of the second wave was 6.2 days (SD = 4.6), which was significantly shorter ($p < 0.001$). Compared to patients in the second wave, patients from the first wave of infections were more likely to be older (58.3 ± 17.2 years vs. 37.5 ± 15.9 years, $p < 0.001$), public rental housing residents (23.6% vs. 11.9%, $p = 0.003$), living in area with higher percentage of population with low education (25.1 ± 5.2 vs. 23.5 ± 6.8 at TPU level, $p = 0.033$; 25.4 ± 8.9 vs. 23.1 ± 8.3 at LSBG level, $p = 0.015$), and local cases/their close contacts (84.4% vs 48.4%, $p < 0.001$). Fig. 2 presents the geographical distribution of the 670 cases across TPU units, (A) the density of public clinics/hospitals, and (B) the density of PMP. (See Appendix Fig. A3 for case distribution across LSBG units).

Table 1
Descriptive statistics of 670 laboratory-confirmed cases of coronavirus disease reported by Hong Kong from 23 January to 9 April, 2020.

Variables	Total (n = 670)	First wave of infections: patients with symptom onset before 1 March (n = 89)	Second wave of infections: patients with symptom onset after 1 March (n = 581)	P-value
Outcome variable				
Time to diagnosis (day)	6.5 ± 4.8	8.6 ± 5.5	6.2 ± 4.6	<0.0001
Sociodemographic factors				
Age (year)	40.3 ± 17.5	58.3 ± 17.2	37.5 ± 15.9	<0.0001
Sex				0.734
Female	320 (47.8)	44 (49.4)	276 (47.5)	
Male	350 (52.2)	45 (50.6)	305 (52.5)	
Individual-level SEP factors				
Public rental housing residence				0.003
Non-public rental housing residents	580 (86.6)	68 (76.4)	512 (88.1)	
Public rental housing residents	90 (13.4)	21 (23.6)	69 (11.9)	
Area-level SEP factors (TPU level)				
Household income				0.416
Below median household income	221 (32.8)	26 (29.2)	195 (33.6)	
Above median household income	449 (67.2)	63 (70.8)	386 (66.4)	
Low education attainment (percent)	23.7 ± 6.6	25.1 ± 5.2	23.5 ± 6.8	0.033
Area-level SEP factors (LSBG level)				
Household income				0.560
Below median household income	208 (31.0)	30 (33.7)	178 (30.6)	
Above median household income	462 (69.0)	59 (66.3)	403 (69.4)	
Low education attainment (percent)	23.3 ± 8.4	25.4 ± 8.9	23.1 ± 8.3	0.015
Geographical accessibility to public and private healthcare services				
Density of public clinics/hospital (number/km^2 increase)	0.3 ± 0.2	0.3 ± 0.2	0.4 ± 0.2	0.287
Density of private medical practitioners (number/km^2)	16.1 ± 19.1	13.9 ± 15.2	16.4 ± 19.7	0.255
Policy-related factor				
Case classification				<0.0001
Local cases/their close contacts	356 (53.1)	75 (84.3)	281 (48.4)	
Imported cases/their close contacts	314 (46.9)	14 (15.7)	300 (51.6)	

Note: p-values were obtained by *t*-test or chi-square test of the variables between patients with symptom onset before or after 1 March.

Table 2 presents the results of multivariable regression on time to diagnosis for the first wave and second wave of infections. In Model 1.1 which examined the first wave of patients using area SEP factors on TPU level, statistically significant excess risk of longer time to diagnosis was observed among public rental housing residents (ER = 146.5%; 95%CI: 14.2 to 432.0) and people living in an area with low education attainment (ER = 0.01%; 95%CI: 0.0 to 0.1). The statistically significant association of SEP factors with time to diagnosis was not observed in the multivariable regressions on the second wave of patients (Model 2.1). Model 1.2 and Model 2.2, which used area-level SEP factors aggregated on LSBG, presented a consistent pattern of associations with Model 1.1 and Model 2.1. In particular, 1% increase in low education attainment on LSBG level was associated with 1.7% increase in time to diagnosis (ER = 1.7%; 95%CI:0.2 to 3.2). The magnitude of the association is higher than that on the TPU level.

There is no statistically significant association between geographical accessibility to healthcare services and time to diagnosis in either the first or second wave of infections. However, the interaction term between public rental housing status and density of public clinics/hospitals nearby was significantly associated with shorter time to diagnosis (ER = −98.4%; 95% CI: 100 to −40.4) while the interaction term between public rental housing status and density of private PMPs presents an inverse association (ER = 5.0%; 95%CI: 0.1 to 10.1) among the first wave of infections. Furthermore, in the second wave of infections (Model 2.1), being imported cases or the close contacts of imported cases was associated with longer time to diagnosis (ER = 21.2%; 95%CI: 6.5 to 37.9). These statistically significant associations were also observed in Model 1.2 and Model 2.2.

4. Discussion

In summary, in the first wave of infections, living in public rental housing and having low education attainment were significantly associated with longer time to diagnosis. No such relations were found in the second wave. Specifically, the risk of delayed diagnosis for public rental housing residents was mitigated by proximity to public clinics or hospitals but increased with higher number of private medical practitioners nearby in the first wave. Case classifications presented a significant association with time to diagnosis, where imported cases or their close contacts had longer time to diagnosis compared with local cases or their close contacts in the second wave of infection.

Our research found socioeconomic gradient in time to diagnosis in the early phase of outbreak in Hong Kong. First, our research suggested that people living in public rental housing was at a disadvantage in receiving timely diagnosis in the first wave of infections. In Hong Kong, public rental housing residents represent a homogenous group with low income and assets. Our finding is consistent with previous studies on COVID-19 pandemic which showed that low SEP groups were less likely to be tested (Borjas, 2020; Kim et al., 2020). Previous research on tuberculosis and cancer also suggested low income was an important risk factor for diagnostic delay (Storla et al., 2008; Henry et al., 2013). Due to the limited provision in public sector and relatively expensive private services, despite Hong Kong's policy that "*no one should be denied adequate healthcare due to lack of means*," (Food and Health Bureau,

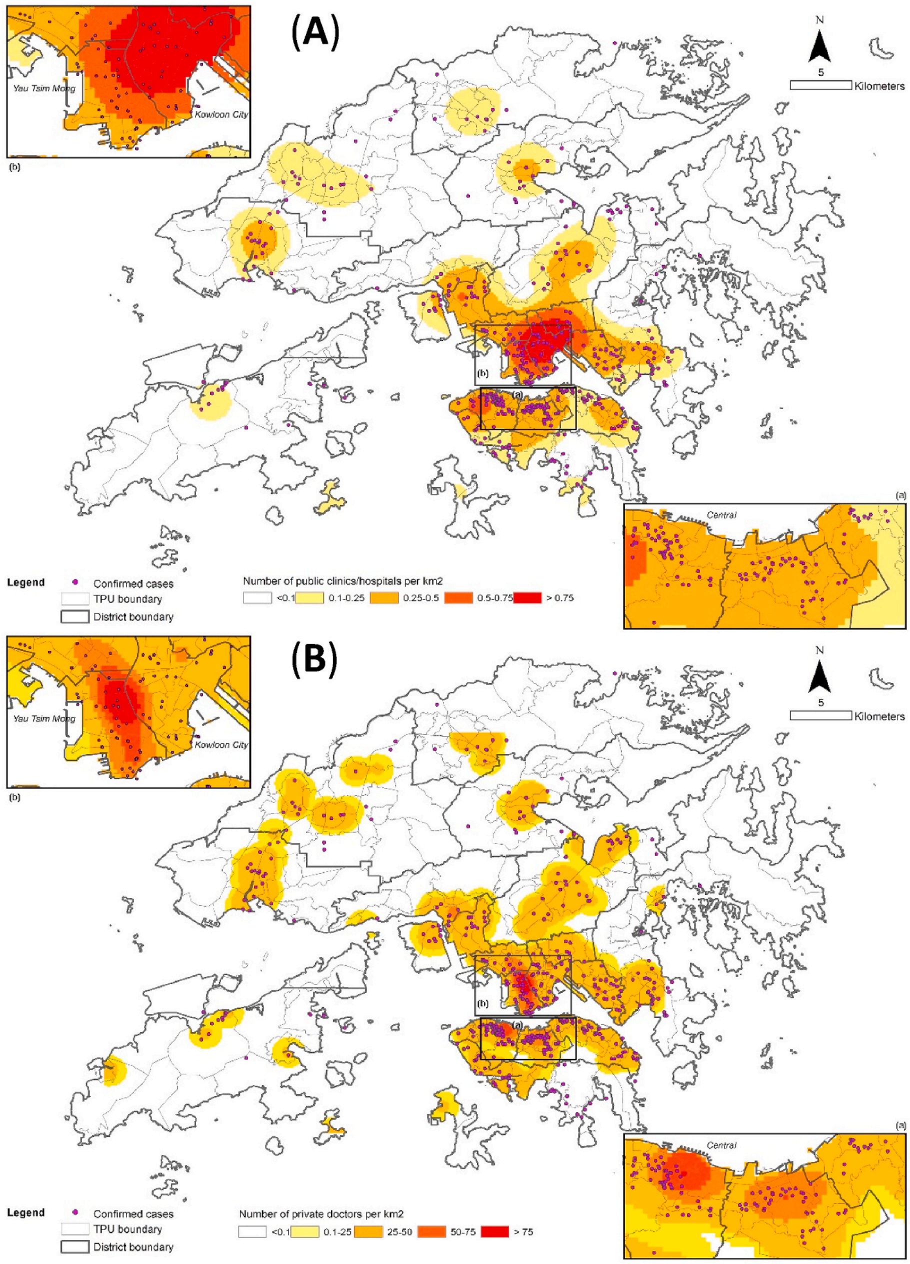

Fig. 2. The residential location of COVID-19 patients reported by the Centre for Health Protection (CHP) from 23 January to 9 April across TPU units with (A) the density of public clinics and hospitals, and with (B) density of private medical practitioners (PMP).
Note: TPU = Tertiary Planning Unit.

2010) low-income and deprived people were less prone to having a regular source of primary care (Chung et al., 2019), which might impose barriers to timely access of healthcare services even when they were sick.

Second, residing in neighbourhoods with low levels of education attainment was found to be slightly but significantly associated with a longer time to diagnosis of COVID-19. There is no previous research that tests the same association on emerging infectious disease, but our finding comports well with previous studies on chronic infections, i.e. tuberculosis and HIV/AIDS, that showed low education was an important predictor of delayed diagnosis (Chen et al., 2012; Li et al., 2013; Storla et al., 2008). Through limited knowledge of diseases and low awareness of the importance of seeking timely care, low education directly impairs an individual's ability to obtain effective care (Rosengren et al., 2019). A recent population survey also showed that low education level was significantly associated with less knowledge of COVID-19 (Zhong et al., 2020).

However, the SEP-related inequality in time to diagnosis found in the first wave was not observed in the second wave of infection. It is possible that the different patterns of associations originated from the heterogeneity in SEP between the two groups of patients. Different from the first wave of infections, which was mainly brought by visitors from Wuhan, China, the second wave was mainly driven by travelers and return-students studying overseas (Chan et al., 2020). Therefore, the imported cases and other infected cases in the second wave tended to have higher SEP and were more likely to cluster in the higher SEP areas compared with those in the first wave. As local studies also showed that the implementation of infection control measures was associated with reduced transmission of COVID-19 in Hong Kong (Chan et al., 2020; Cowling et al., 2020), it is also possible that the strengthened

Table 2
Association of time to diagnosis with individual- and area-level SEP factors and geographical accessibility to medical care for COVID-19 patients with symptom onset before and after March 1st in Hong Kong.

Variables	First wave of infection: patients with symptom onset before 1 March (n = 89)		Second wave of infection: patients with symptom onset after 1 March (n = 581)	
	Model 1.1	Model 1.2	Model 2.1	Model 2.2
	ER (%) (95%CI)	ER (%) (95%CI)	ER (%) (95%CI)	ER (%) (95%CI)
Individual-level SEP factors				
Public rental housing residence				
Not public rental housing residents	Reference	Reference	Reference	Reference
Public rental housing residents	146.5* (14.2, 432.0)	80.6* (14.4, 280.8)	−28.9 (−52.6, 6.8)	−29.1 (−52.7, 6.1)
Area-level SEP factors				
Household income				
Below median household income	Reference	Reference	Reference	Reference
Above median household income	−30.70 (−55.5, 7.7)	43.0 (−0.2, 104.8)	−10.3 (−28, 11.8)	−6.6 (23.4, 13.8)
Low education attainment (per 1 percent increase)	0.01* (0.0, 0.1)	1.7* (0.2, 3.2)	−0.6 (−2.2, 1.1)	−0.7 (−1.8, 0.4)
Geographical accessibility to public and private healthcare services				
Density of public clinics/hospital (number/km^2 increase)	−35.4 (−78.1, 90.5)	−0.6 (−73, 167.5)	−20.3 (−43.1, 11.8)	−18.2 (−41.6, 14.5)
Density of private medical practitioners (number/km^2 increase)	−0.7 (−2.2, 0.8)	−0.8 (−2.3, 0.7)	0.3 (0, 0.7)	0.3 (−0.1, 0.7)
Interaction between individual-level SEP and geographical accessibility to public and private healthcare services				
Public rental housing residence × Density of closest public clinics/hospital	−98.4* (−100, −40.4)	−96.6* (−99.9, −63.7)	36.1 (−56.7, 327.8)	48.0 (−52.1, 357)
Public rental housing residence × Density of private medical practitioners	5.0* (0.1, 10.1)	6.7** (2.0, 11.7)	1.1 (−0.4, 2.7)	1.0 (−0.4, 2.5)
Sociodemographic factors				
Age	0.0 (−0.9, 0.8)	0.0 (−0.8, 0.8)	0.2 (−0.2, 0.6)	0.2 (−0.2, 0.6)
Sex				
Female	Reference	Reference	Reference	Reference
Male	0.9 (−22.8, 31.8)	2.5 (−21.2, 33.2)	1.8 (−9.9, 14.9)	1.2 (−10.4, 14.3)
Policy-related factor				
Case classification				
Local cases	Reference	Reference	Reference	Reference
Imported cases	−2.8 (−34.9, 32)	−3.6 (−32.4, 37.3)	21.2** (6.5, 37.9)	19.8** (5.3, 36.4)

Note: Multivariable nonlinear regressions were applied to assess the independent associations of SEP factors and geographical accessibility of public and private healthcare services with time to diagnosis. Model 1.1 and Model 2.1 used area SEP factors compiled at the level of Tertiary Planning Unit (TPU, n = 214), while Model 1.2 and Model 2.2 used area SEP factors compiled at the level of the large street block groups (LSBG, n = 1622). We modeled the outcome variable by a Gamma process likelihood framework with log-transformation. Excess risk (ER) was used to quantify the effect size. ER is defined as the exponentiated parameter estimates minus 1, i.e., ER = [exp(parameter) – 1] × 100%, and it is interpreted as the percentage change in time to diagnosis when there is one unit increase in the dependent variable. The ER was estimated by using the maximum estimation approach; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

surveillance and testing in the community and among the inbound travellers, contact tracing, and the communication with public (Wong et al., 2020) might have facilitated more timely diagnosis of COVID-19, resulting in shorter time to diagnosis and the reduced inequality in the second wave of infections.

We also examined the interplay between individual SEP factor and geographical accessibility to healthcare services and found the effect of geographical accessibility to public and private healthcare services on time to diagnosis differed between public rental housing residents and the others. Playing an important role in infection control of emerging infectious diseases in Hong Kong, public healthcare system had enhanced surveillance of COVID-19 among patients presenting to public clinics and hospitals even before the first case was reported. Compared with the private sector, public healthcare system is also more affordable to the low SEP groups by charging relatively lower prices. These facts may explain why the risk of delayed diagnosis among public housing residents was mitigated by proximity to public clinics/hospitals.

Private sector plays a dominant role in primary care services in Hong Kong. Nevertheless, we found that the risk of delayed diagnosis increased when there was a higher density of private medical practitioners among people living in public rental housing in the first wave of infections. There are two possible explanations. First, this result is consistent with previous research which suggested that private practitioners with limited knowledge of infectious disease could have exerted a higher risk of diagnostic delay in low-income area (Storla et al., 2008). In Hong Kong, people in poorer areas use more public health care but less private health care as a result of worse affordability (Wong et al., 2009). Consequently, private health care with better quality tend to be located in more affluent areas (Chan et al., 2006), and the quality of private healthcare services in lower SEP areas where public rental housing estates are located could be of concern and might not help with the early diagnosis of such emerging infectious disease as COVID-19. Furthermore, only after 9 March government started to provide free testing to symptomatic patients of all private practitioners to enhance the surveillance in the community. In the first wave, the limited provision and the high prices of testing services in the private sector may present a barrier for patients with low income to receive timely testing.

Our study has some limitations. First, the geographical accessibility was calculated based on the residential address of each patient without considering their mobility. Nevertheless, as some people were working from home and the social activity of the general public was largely restricted during our study period, their movement was largely minimized. Second, our research only examined a limited number of SEP indicators considering the multidimensional nature of SEP (Khalatbari-Soltani et al., 2020). Nevertheless, our selected SEP factors were based on previous reviews on the key determinants of diagnostic delay of infectious disease (Mukolo et al., 2013; Storla et al., 2008) and the small number of variables could help reduce multi-collinearity given the relatively small number of observations. Third, due to data availability, the health status of individuals was not controlled in our present study. Forth, 17.8% of the symptomatic patients who did not report their residential addresses in Hong Kong were excluded from our analysis. As the missing home addresses were mainly from imported cases who had symptom onset upon arriving in Hong Kong without residing in Hong Kong, we controlled for the case types and got a random subsample.

Notwithstanding these limitations, this study found significant SEP associations with time to diagnosis of COVID-19 patients. Our results indicated the importance of paying more attention to the low SEP groups, e.g., providing more information on the disease and providing better access to testing services. The findings of this study also demonstrated the potential impact of the healthcare system, which suggested the protective effect of a universal and active public healthcare system on lowincome groups during the pandemic. Furthermore, although primary care services provided in the private clinics presented better quality in terms of accessibility and person-centred care in Hong Kong as compared with the ones in public clinics (Wong et al., 2010), the delayed diagnosis for patients in the private sector may indicate that there is a challenge in engaging the private sector in the surveillance of the COVID-19 (Berwick and Shine, 2020).

5. Conclusion

To the best of our knowledge, this is the first research examining the association of time to diagnosis with socioeconomic factors and geographical accessibility to healthcare services among COVID-19 patients. We found patients living in public rental housing and those living in low education areas were prone to having longer time to diagnosis. However, by looking at the two waves of infections separately, the socioeconomic gradient in the time to diagnosis was only observed in the first wave but not in the second one. Further research is needed to establish the explanations – whether the different pattern originated from the different characteristics of the two samples or the enhanced surveillance of infections in the second wave. Specifically, living in public housing residence was counterbalanced by the proximity to public clinics/hospitals, which implied the importance of universal public healthcare services in protecting the socioeconomically disadvantaged groups from the impact of the pandemic. However, a weak but significant association was found between the density of private healthcare practitioners and the time to diagnosis among public housing residents, suggesting the challenge in engaging the private sector in the surveillance system. Given the grave impact of the COVID-19 pandemic on public health, our findings call on taking inequalities into account while policies are being devised.

Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2020.102465.

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