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Exploring the nexus between social vulnerability, built environment, and the prevalence of COVID-19: A case study of Chicago

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ABSTRACT

COVID-19 has significantly and unevenly impacted the United States, disproportionately affecting socially vulnerable communities. While epidemiologists and public health officials have suggested social distancing and shelter-in-place orders to halt the spread of this virus, the ability to comply with these guidelines is dependent on neighborhood, household, and individual characteristics related to social vulnerability. We use structural equation modeling and multiple data sources, including anonymized mobile phone location data from SafeGraph, to examine the effects of different social vulnerability and built environment factors on COVID-19 prevalence over two overlapping time periods (March to May and March to November of 2020). We use Chicago, Illinois as a case study and find that zip codes with low educational attainment consistently experienced higher case rates over both periods. Though population density was not significantly related to the prevalence in any period, movement of people made a significant contribution only during the longer time period. This finding highlights the significance of analyzing different timeframes for understanding social vulnerability. Our results suggest social vulnerability played an influential role in COVID-19 prevalence, highlighting the needs to address socioeconomic barriers to pandemic recovery and future pandemic response.

1. Introduction

Since January 2020, the novel Coronavirus Disease 2019 (COVID-19) has significantly impacted U.S. communities' health and socioeconomic vitality. The U.S. has the most cases in the world, or more than 34.2 million cases and more than 610,000 deaths as of July 2021 (Johns Hopkins University & Medicine, 2021). These impacts are unevenly distributed due to neighborhood, household, and individual characteristics that exacerbate social vulnerabilities. Early research has shown the virus spreads from person-to-person through respiratory droplets when in close physical proximity (Badr et al., 2020). Considering the mechanisms of spread, researchers have accordingly sought to understand what aspects of the built environment impact COVID-19 cases, particularly the role of urban density and social distancing (Megahed & Ghoneim, 2020; Sun & Zhai, 2020). For instance, (Li et al., 2021) found that density around railway stations and density in developed areas were associated with increased COVID-19 infection probability in intercity and intracity levels in China.

While studies have attributed density as the cause of COVID-19 spreading at the local level (Q. C. Nguyen et al., 2020) or overcrowded housing conditions as a predictor of COVID-19 death (Hu et al., 2021), ongoing debates exist concerning how density and overcrowding impact virus transmission. For example, Hamidi et al. (2020) found that larger metropolitan areas have higher COVID-19 infection and mortality rates, but they did not find any significant influence of county density. They attributed these findings to dense areas having more established health care systems. Other evidence suggests that spread of COVID-19 cases does not always align with density. Dense cities and countries like Singapore, Taiwan, Hong Kong, and South Korea have fewer case rates than the United States (Beech, 2020; Diplomat Risk Intelligence, 2020; Fang & Wahba, 2020). Nevertheless, this pandemic created a negative public perception about urban density, prompting people to

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leave cities like New York, Chicago, and San Francisco (Ramani & Bloom, 2021). The resulting exodus to suburbs goes against the visions for densification and urban sustainability, as sought by the urbanists to reduce the carbon footprint of cities and to mitigate climate change impacts.

In addition to built environment factors (Q. C. Nguyen et al., 2020; Rocklöv & Sjödin, 2020), sociodemographic characteristics affect COVID-19 prevalence and death (Bryan et al., 2020; Kim & Bostwick, 2020). For example, demographics and occupation were associated with higher COVID-19 incidence and mortality rates in Washington, D.C. (Hu et al., 2021). Majority U.S. Black counties had more than three times the infection rate compared to predominantly White areas (Yancy, 2020). In Chicago, Black residents accounted for 42% of COVID-19 deaths, though they account for less than a third of the city population (Bryan et al., 2020). Immigrant neighborhoods and Black neighborhoods also had the highest rates of reported infection in New York City (Borjas, 2020). Studies have further identified how employment, income, and educational attainment affect COVID-19 prevalence. For instance, Ray and Ong (2020) have found that educational attainment is related to the ability to switch to remote work. They found that about 11% of workers without formal high-school degrees and 15% of workers with a high school degree could work remotely, compared to 58% of workers with a bachelor's degree or higher. Neighborhoods with a large share of low-wage and service sector employees also tend to house a large share of families of color (Dey et al., 2020; Ray & Ong, 2020).

Given the profound and emerging social equity implications of the pandemic, we position our study in the social vulnerability framework to highlight how built environment and socioeconomic factors contribute to the COVID-19 prevalence in Chicago, Illinois. Building on Hamidi et al. (2020), we use structural equation modeling (SEM) to model cumulative case rates at the zip code level. This study makes two major contributions to the current research on urban sustainability, social vulnerability, and COVID-19 pandemic. First, we demonstrate the importance of evaluating COVID-19 data at different time frames to understand the dynamics of contributing factors over time. Here, we analyzed cumulative COVID-19 cases over two overlapping time-periods: the initial peak phase from March to May 2020 and a longer phase from March to November 2020. Second, we consider people's mobility patterns over time using anonymized mobile phone location-based mobility data to understand if social vulnerability and built environment factors affect COVID-19 cases, after controlling for such mobility patterns.

2. Planning, Disease Spread, and Social Vulnerability

Planners have designed cities to minimize disease spread since the 19th century (Megahed & Ghoneim, 2020). With rapid industrialization and urbanization, planners had to contend with poorly managed sewage systems, housing, and work conditions after deadly cholera and typhoid outbreaks, considering that overcrowded living conditions helped spread respiratory and/or droplet-transmitted infections (Corburn, 2007; Megahed & Ghoneim, 2020; Peterson, 1979). Cities have accordingly been organized to contain or remove perceived threats to public health. With COVID-19, emerging urban planning and design literature have similarly identified ways to reduce transmission, including a focus on individual building design, improved ventilation and air filtration systems (Dietz et al., 2020), building private outdoor spaces and balconies (Poon, 2020), and integrating touchless technology (Giacobbe, 2020). Focusing specifically on courtyard space, Leng, et al. (2020) argue that courtyards in China can act as a public gathering space shared by several households. This kind of built form would be designed optimally to best utilize space, comfort, and airborne disease control.

Beyond building design, others suggest a re-examination of neighborhood-level built environment factors that impact disease spread. For instance, Kimmelman (2020) argues for increased bicycle and active transportation infrastructure while others argue for streets to be designed for multimodal options (Capolongo et al., 2020; Hishan et al., 2020). In their study of dilapidated buildings, sidewalks, and green landscaping through Google Street View, Nguyen et al. (2020) found that single-lane residential roads and green streets were associated with fewer COVID-19 cases while multi-family home areas with physical disorder had more COVID-19 cases. Others made the case for less household crowding (Emeruwa et al., 2020; Hu et al., 2021).

Researchers have additionally begun to evaluate cities' built environments after the COVID-19 pandemic. Megahed and Ghoneim (2020) argue for an antivirus-built environment with increased and added security layers to help fight against disease spread, including decentralization, fewer cars and more pedestrian friendly spaces, adaptive reuse, or work-from-home capabilities. Planners have similarly suggested many of these concepts for more sustainable urban spaces prior to and apart from the COVID-19 pandemic (Freudendal-Pedersen, 2020; Kim & Kwon, 2018; Liu & Sun, 2020; Pintossi et al., 2021). Others further suggest greater balance between public green space and private dwellings (Leng et al., 2020; Megahed & Ghoneim, 2020). Yet, solely focusing on the built environment overlooks the influence of social vulnerability on virus spread. A myopic view of the built environment also ignores how planners have historically used social and demographic factors to determine built environment characteristics - often to the detriment of lower-income and racial/ethnic minority residents. As such, a social vulnerability framework is useful to help cities incorporate race and other socioeconomic factors to mitigate impacts from the pandemic.

Social vulnerability is widely applied to investigate the vulnerability or exposure to broader environmental and natural hazards (Adger, 1999; Cutter et al., 2003; Cutter & Emrich, 2006; Cutter & Finch, 2008; Flanagan et al., 2011; Kashem et al., 2016) and is emerging as a framework to identify neighborhoods for regeneration purposes post-pandemic (Mercader-Moyano et al., 2021). The social vulnerability framework focuses on "the potential for loss" (Cutter et al., 2003, p. 242) particularly for vulnerable groups who are more likely to incur losses and deaths (Yoon, 2012). Related studies have also documented lower disaster preparedness of racial/ethnic minority and low-income households (Mileti & Darlington, 1997; Peacock, 2003), and how those households are less likely to receive and/or comply with official disaster warnings (Fothergill & Peek, 2004; Perry & Nelson, 1991). Inadequate access to quality healthcare, preventive resources, and information on COVID-19 has had a disastrous effect on racial/ethnic communities (Louis-Jean et al., 2020; Velasquez et al., 2020) as has historical discrimination and distrust in the health care system (Bazargan et al., 2021).

Studies have quantified social vulnerability based on variables representing social, demographic, and built and natural environments into an index that represents a multidimensional, latent variable (C. V. Nguyen et al., 2017; Spielman et al., 2020). Studies also composed indices with race, age, gender, and socioeconomic status (Bjarnadottir et al., 2011; Kashem et al., 2016; Yoon, 2012). Using similar factors, emerging studies have examined how social vulnerability and socio-economic conditions influence COVID-19 prevalence (Kim & Bostwick, 2020; Ong et al., 2020; Sannigrahi et al., 2020; (Yang et al., 2020)). (Das et al., 2021) argue that sociodemographic factors negatively influence living arrangements or environments which can in turn influence greater susceptibility to COVID-19 infections and deaths. Using indicators of urban living deprivation - similar to a social vulnerability index - Das et al. (2021) construct an index of multiple deprivation (IMD) for Kolkata, India based on globally weighted principal component analysis. They found that spaces with high IMD were 37% more likely to have a COVID-19 containment zone than spaces with lower IMD scores. In considering both space and time, Maiti et al. (2021) found that ethnicity, crime, and income help explain COVID-19 cases, and income and migration help explain COVID-19 deaths for the contiguous U.S. at the county level. In examining COVID-19 incidence rate also at the county level in the U.S., Mollalo et al. (2020) found that only four socioeconomic factors (household income, income inequality, percentage of nurse practitioners, and percentage of Black females) out of thirty-five environmental, socioeconomic, and demographic variables help explain variations in incidence rates. As Das et al. (2021) and other scholars (Baena-Diez et al., 2020; Sannigrahi et al., 2020) show, such relationships are not limited to the United States. For instance, Baena-Diez, et al. (2020) found higher COVID-19 incidence rates associated with lower incomes in Barcelona, Spain.

Yet, in examining early COVID -19 infections in Huangzhou, China's urban districts, Li, et al. (2021) found limited socio-economic impacts. Instead, they found that built environment characteristics like commercial prosperity (e.g., markets or food service), medical service, transportation infrastructure, and even housing prices may increase the spread of COVID-19. For the authors, commercial prosperity and well-developed transportation infrastructure create more urban mobility which increases the chances of more person-to-person contact and, thus, enables the virus to spread. Similarly, Viezzer and Biondi (2021) found weaker but meaningful correlations between socio-economic variables and COVID-19 cases, deaths, and mortality rate in Brazil's Atlantic Forest municipalities, but did find that higher populations, densities, and built areas are strongly correlated with COVID-19 outcomes. However, initial spread of COVID-19 infections and deaths in the northern states of Brazil were mostly affected by the patterns of socioeconomic vulnerability (Rocha et al., 2021), even in rural areas (Pires et al., 2021; Martins-Filho et al., 2020).

As discussed above, emerging research has examined how social vulnerability and the built environment factors have contributed to COVID-19 pandemic. However, limited research explores how these factors affected COVID-19 cases over time or how study time-periods may influence the findings. Mobility patterns at the local level are also not considered in most studies, although studies at broader geographic level (e.g., County or city level) showed the significance of mobility on COVID-19 transmission (Badr et al., 2020; (Silva et al., 2021)). This study aims to fill these research gaps while highlighting the importance of considering social vulnerability at different stages in COVID-19 recovery strategies.

3. Methodology

Our methodology captures which social and built environment factors consistently contributed to virus prevalence over time, although the COVID-19 pandemic is ongoing. We hypothesize that the overlap of social vulnerability and built environment factors contribute more to the spread of the virus than solely density or other built environment factors. To test this hypothesis, we used the structural equation modeling (SEM) technique which specifies, estimates, and tests causal relationships among a set of variables (Kline, 2016; Pearl, 2000).

We focus on the City of Chicago (Chicago) and 58 zip codes within the jurisdiction of this city for which COVID-19 cases are reported. Since the first week of March 2020, the City of Chicago started reporting a weekly aggregate number of positive cases, number of tests, and number of deaths due to COVID-19 complications (City of Chicago, 2020). Here, we focused on the number of positive cases to explore which factors contributed to the prevalence of the virus. For that, we include data up to two weekly case rate peaks in the city. Figure 1 shows that the weekly case rates peaked during the week of May 2, 2020 and then again November 14, 2020. Taking the cumulative case rates at these two time periods allow us to identify whether some factors are only important in the initial pandemic and/or persisted over the longer time period.

Confirmed cases are counted based on the week test specimen were collected (City of Chicago, 2020). The number of deaths or hospitalizations are beyond the scope of the study because they are highly correlated to healthcare accessibility and pre-existing health conditions, and it is difficult to measure and collect those data at the local level. One consideration of using positive confirmed cases is the limited availability of testing services in the early days of the pandemic. Studies have shown spatial inequality in access to testing sites (Rader et al., 2020) and that neighborhoods with higher social vulnerability had lower testing rates (Bilal et al., 2021). Asymptomatic spread of the virus is also not captured in the reported cases, but we surmise that such cases should not have significant spatial variation within the city and they eventually will be reflected through the number of positive cases (i.e., areas with higher positive cases may also have higher asymptomatic cases).

Another limitation of these data is that they are based on where people live rather than where they were infected, which can include

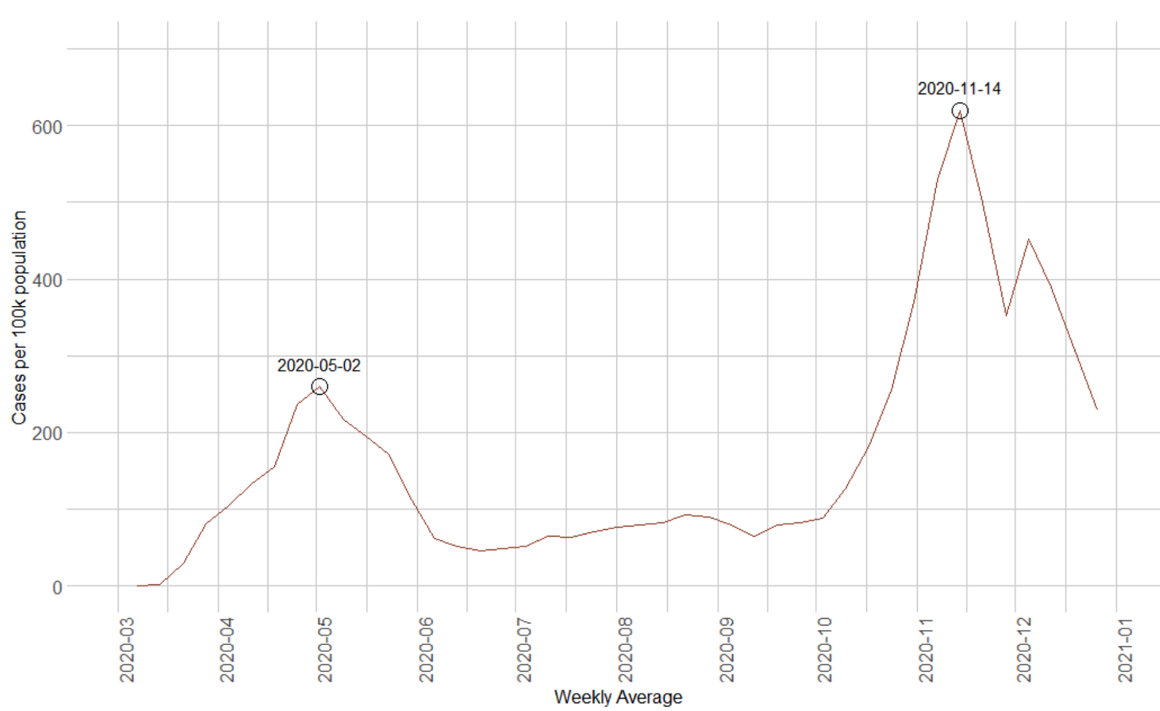

Figure 1. Weekly average COVID-19 case rate (per 100,000 population) in Chicago (Source: City of Chicago, 2020).

locations outside of the city or country. We address this limitation by using anonymized mobile phone movement data from SafeGraph. Recent research has similarly used mobile phone data to highlight mobility patterns during the pandemic to identify the effectiveness of control measures, social distancing, and isolation (Aleta et al., 2020; Pepe et al., 2020; (Silva et al., 2021)). Illinois also instituted a stay-at-home order on March 20 and closed all public and private schools on March 13, which decreases the possibility of any significant rise of cases due to people infected with the virus moving into the city. Use of cumulative number of cases for the outcome variables further addresses any temporary fluctuation of cases.

Our variables of interest related to the built environment and social vulnerability are presented in Table 1. These variables are selected based on our review of the literature on COVID-19 transmission, disease spread, and other recent studies on urban areas (Bryan et al., 2020; Hamidi et al., 2020; Kim & Bostwick, 2020). For built environment variables, we included population density, multi-occupancy, open space accessibility, and walkability. We assess land-use mix, a key attribute of the built environment, using the U.S. Environmental Protection Agency's (EPA) Walkability Index reported at the census block group level, which we allocated to the zip code level using aerial interpolation (Flowerdew et al., 1991). Higher index values indicate more diverse housing, employment, and street characteristics that are correlated with increased walkability. We assume that improved walkability may allow people to maintain social distance while moving in their neighborhood streets. However, studies have shown positive correlation between walkability, higher housing prices, and low minority populations (Gilderbloom et al., 2015; Knight et al., 2018), characteristics which may also influence COVID-19 prevalence.

Table 1
List of variables used in this study

	Description	Mean	SD	Source
Outcome variable				
Cumulative Case Rate over short-term period	Total confirmed case until May 2 per 1,000 people	8.94	4.39	City of Chicago, (2020)
Cumulative Case Rate over long-term period	Total confirmed case until November 14 per 1,000 people	46.88	15.99	
Neighborhood Built Environment Factors				
ln of Density	ln of Population per sq mile	8.59	0.6	ACS 5-year estimates (US Census Bureau, 2020)
Multi-occupancy	% rooms with 2 or more occupants	0.28	0.32	
Open Space Accessibility	% of area for parks and playgrounds	9.67	9.72	City of Chicago Data Portal
Neighborhood Walkability	EPA Walkability Score	14.37	1.87	(US EPA, 2014)
Neighborhood Social Vulnerability Factors				
Household Characteristics				
Average HH size	Average Household Size	2.42	0.54	ACS 5-year estimates (US Census Bureau, 2020)
% HH without internet	% households without internet or computer	21.2	9.81	
ln of median family income	ln of median family income in last 12 months	11.31	0.6	
ln of median rent	ln of median gross rent	7.09	0.33	
Race/Ethnicity				
% Latinx	% of total population from Hispanic or Latino ethnicity	21.34	21.57	
% Black	% of total population that is non-Hispanic/ Latino Black	29.28	33.81	
Workforce and Mobility Characteristics				
% using public transport	% of workers using public transport to commute to work	23.1	10.13	
% less than high school	% of population above 25 years of age with less than high school diploma	12.48	9.37	
% in service occupation	% of workers employed in service occupations	16.45	7.57	
Avg. % stayed home-1	Average % of devices fully stayed home per day till May 2	39.37	4.53	SafeGraph
Avg. % stayed home-2	Average % of devices fully stayed home per day till November 14	36.84	2.89	

Household characteristics and race/ethnicity data were collected from the American Community Survey's (ACS) 5-year estimates for 2019 at the Zip Code Tabulation Area (ZCTA) level (US Census Bureau, 2020). We also considered workforce and mobility characteristics in our models. Public transit usage is found to have contributed to the early spread of COVID-19 in China (Zheng et al., 2020), prompting most cities worldwide to either completely shut down their transit system or to operate with reduced capacity. Chicago Transit Authority (CTA) took several measures to reduce the virus spread and the stay-at-home order in Chicago reduced the transit ridership significantly. We measured the share of workers that commute by transit, as reported in the ACS, as proxy for transit usage. We use this measure of transit usage because actual transit ridership during the overall study time period (March 1 to November 14, 2020) is unavailable at the zip code level. We assume that reduced ridership should follow the proportion of regular transit usage and it should not vary significantly throughout the system.

Studies have also documented how lower education levels contributed to previous epidemics, like the 2009 H1N1 (Lowcock et al., 2012), and during COVID-19 (Bryan et al., 2020; C. Yang et al., 2020). Accordingly, we included ACS data on the share of population 25 and older with less than a high school education to measure lower educational attainment. Besides education, specific occupation types can contribute to the exposure of COVID-19. Those who are employed in occupations that require interactions with people (e.g., restaurants, bar, and public transportation) are at higher risk of exposure and infection. We also considered the share of those service occupations as reported in ACS.

The ability of residents to follow stay-at-home order could also significantly impact the spread of the COVID-19 virus. In this study, we measured the mobility of residents to evaluate the extent to which stay-at-home order was maintained by using the average percentage of mobile devices that stayed at home all day within a zip code. We used anonymized mobile phone data from SafeGraph Inc, which tracks the locations of millions of mobile devices through location-enabled applications. SafeGraph provides access to their data through free, non-commercial agreements to facilitate COVID-19 research (SafeGraph, 2020). The fraction of mobile devices that were detected to be entirely at home during the day are calculated as a measure of proportion of people maintain stay-at-home order. The average stay-at-home measure (i.e., % of devices staying at home per day) is measured for both time periods.

We used the "lavaan" package of R to implement the SEM model (Rosseel, 2012) for this study. We opted for SEM due to its flexibility and rigorous approach for testing the linear relationships between observed variables and latent variables, and the possibility to consider several dependent variables simultaneously (Hoyle, 2012). We carried out extensive robustness tests, such as models with alternative specifications. Details on variable selection and SEM implementation process are provided in the Appendix. A limitation of this study is the modifiable areal unit problem (MAUP) which should be addressed by future research when detailed data becomes available at different geographic scales.

4. Findings

Correlations between the outcome and explanatory variables were explored before developing the SEM. Table 2 shows the correlation between each of the explanatory variables and the two outcome variables. This simple correlation does not show any significant influence of density to the cumulative case rates in both the short-term period (March to May) and the long-term period (March to November 2020). We kept density in the model considering its importance shown in previous studies (Q. C. Nguyen et al., 2020; Zheng et al., 2020) and to evaluate if it indirectly contributed to the outcome variables through any other explanatory variables. For correlations of other socioeconomic and built environment variables, we see the expected signs as found by other studies (Bryan et al., 2020; Kim & Bostwick, 2020). These relationships change after considering the confounding factors in the SEM model.

Figure 2 shows a simplified version of the best fit SEM path diagram for this analysis. The model selection process and the full model with all causal paths is presented in the Appendix. Overall, the SEM path diagram shows the direct contributors to cumulative case rates are education, occupation, internet accessibility, walkability, density, occupancy, transit dependency, open space accessibility, and mobility during the pandemic. Race/ethnicity and income contribute to the outcome variables mainly through education, occupation, and movement pattern (i.e., extent to which stay-at-home orders were maintained).

Table 3 presents direct, indirect, and total effects of all explanatory variables on both outcome variables. Low education level (percentage with less than a high school diploma) is a consistently significant contributor to the prevalence of COVID-19 in Chicago for the immediate (March to May 2020) and long-term period (March to November 2020). Consistent with correlation analysis, as discussed earlier, we do not find any significant influence of density to the prevalence of COVID-19 at either point in time. These results are discussed below in detail under the broad groups of built environment and social vulnerability factors.

4.1. Built Environment and COVID-19

Our results do not show a consistent influence of built environment parameters on COVID-19 prevalence. For instance, neither open space accessibility (measured by % of area for parks and playgrounds) nor population density show any significant effect in both time periods. However, walkability shows a significant direct effect only at the early stage of the pandemic. Although density is popularly considered as a cause for the quick spread of COVID-19 (Q. C. Nguyen et al., 2020; Rocklöv & Sjödin, 2020) due to the difficulty of maintaining physical distance in a dense environment, our results indicate density is not a significant predictor of COVID-19 prevalence at the local level. On the other hand, multi-occupancy (measured by % of rooms with 2 or more occupants), shows a significant effect on the case rates at both time periods. Neighborhood walkability, which includes a wide array of connectivity and accessibility measures, had a significant direct effect in the short-term but indirect effect in the long-term.

Table 2
Pearson correlation between explanatory variables and outcome variables

Cumulative Case Rates	Short-Term Period	Long-Term Period
Neighborhood Built Environment Factors		
ln of Density	-0.21	-0.25
Multi-occupancy	0.23*	0.17
Open Space Accessibility	-0.26**	-0.27**
Neighborhood Walkability	-0.48**	-0.21
Neighborhood Social Vulnerability Factors		
Household Characteristics		
Average HH size	0.66**	0.62**
% HH without internet	0.62**	0.2
ln of median family income	-0.64	-0.23
ln of median rent	-0.53	-0.23
Race/Ethnicity		
% Latinx	0.46**	0.75**
% Black	0.32**	-0.21
Workforce and Mobility Characteristics		
% using public transport	-0.1	-0.35**
% less than high school	0.75**	0.58**
% in service occupation	0.62**	0.31**
Avg. % stayed home-1	0.03	
Avg. % stayed home-2		-0.39**

Note:
[*] Correlation is significant at the 0.1 level (two-tailed);
[**] Correlation is significant at the 0.05 level (two-tailed)

4.2. Social Vulnerability and COVID-19

Of the household characteristics, average household size and limited internet access played a significant indirect role in explaining COVID-19 spread rates in both short-terms and long-term periods. Similarly, the share of the population of Latinx ethnicity also shows a significant indirect effect across both time periods. In our model, Latinx ethnicity is connected to the outcome variables through education, occupation, and internet connectivity

Workforce and mobility characteristics are more nuanced. Lower educational attainment shows a consistently significant direct and total effect on the spread of COVID-19 in Chicago. Low education levels may influence COVID-19 health literacy, including precautions to limit exposure and disease spread. Our proxy of transit usage (share of workers that commute to work by transit) still captures a slight significant influence ($.1>p>.05$) at the early stage of the pandemic, despite not measuring actual ridership.

The extent to which stay-at-home order was maintained (the average percentage of mobile devices that stayed at home all day) did not have any significant influence at the early stage of the pandemic but, looking at the longer time period data we see that it significantly reduced virus prevalence.

5. Discussion and Implications

Our study found few built environment characteristics were significant predictors of COVID-19 prevalence in Chicago at the neighborhood (zip code) level. Population density at the local level was not a significant predictor of COVID-19 prevalence. This result is consistent with the findings of Hamidi et al. (2020) that evaluated density measures at county level. We also found that multi-occupancy households was a consistent significant predictor of cases in both time periods, which highlights how it may be challenging to quarantine an exposed person and that multi-occupancy households increases virus transmission. Walkability was only significant in the immediate time period. Studies have shown walkability to increase property values (Gilderbloom et al., 2015), making any area only affordable to higher income skilled laborers who can avoid exposure to the virus by working from home. At the same time, higher walkability may also encourage more people to walk without the physical distance suggested to avoid virus exposure. Such mixed influence of walkability is reflected within the results of this study.

Our results show the significance of socioeconomic characteristics both in the immediate and long-term period. Variables related to lower socioeconomic status (e.g., lower education levels and service sector employment) were consistent predictors. Our most significant results stem from the educational attainment variable. Education - or a limited formal education - plays an important role in the virus's prevalence and is also related to other variables - especially occupation and income. Lower levels of education or training generally result in lower-paid work where remote work is often not possible. Instead, residents with less-than a high school diploma are likely to hold jobs that require face-to-face interactions. At the early stage of the pandemic, there were also few safety measures required from service sector employers (e.g.,

Table 3
Direct, indirect, and total effects of the variables on Covid-19 case rate

	Short-Term Period Rate			Long-Term Period Rate		
	Direct	Indirect	Total	Direct	Indirect	Total
Neighborhood Built Environment Indicators						
ln of Density	-0.086	-0.02	-0.106	-0.140	-0.041	-0.181
Multi-occupancy	0.101	0.067**	0.168*	0.125	0.053	0.178*
Open Space Accessibility	-0.012		-0.012	-0.124		-0.124
Walkability	0.318*	0.063	0.381*	-0.049	0.166*	0.117
Neighborhood Social Vulnerability Indicators						
Household Characteristics						
Average HH size		0.329**	0.329**		0.300**	0.300**
% HH without internet	0.138	0.310**	0.448**	-0.494*	0.360*	-0.134
ln of median family income		-0.068	-0.068		0.244	0.244
ln of median rent		0.063	0.063		0.129	0.129
Race/Ethnicity						
% Latinx		0.244**	0.244**		0.364**	0.364**
% Black		0.113	0.113		-0.16	-0.16
Workforce and Mobility Characteristics						
% using public transport	0.133	0.056*	0.189*	-0.038	0.018	-0.02
% less than high school	0.599**	0.025	0.624**	0.831**	-0.09	0.742**
% in service occupation	0.327*		0.327*	-0.112		-0.112
Avg. % stayed home-1	-0.08		-0.08			
Avg. % stayed home-2				-0.311**		-0.311**

* $p < 0.10$;
** $p < 0.05$.

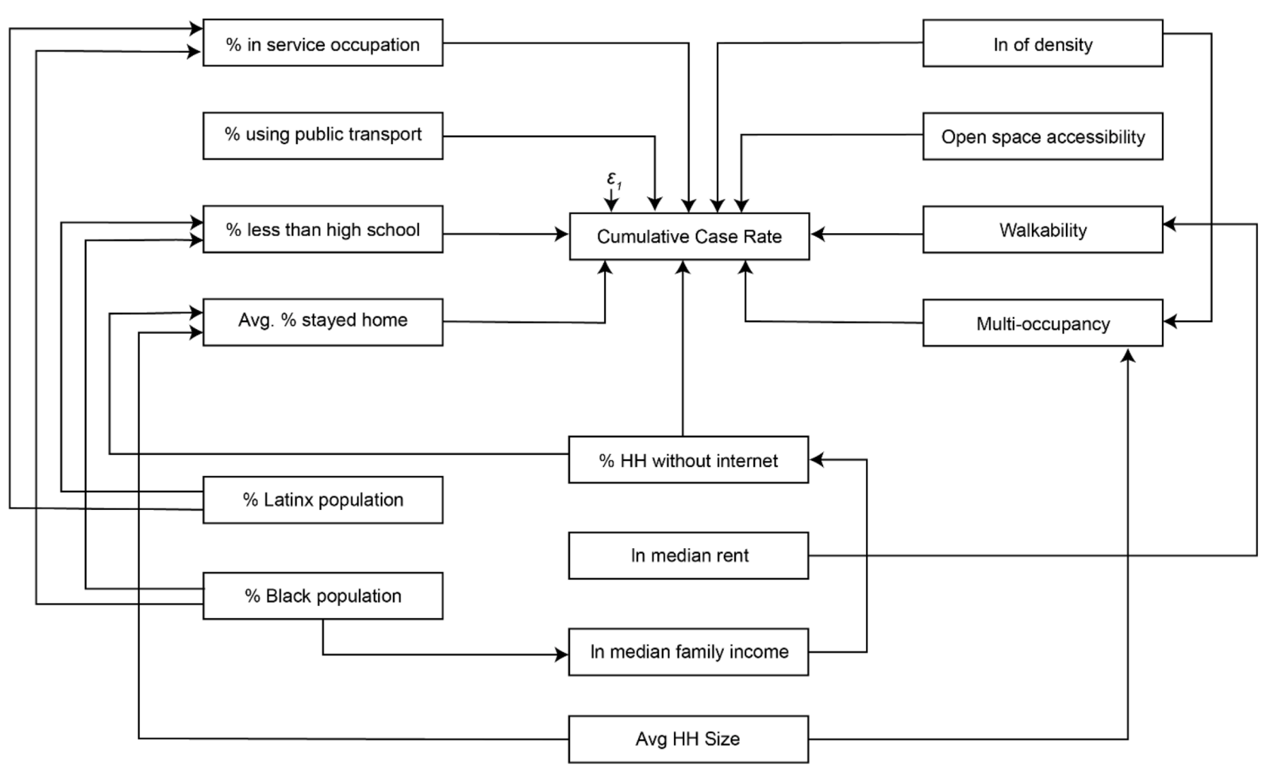

Figure 2. SEM Path Diagram (showing only the major paths). Full model with all causal paths is presented in the Appendix.

providing personal protective gear to grocery workers, etc.), which may have caused higher exposure to the virus. After stay-at-home orders and adoption of safety measures, this exposure may have reduced.

Our findings also highlight that Latinx areas have higher rates of COVID-19 cases, which corroborates other studies on racial/ethnic disparities (Bryan et al., 2020; Carrión et al., 2020; Ong et al., 2020). Initial research on the pandemic offers explanations for these trends. Though Latinx adults viewed COVID-19 as a major threat (Krogstad et al., 2020), local and state government agencies lagged in providing reliable translation of COVID-19 educational materials into Spanish and other languages (Calo et al., 2020; Foy, 2020). As a result, monolingual Spanish speakers were at elevated risk to infection due to lower levels of COVID-19 health literacy as well as higher rates of heart disease and lung infection, and service sector employment (Joseph et al., 2020; Rodriguez-Diaz et al., 2020). Our analysis shows this lag could have led to short- and long-term consequences for Latinx communities.

Additionally, fears of public transport use contributing to COVID-19's spread may be unfounded. The relationship between public transport use and prevalence were insignificant in the longer time period of the pandemic. Reduced transit usage during this time (particularly after stay-at-home orders) and the safety measures taken by Chicago Transit Authority to reduce the spread of COVID-19 through their buses and trains, may have reduced COVID-19 transmission. Further research is needed to fully examine the role of transit on transmission rates. For instance, if, after the resuming of transit operations, COVID-19 cases increase due to increased transit use.

6. Conclusion

Findings from this study highlight the complex and intersectional nature of race and class and the built environment on airborne disease spread. Education, household size, and percentage of Latinx population show consistent positive relationships with virus prevalence over time. A major takeaway of our results is that socioeconomic characteristics played a more important role in COVID-19 spread compared to population density and other built environment characteristics. These findings align with other studies that identified socioeconomic factors as strong predictors of COVID-19 outcomes in other contexts, such as lower-income European countries (Sannigrahi et al., 2020); and in Washington, DC (Hu et al., 2021).

The COVID-19 pandemic has rapidly changed our modality of work-shifting a significant share of our workforce to work from home. However, not all occupations can shift quickly to remote work, and the lack of internet connectivity leaves certain segments of the population unable to work from home. Our results reflect this phenomenon at the early stage of the pandemic, which is mediated by both education and occupation.

An essential finding for planners and policymakers is the importance of socioeconomic characteristics in identifying virus prevalence - and more importantly, the impact of racial and class segregation on U.S. cities' livelihoods. The public's fears of density and public transport exacerbating virus transmission, which have contributed to exoduses from major U.S. urban centers, are unfounded. While halting or limiting public transport operations was indeed necessary, planners should continue embracing, advocating for, and expanding public transport operations if appropriate preventive approaches are into place. Instead, racial/ethnic and class segregation are greater threats to the health and economic vitality of cities. As the built environment evolves to enhance public safety, the social crisis brought on by the COVID-19 pandemic also presents an opportunity for cities to rethink and reshape its relationship with our urban spaces' most vulnerable populations.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships with other people or organizations that can inappropriately influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.scs.2021.103261.

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