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The impact of ethnic segregation on neighbourhood-level social distancing in the United States amid the early outbreak of COVID-19

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Abstract

The COVID-19 pandemic has been argued to be the 'great equaliser', but, in fact, ethnically and racially segregated communities are bearing a disproportionate burden from the disease. Although more people have been infected and died from the disease among these minority communities, still fewer people in these communities are complying with the suggested public health measures like social distancing. The factors contributing to these ramifications remain a long-lasting debate, in part due to the contested theories between ethnic stratification and ethnic community. To offer empirical evidence to this theoretical debate, we tracked public social-distancing behaviours from mobile phone devices across urban census tracts in the United States and employed a difference-in-difference model to examine the impact of racial/ethnic segregation on these behaviours. Specifically, we focussed on non-Hispanic Black and Hispanic communities at the neighbourhood level from three principal dimensions of ethnic segregation, namely, evenness, exposure, and concentration. Our results suggest that (1) the high ethnic diversity index can decrease social-distancing behaviours and (2) the high dissimilarity between ethnic minorities and

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non-Hispanic Whites can increase social-distancing behavior; (3) the high interaction index can decrease social-distancing behaviours; and (4) the high concentration of ethnic minorities can increase travel distance and non-home time but decrease work behaviours. The findings of this study shed new light on public health behaviours among minority communities and offer empirical knowledge for policymakers to better inform just and evidence-based public health orders.

Keywords
big data, COVID-19, ethnic segregation, social distancing

摘要
新冠肺炎大流行被一些人认为是"伟大的均衡器"，但事实上，种族和民族隔离社区正承受着不成比例的疾病负担。尽管这些少数族裔社区中有更多人感染并死于这种疾病，但这些社区中遵守公共卫生措施建议（如保持社交距离）的人仍然很少。对于导致这些后果的因素，人们一直在争论，部分原因是相互对立的种族分层和种族社区理论。为了为这一理论辩论提供经验证据，我们通过美国城市人口普查区移动电话设备来追踪人们保持社交距离的行为模式，并采用双重差分模型来检验种族/民族隔离对这些行为模式的影响。具体而言，我们从种族隔离的三个主要维度（即均匀度、接触度和集中度）出发，在街区层面关注非西班牙裔黑人和西班牙裔社区。我们的研究结果表明：(1) 高种族多元化指数可能会损害保持社交距离的行为；(2) 少数民族和非西班牙裔白人之间的高度差异可能会促进保持社交距离的行为；(3) 高互动指数可能会损害保持社交距离的行为；(4) 少数民族的高度集中可能会增加出行距离和非在家时间，但会减少工作行为。这项研究的结果为少数民族社区的公共卫生行为提供了新的视角，并为决策者提供了经验知识，并为其创建公正和循证的公共卫生秩序提供了更好的参考。

关键词
大数据、新冠肺炎、种族隔离、社交距离

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Introduction

COVID-19 has posed unprecedented challenges for cities around the world. Many precautionary measures such as border closure, screening and testing at a massive scale, social distancing, and many others have been adopted by governments internationally to slow the viral transmission, to relieve the burden on health care facilities, and, simply, to avoid increasing deaths (Anderson et al., 2020). Most of these interventions have proven to be significantly effective evidenced by the successes of multiple countries, such as China (Kraemer et al., 2020). However, in the United States (US), the federal government has been widely criticised for its failure to cope with this pandemic due to the lack of action and cooperation among different levels of government. Thus, responses greatly vary across localities and states amid the pandemic, which has consequently contributed to enormous variations in the incidence of cases and fatalities across jurisdictions (Zhai et al., 2021a, 2021b). The interplay between the differing policies and implementation and the diverse US communities has significantly complicated the adoption of effective policy measures (e.g. stay-at-home orders) and their compliance (Brzezinski et al., 2020).

Fundamentally, complying with policies to slow viral transmission requires significant shifts in behaviours (van Bavel et al., 2020). Given the diversity of the community and the existing polarising socio-political environment in the US, the varying degrees of community responses to the governmental orders are foreseeable. This is also evidenced by empirical research on political partisanship, age, education, income and social capital (Brzezinski et al., 2020; Fu and Zhai, 2021). The disproportionate spread of COVID-19 has highlighted an ethnic/racial disparity in communities, as ethnic minority groups are more susceptible to COVID-19 with a higher mortality and infection rate due to a lack of access to resources (Hawkins, 2020; Zhai et al., 2021b). Such inequality is generally a matter of economic disadvantage that is more pronounced in ethnically or racially segregated neighbourhoods (Tai et al., 2021). Ethnic segregation can also affect various health behaviours, such as smoking, substance use, diet, physical activity, sleep, risky health activities, etc., due to poverty and the poorly built environment of the neighbourhood (Acevedo-Garcia et al., 2003). Moreover, ethnic minorities are more exposed to the virus due to their participation in essential occupations compared to Whites (Rogers et al., 2020).

Nevertheless, it remains uncertain to what extent and how ethnic segregation has influenced public health behaviours because of the contradictory findings from the ethnic stratification perspective (Logan, 1978) and the ethnic community perspective (Logan et al., 2002). However, such empirical evidence is vital to inform policymaking for slowing the community transmission of COVID-19 in a way that is effective and equitable. Thus, this research aims to contribute to this body of growing literature by empirically investigating how ethnic segregation across US communities can lead to varying social-distancing behaviours at the neighbourhood level during this pandemic.

In the following, we first provide a theoretical framework through a review of the relationship between ethnic segregation and public health behaviour. We then present the data sources and methodology, followed by a presentation of the results. In the end, we will discuss the theoretical contribution, limitations and conclude with implications for policymaking.

Theoretical framework: From social distancing to ethnic segregation

Social distancing: A typical health behaviour during the pandemic

There is ample literature on behaviour change in the public health domain and many of them remain highly relevant for managing the current COVID-19 pandemic. Empirical evidence has shown a strong similarity between social-distancing behaviour during COVID-19 and other conventional health behaviours (Bourassa et al., 2020). Because of the human-to-human transmission patterns of the COVID-19, continued social distancing will remain essential until the deployment of effective pharmaceutical interventions (Lewnard and Lo, 2020). Drawing from the public health literature, such significant behaviour changes can be influenced by both external and internal factors (van Bavel et al., 2020).

Externally, public health behaviours can be influenced by governmental leadership and scientific communication at varying levels, from families to communities, from cities to the nation (Krause et al., 2020). During a pandemic, the desirable approach for the government is to implement coordinated public orders at all levels and to provide consistent and reliable public health information on the disease so that people can legitimately practice social distancing (Green et al., 2020). However, in the US, the inconsistent and uncoordinated public orders, the mixed, sometimes even contradictory, public health advice and the proliferating fake news and miscommunications (Haffajee and Mello, 2020) are almost the opposite of a desirable approach. Consequently, these circumstances have collectively worsened the effects of pandemic responses by failing to build public trust and encouraging prosocial behaviours.

Internally, public health behaviours can also be greatly influenced by factors such as individuals' ability to perceive the threat. For example, people who feel that they are highly threatened would choose to follow the public health advice while others might doubt that threat and choose to ignore the advice. However, these individuals' behaviours can still be greatly affected by collective community behaviours (van Bavel et al., 2020). Hence, people who do not believe in public advice might conform to prosocial behaviours under community peer pressure and vice versa. As the behaviour of individuals is difficult to observe and monitor at a fine scale, existing studies on social distancing primarily focus on the county level (Egorov et al., 2021).

Furthermore, social-distancing behaviour clashes with the inherent human instinct to connect with people (Barrios et al., 2021). Social connections can intensify the spread of social-distancing behaviours that may be both beneficial and detrimental amid the pandemic, and these impacts could spread via the social network (Christakis and Fowler, 2013). Some interventions can be effective for people who are directly informed of the intervention, but have indirect and positive impacts on people whose friends or relatives copied the behaviour (Bond et al., 2012). In contrast, social isolation worsens pressures and often produces harmful impacts on people's health behaviours (Haslam et al., 2018). Particularly, social distancing threatens to exacerbate social isolation and thus leads to long-term health issues (Wilder-Smith and Freedman, 2020). While these studies are important to understand how social isolation can affect people amid a pandemic, little is known about how much the connection or isolation of ethnic minorities would influence social-distancing behaviours and pandemic consequences.

Ethnic segregation for health behaviours: Ethnic stratification or ethnic community?

In the US, ethnic segregation has long been known to shape public health behaviours (Acevedo-Garcia et al., 2003). The conventional wisdom that ethnic segregation adversely impacts health behaviours is anchored in the perspective of ethnic stratification (Logan, 1978). When considering ethnic stratification as a structural manifestation of discrimination against ethnic minorities (Yang et al., 2020), its effects are usually examined through a social and environmental lens.

First of all, political alienation and powerlessness are related factors of ethnic segregation, which could lead to inequitable allocation of resources in marginalised communities. As a result, people in ethnically segregated neighbourhoods often fail to have equal education or communication opportunities (Yang et al., 2020). Ethnic segregation is also associated with distrust of science and social institutions, in part, due to a lack of education, and therefore these communities are often found to be more susceptible to misinformation and 'fake news'

(Bakker and Dekker, 2012; van Bavel et al., 2020). This was evident during the COVID-19 pandemic as ethnic minorities such as non-Hispanic Blacks in the US were less likely to comply with the stay-at-home orders during this pandemic (Block et al., 2020).

Additionally, higher crime and poverty rates have been observed in communities with higher levels of ethnic segregation, which tends to be overlooked by the government (Williams and Collins, 2001). Also, these minority populations often lack access to public health facilities, and the majority do not hold occupations that offer working flexibilities such as working from home or sick leave (LeClere et al., 1997). For instance, Rogers et al. (2020) found that the COVID-19 mortality was higher among non-Hispanic Blacks compared with non-Hispanic Whites due to more non-Hispanic Blacks holding essential worker positions with higher exposure to the virus. Hawkins (2020) also found that people of colour were more likely to be employed in low-wage, essential occupations with closer proximity to others and greater exposure to infections. Hence, the interplay between ethnic segregation and poverty has significantly increased their risk to the virus and lowered their chances of recovery (Kramer and Hogue, 2009).

Lastly, the built environment of ethnically segregated neighbourhoods is often inferior in condition. Based on the perspective of ethnic stratification, a process of sustaining advantages for the dominant ethnic group (Logan, 1978), a higher degree of ethnic segregation can dramatically reduce the accessibility to public health resources, such as virus-free areas for physical activity. Thus, the poorly built environment is more likely to expose ethnic minorities to multiple health risks, supporting the argument that ethnic segregation has a negative outcome for public health (Brulle and Pellow, 2006). Furthermore, ethnically segregated areas have been commonly characterised by disordered communities, which may imply that objectionable and risky behaviours could turn to be normative (Biello et al., 2013). This is particularly harmful during this pandemic because it requires collective social-distancing behaviours.

However, the ethnic community holds an opposite proposition on these issues. The ethnic community (or ethnic enclave) perspective, which is originated from the spatial assimilation model, has been adopted to substantiate the protective effect of ethnic segregation on health behaviours (Logan et al., 2002). It implies that sometimes ethnic segregation could be as a result of personal intention, although there is a long history of most ethnic minorities suffering forced segregation because the structural discrimination against ethnic minorities is inevitably rooted in society (Yang et al., 2020).

Theoretically, the ethnic community could also benefit from both tangible and invisible resources due to social connections, thereby enhancing people's health behaviours. That is, minorities living in an ethnically segregated neighbourhood can benefit from enhanced social support, reduced influences from cultural barriers, and frequent social engagement with individuals of the same ethnic group (LeClere et al., 1997). These characteristics contribute to solidarity and social connection in communities, which helps ethnic minorities collectively comply with public health guidelines and orders (Yang et al., 2020). For example, in the context of an emergency or crisis, ethnic minorities may not trust governmental guidance without confirmations from friends/relatives of the same ethnicity (Lindell and Perry, 2003). Additionally, due to the close-knit social cohesion, high segregation could facilitate better socio-economic and structural resources, representing positive influences of co-ethnics on people's health behaviours (Lee and Ferraro, 2007). For instance, when the dominant ethnic group exhibits poor health behaviours (e.g. tobacco use in the public space), segregation from the majority could be beneficial to ethnic minorities (Yang et al., 2014). Last but not least, for ethnic minorities, being segregated could also mean being less exposed to ethnic discrimination, especially institutional-level discrimination, which can adversely impact health behaviours (Williams and Collins, 2001). Being free from ethnic discrimination may also be beneficial to self-esteem and mutual respect among people, thus positively contributing to collective health behaviours (Yang et al., 2020).

In summary, how ethnic segregation impacts people's health behaviour has been a long-lasting debate because of the mixed empirical findings and contested theories. The existing literature primarily explores the impacts of segregation on health behaviours at the individual level (e.g. Biello et al., 2013; Williams and Collins, 2016), which significantly ignores the importance of collective public behaviours from a community standpoint. This is particularly true for the COVID-19 pandemic where collective behaviours such as social distancing and universal masking are essential public health measures.

Moreover, the existing studies were largely focussed on the association between ethnic segregation and COVID-19 infections. Hu et al. (2020) is the first study to apply spatial analysis methods to the neighbourhoods' COVID-19 data in the US to investigate whether neighbourhoods with higher COVID-19 incidence rates are positively associated with highly isolated areas for ethnic minorities. Yang et al. (2021) discovered that high levels of residential segregation between non-Hispanic Whites and non-Hispanic others increased the number of COVID-19 infections in a county. Millett et al. (2020) found that counties with the highest proportion of non-Hispanic Whites have the fewest cases of COVID-19 irrespective of geographic region or state political party inclination. This study, therefore, aims to empirically complement these studies by offering pieces of evidence for the relationship between ethnic segregation and social-distancing behaviours during the pandemic.

Data and method

Study areas

This study chose to include all urban census tracts in metropolitan statistical areas (MSA) across the US for two reasons. First, urban areas are where population aggregates in a high-density space with inevitably higher chances of physical interactions and less space for exercising public health measures like social distancing, thereby suggesting that cities are at the greatest risk in this pandemic. Second, cities are very different in the context of ethnic segregation during this pandemic. On the one hand, urban areas are the most racially and ethnically segregated places and the spatial distribution of minorities can vary significantly across cities, especially for Hispanics and non-Hispanic Blacks. For example, some of the nation's largest Hispanic populations are primarily in the cities within four states that border Mexico – California, Texas, Arizona and New Mexico, while states such as Alabama, Louisiana and Mississippi have a relatively high proportion of non-Hispanic Blacks. On the other hand, COVID-19 emergency declarations and associated social distancing orders vary largely across cities and states in the US, which are strongly differentiated by income and partisanship (Gollwitzer et al., 2020; Weill et al., 2020). Hence, this points to the need for a national study to compare urban areas in varying contexts and the associated public health outcomes. Furthermore, we use the census tracts as our granular analytical units because community interactions and consequences generally occur at a finer neighbourhood scale and census tracts are the finest level at which we can obtain a national dataset.

In total, there are 74,134 census tracts in the US. We first aimed to select all the census tracts within 954 counties in all the 384 MSAs. Thus, by excluding 21,737 census tracts that are outside of MSAs and have missing social-distancing data and socio-economic and demographic data, 52,397 census tracts were finally used (Table 1, Group 1). The MSAs usually consist of a core urban centre and its surrounding sub-regions, which may include several adjacent counties. Thus, some census tracts in the surrounding sub-regions could be significantly less densely populated compared to those in the urban centre. Thus, to account for such substantial variations between the urban centres and their surrounding sub-regions, we also performed an analysis using only the 15,735 census tracts from the 100 largest cities (Table 1, Group 2). The boundaries of the cities are from the 'Places' shapefiles provided by United States Census Bureau (2020). Table 1 summarises the descriptive statistics of all variables for the two groups.

Dependent variables

To represent the social-distancing behaviours during the pandemic, we collected the daily human mobility data from the SafeGraph platform, representing 45 million anonymous smartphone devices in the US. The home location of each device is determined based on the most frequent night-time place of the smartphone over six weeks at a Geohash-7 scale (153 m × 153 m). Based on the home location, we can get the following three types of social-distancing metrics, which are work behaviour share, distance travelled from home and non-home dwell time, between March 1st, 2020, and May 15th, 2020. The measurements of three metrics are specified below:

(1) Work behaviour rate indicates the percentage of mobile phone users who go to work. A device would be defined as a part-time work-behaviour device if it spent one period of between three and six hours at a place other than the identified home during the daytime (8 am–6 pm). Likewise, the device, which spent more than six hours at a place other than the identified home during the daytime, would be defined as a full-time work-behaviour device. In this study, we considered both part-time and full-time work behaviours.

(2) Distance travelled from home represents the median distance travelled from home as tracked by the mobile devices during the time period (excluding any distances of 0).

(3) Non-home dwell time is the median dwell time at places outside the home for all devices during the time period. For each device, we summed the observed minutes outside of home across the day (whether or not these were contiguous) to get the total hours.

Independent variables

Variables of interest. We adopted the analytical framework by Massey and Denton (1988) that summarised five mutually independent dimensions of segregation including evenness, exposure, concentration, centralisation and clustering. We removed the centralisation and clustering dimensions from our analysis because they must be calculated at the city level, which was incompatible with our analysis units at the census tract level, also our definition of the neighbourhoods in this study. Additionally, segregation measures developed by Massey and Denton (1988) were not in a spatial context, meaning that if any two neighbourhoods

Table 1. Descriptive statistics of all variables.

	Group 1: metropolitan statistical areas					Group 2: top 100 largest cities				
	N	Mean	Std	Min	Max	*N*	Mean	Std	Min	Max
Dependent variables										
Work behaviour rate (%)	3,665,579	10.12	6.02	2.43	83.10	994,358	12.21	7.03	3.12	63.23
Distance travelled (km)	3,665,579	8.93	38.07	0.00	130.21	994,358	9.63	22.50	0	112.32
Non-home time (hours)	3,665,579	1.03	1.64	0.00	23.43	994,358	1.65	1.93	0	23.41
Independent variables										
Time window										
Before order/first case	1,131,167					288,430				
0–5 days	314,201					85,130				
6–14 days	471,315					127,692				
15–19 days	261,854					70,946				
20 + days	1,487,042					420,900				
Ethnic segregation index										
Ethnic diversity	52,397	0.69	0.28	0.01	1.44	15,735	0.45	0.25	0.01	1.40
Black–White dissimilarity	52,397	0.01	0.14	0	0.80	15,735	0.05	0.20	0	0.73
Hispanic–White dissimilarity	52,397	0.01	0.18	0	0.64	15,735	0.03	0.17	0	0.62
Black-White interaction	52,397	0.01	0.12	0	0.96	15,735	0.05	0.14	0	0.98
Hispanic-White interaction	52,397	0.01	0.10	0	0.96	15,735	0.05	0.16	0	0.93
Black concentration	52,397	0.002	0.11	0	0.99	15,735	0.01	0.20	0	0.97
Hispanic concentration	52,397	0.002	0.13	0	0.83	15,735	0.01	0.17	0	0.78
Control variables										
Essential occupation rate (%)	52,397	17.32	5.02	0	33.32	15,735	15.45	4.12	0	32.46
Poverty rate (%)	52,397	15.43	7.64	0	100	15,735	15.24	8.02	0	63.64
No-college-degree rate (%)	52,397	77.26	12.78	0	100	15,735	80.24	14.64	45.85	100
POI mix index	52,397	1.56	0.82	0.10	1.78	15,735	1.54	0.76	0.55	1.70
County-level Trump share (%)*	954	56.98	15.55	4.12	89.85	105	38.22	16.00	4.12	73.50
COVID-19 new cases	71,550	30	162	0	5900	7,875	42	154	0	5900

*There are 954 counties in all the 384 MSAs; 105 counties have overlaps with the top 100 cities.

were swapped, the segregation index remains unchanged. In other words, these measures did not consider population characteristics in the neighbouring neighbourhoods. To address this deficiency, we replaced the population of an ethnic group with the composite population based on Oka and Wong (2014). The composite population count means considering the population of neighbouring neighbourhoods into the population estimate of a reference neighbourhood. The composite population count of group g in neighbourhood unit i (cg_i) can be modelled by equations (1) and (2):

$$cg_i = \sum_j c_{ij} g_j \quad (1)$$

$$c_{ij} = \frac{1}{d_{ij}^{-\alpha}} (i \neq j) \ or \ c_{ij} = 1(i = j) \quad (2)$$

where g_j represents the population of ethnic group g in neighbourhood j; c_{ij} represents the inverse-distance weight between neighbourhood i and neighbourhood j, capturing the distance decay effect; d_{ij} represents the distance between neighbourhood i and neighbourhood j; α determines the effects of distance on the weight, which was tested from 1 to 5. It should be noted that we considered four primary ethnic groups based on the 2014–2018 ACS database: non-Hispanic Whites, non-Hispanic Blacks, Hispanics and non-Hispanic others considering that Hispanics and non-Hispanic Blacks account for the largest and second-largest ethnic minority populations, respectively (United States Census Bureau, 2018). For the ease of presentation, we called them Whites, Blacks, Hispanics and others in the following analysis and tables.

We acknowledge that the definition of neighbouring neighbourhoods would impact our measurement of segregation. Thus, we considered multiple definitions including the closest 10 neighbourhoods, 20 neighbourhoods, 30 neighbourhoods, 40 neighbourhoods and 50 neighbourhoods. Another approach of defining neighbouring neighbourhoods is only considering the adjacent ones. In this case, c_{ij} is the element of a binary matrix where '1' indicates neighbourhood i and j are neighbours and '0' means otherwise. In other words, a composite population count refers to the population count in areal unit i plus the population counts in its neighbouring units. We performed a robustness analysis using different values of α and definitions of neighbouring neighbourhoods. The comparative outcomes suggest that the model results are not sensitive to the varying definitions because the signs and coefficients of the variables are generally consistent.

By using the composite population of each ethnic group, we can measure the following three dimensions of neighbourhood-level ethnic segregation:

(1) Evenness represents the differential distribution of population groups. The commonly used method for the evenness is to calculate the ethnic diversity using the following equation:

$$\mathrm{Diversity_i} = -\sum_{k}^{n} \left(\frac{\mathrm{cp_{ik}}}{\mathrm{ct_i}}\right) \ln\left(\frac{\mathrm{cp_{ik}}}{\mathrm{ct_i}}\right) \quad (3)$$

where ct_i represents the composite population count of the total population for neighbourhood i, cp_{ik} represents the composite population count of mutually exclusive ethnic group k for neighbourhood i.

Even though Reardon and Firebaugh (2002) advocated the use of the ethnic diversity index, Massey and Denton (1988) claimed that the traditional dissimilarity index is best to capture the evenness dimension. This index measures the fraction of one group that would have to move to another area, in order to equalise the population distribution. The index ranges between 0 and 1, with 0 being pure integration and 1 being perfect segregation. Therefore, we also measure the Black-White Dissimilarity index and Hispanic-White Dissimilarity index using the following equations:

$$\text{Black} - \text{White Dissimilarity}_i = \left|\frac{cb_i}{CB} - \frac{cw_i}{CW}\right| \quad (4)$$

$$\text{Hispanic} - \text{White Dissimilarity}_i = \left|\frac{ch_i}{CH} - \frac{cw_i}{CW}\right| \quad (5)$$

where *cbi*, ch_i and cw_i are the composite population counts of Blacks, Hispanics and Whites in neighbourhood *i*, respectively; *CB*, *CH* and *CW* are the composite population counts of Blacks, Hispanics and Whites for the corresponding county, respectively.

(2) Exposure represents the extent to which the ethnic minority group is exposed to the dominant ethnic group using the index of *Interaction*. The Black-White Interaction and Hispanic-White Interaction are calculated by the following equations:

$$\text{Black} - \text{White Interaction}_i = \frac{cb_i}{CB} * \frac{cw_i}{ct_i} \quad (6)$$

$$\text{Hispanic} - \text{White Interaction}_i = \frac{ch_i}{CH} * \frac{cw_i}{ct_i} \quad (7)$$

(3) Concentration quantifies the distributional intensity of minority groups of a neighbourhood, using the proportion of the minority group and the proportion of the area. The formula for Black Concentration and Hispanics Concentration are below:

$$\text{Black Concentration}_i = \frac{cb_i}{CB} - \frac{\text{Area}_i}{\text{Area}_{\text{total}}} \quad (8)$$

$$\text{Hispanic Concentration}_i = \frac{ch_i}{CH} - \frac{\text{Area}_i}{\text{Area}_{\text{total}}} \quad (9)$$

where $Area_i$ represents the geometric area of neighbourhood *i* and $Area_{total}$ represents the total area of the county.

Control variables. Several control variables were also included in our study. From the *New York Times* data repository, we retrieved daily county-level infection cases (New York Times, 2020a) and the 2020 election results (New York Times, 2020b). Although the county-level data were less granular than our census-tract level data on the social-distancing behaviours, it was the best data we could obtain. We then used the 2014–2018 American Community Survey (ACS) five-year data to construct estimates of socio-demographic control variables such as the essential occupation rate, the poverty rate and the no-college-degree rate at the census tract level. The Department of Homeland Security's Cybersecurity and Infrastructure Security Agency (CISA) released an 'Essential Critical Infrastructure Workforce' advisory list of occupations necessary to the 'continuity of functions critical to public health and safety' in March 2020. Given that, we identified essential workers in each census tract by connecting the advisory list of occupations necessary with the occupation types in the 2014–2018 ACS database. Selected occupations include healthcare practitioners, production, transportation and material moving occupations, sales and office occupations, natural resources, construction and maintenance occupations and service occupations.

Land use mix index has been a popular indicator for the built environment, but, after considering that the land use categories are generally inconsistent across the different MSAs and cities, we use the Points of Interest (POI) data from SafeGraph as an alternative proxy for this index (Long and Liu, 2013). Specifically, there are over 40 million POIs in all MSAs with unified categories in commercial places, offices, hotels, industry, public services, schools, transportation and others. We computed the POI mix index using the following equation:

$$\mathrm{POI\ Mix_i} = -\sum_{L} \mathrm{p_L ln(p_L)} \quad (10)$$

where p_L represents the percentage of POI category L in the neighbourhood i.

Public orders are also an important variable to consider because they will guide and influence public health behaviours like social distancing, despite the fact that such influences may vary largely across US communities. To this end, we collected statewide stay-at-home orders from Mervosh et al. (2020). Specifically, 43 states had issued stay-at-home orders to encourage residents to shelter in place and practice social distancing. However, some counties and cities had also issued a more stringent local order than the state. For instance, the Florida governor did not issue the state-level stay-at-home order until April 1st, while most Florida counties and cities had already put directives in place by March 25th. Hence, we also collected the local-level stay-at-home order from Keystone Strategy (2020). We later combined the local-level and state-level orders to determine whether one urban census tract was under a stay-at-home order based on the earlier one.

Method

To examine the effects of ethnic segregation on social distancing, we adopted the difference-in-difference (DID) estimation method that compared neighbourhoods, census tracts in this study, with varying level dimensions of ethnic segregation before and after the stay-at-home order. The DID model specification can be written as follows:

$$\begin{aligned}&Behavior_{irt} = \alpha_i + \theta_t + \gamma_1 0to5days_{rt} \\ &\quad + \gamma_2 6to14days_{rt} + \gamma_3 15to19days_{rt} + \\ &\gamma_4 20plusdays_{rt} + \gamma_5 0to5days_{rt} \times \boldsymbol{Dimensions}_i \\ &\quad + \gamma_6 6to14days_{rt} \times \\ &\boldsymbol{Dimensions}_i + \gamma_7 14to19days_{rt} \\ &\quad \times \boldsymbol{Dimensions}_i + \gamma_8 20plusdays_{rt} \times \\ &\boldsymbol{Dimensions}_i + \boldsymbol{X}_{irt}\boldsymbol{\delta} + \varphi DailyCase_{rt} + \varepsilon_{it}\end{aligned} \quad (11)$$

where $Behavior_{irt}$ represents three types of social-distancing metrics of neighbourhood i in county r on day t. 0 to 5 days_{rt} represents a dummy variable that equals 1 for the period 0 to 5 days following a stay-at-home order adoption in county r on day t; 6 to 14 days_{rt} is an analogous dummy variable for the period 6 to 14 days following adoption; 15 to 19 days_{rt} represents the dummy variable for the period 15 to 19 days following adoption; $\mathrm{20plusdays}_{rt}$ represents the dummy variable for 20 or more days following adoption. The time windows are categorised based on the incubation period of COVID-19 (Lauer et al., 2020). We also plot the distribution of '20 plus days' (Figure 1). It shows that the longest number is 60 days in our analysis, and most census tracts are at least under 40 days following a stay-at-home order. $\boldsymbol{Dimensions}_i$ represents the selected dimensions of ethnic segregation of neighbourhood i. α_i represents the neighbourhood fixed effects; θ_t represents the day fixed effects. $\boldsymbol{X}_{irt}$ is a vector of interaction variables by interacting time periods with control variables.

Results

Table 2 shows the raw effect of stay-at-home order on social-distancing behaviours. Table 3 reports the regression results based on the

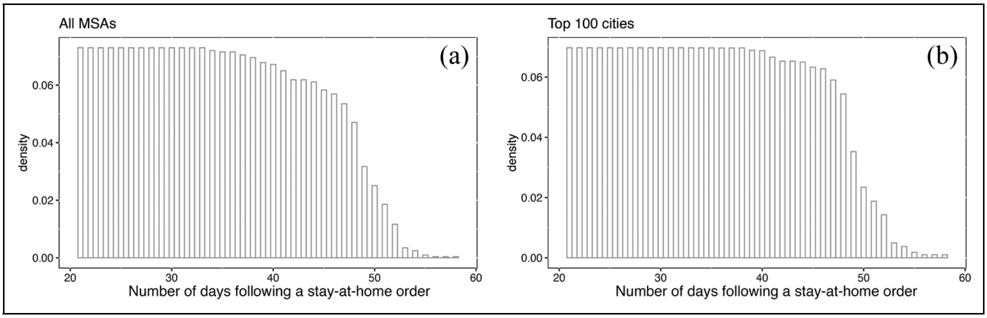

Figure 1. The distribution of '20 + days' following a stay-at-home order.

DID model specification. The interaction terms with ethnic segregation dimensions and control variables examine how the effect of the order was moderated by the different variables. For example, the negative coefficient estimate (– 0.009) of the interaction term of the '0–5 day × Black-White Dissimilarity' (row 9, column 1, Table 3) represents that the Black-White Dissimilarity moderates the effect of '0–5 days' on work behaviour by further reducing the percentage of users going to work.

Overall, the model results show that all the interaction terms are statistically significant, which supports our selection of variables. Also, it is not surprising that the reported coefficients are highly statistically significant because we have relatively huge sample sizes. The control variables also show consistent coefficients and significance (row 33–53). At first glance, the essential occupation variable is positively associated with all the social distancing metrics, which implies that people who work in essential occupations are generally less likely to practice social distancing. The reported number of cases appears to positively influence public social-distancing behaviours as more cases are being reported in a community would increase fear and worries about the virus and thus lead to greater protective measures such as social distancing. Furthermore, the coefficients of Trump Share are all negative, which aligns with the findings of Gollwitzer et al. (2020) indicating that Republicans are generally less likely to comply with stay-at-home orders. In the following, we will disentangle the model results in greater detail concerning each of the social distancing metrics.

Work behaviour

The overall work behaviours would generally decrease after the issuance of stay-at-home (Table 2). However, the trends were obviously different when comparing our sample of MSAs to the largest cities. That is the decreases of work behaviours were relatively stable over time in the MSAs, while the decreases were accelerating in the largest cities. It seems reasonable that people in big cities are more likely to work from home due to fewer essential workers so that the decreases of work behaviours accelerated whereas there are still some surrounding counties that may have relatively more essential workers in MSAs. It might also be that the major city has a more stringent order due to continuous enforcement.

From row 5–8 in both column 1 and 4 (Table 3), the coefficients of ethnic diversity are consistently positive and statistically significant, which implies that the percentages of work behaviours were more likely to be

Table 2. Raw effects of stay-at-home order.

Independent variables	Group 1: metropolitan statistical areas			Group 2: top 100 largest cities		
	(1) Work behaviour	(2) Distance travelled	(3) Non-home time	(4) Work behaviour	(5) Distance travelled	(6) Non-home time
0–5 Days	−0.032*** (0.001)	0.023*** (0.001)	−0.043*** (0.001)	−0.057*** (0.005)	0.054*** (0.007)	−0.056*** (0.005)
6–14 Days	−0.024*** (0.002)	0.011*** (0.002)	−0.012*** (0.001)	−0.065*** (0.006)	0.121*** (0.007)	−0.025*** (0.005)
15–19 Days	−0.023*** (0.002)	0.073** * (0.003)	−0.048*** (0.002)	−0.079*** (0.007)	0.153*** (0.009)	−0.024*** (0.007)
20 + Days	−0.022*** (0.003)	0.101*** (0.003)	−0.074*** (0.002)	−0.085*** (0.008)	0.214*** (0.009)	−0.020*** (0.007)
Census tract fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,665,579	3,665,579	3,665,579	994,358	994,358	994,358
R-squared	0.63	0.55	0.72	0.74	0.60	0.73

Note: The number in parentheses is a standard error; Each column reports the standardised coefficient.
***$p < 0.01$.

Table 3. Regression results (α = 2, number of neighbouring neighbourhoods = 20).

Row	Independent variables	Group 1: Metropolitan Statistical Areas			Group 2: Top 100 Largest Cities		
		(1) Work behaviour share	(2) Distance travelled	(3) Non-home time	(4) Work behaviour share	(5) Distance travelled	(6) Non-home time
1	0–5 days	−0.049 (0.002)***	0.011 (0.002)***	−0.048 (0.002)***	−0.021 (0.006)***	0.023 (0.003)***	−0.089 (0.011)***
2	6–14 days	−0.026 (0.002)***	0.028 (0.002)***	−0.047 (0.002)***	−0.027 (0.003)***	0.025 (0.007)***	−0.049 (0.014)***
3	15–19 days	−0.022 (0.003)***	0.027 (0.003)***	−0.045 (0.002)***	−0.019 (0.004)***	0.024 (0.005)***	−0.029 (0.008)***
4	20 + days	−0.013 (0.001)***	0.041 (0.004)***	−0.045 (0.003)***	−0.024 (0.008)***	0.033 (0.005)***	−0.027 (0.007)***
	Evenness of segregation						
5	0–5 days×Ethnic diversity	0.039 (0.002)***	0.003 (0.001)***	0.015 (0.002)***	0.060 (0.011)***	0.019 (0.003)***	0.016 (0.001)***
6	6–14 days×Ethnic diversity	0.031 (0.003)***	0.006 (0.001)***	0.024 (0.003)***	0.044 (0.009)***	0.028 (0.004)***	0.030 (0.005)***
7	15–19 days×Ethnic diversity	0.020 (0.002)***	0.008 (0.001)***	0.040 (0.002)***	0.045 (0.012)***	0.069 (0.015)***	0.047 (0.008)***
8	20 + days×Ethnic diversity	0.019 (0.001)***	0.010 (0.002)***	0.043 (0.003)***	0.035 (0.007)***	0.078 (0.019)***	0.057 (0.007)***
9	0–5 days×Black–White dissimilarity	−0.009 (0.002)***	−0.005 (0.002)* *	−0.009 (0.002)***	−0.024 (0.011)* *	−0.024 (0.007)***	−0.018 (0.005)***
10	6–14 days×Black–White dissimilarity	−0.006 (0.001)***	−0.007 (0.002)***	−0.003 (0.001)***	−0.028 (0.009)***	−0.022 (0.006)***	−0.017 (0.003)***
11	15–19 days×Black–White dissimilarity	−0.004 (0.002)* *	−0.006 (0.003)* *	−0.009 (0.003)***	−0.036 (0.010)***	−0.011 (0.002)***	−0.015 (0.003)***
12	20 + days×Black–White dissimilarity	−0.004 (0.001)***	−0.005 (0.001)***	−0.004 (0.001)***	−0.033 (0.009)***	−0.018 (0.006)***	−0.022 (0.004)***
13	0–5 days×Hispanic–White dissimilarity	−0.006 (0.002)***	−0.006 (0.002)***	−0.013 (0.002)***	−0.021 (0.010)* *	−0.024 (0.010)* *	−0.032 (0.011)***
14	6–14 days×Hispanic–White dissimilarity	−0.008 (0.001)***	−0.002 (0.001)* *	−0.006 (0.001)***	−0.010 (0.002)***	−0.018 (0.005)***	−0.051 (0.010)***
15	15–19 days×Hispanic–White dissimilarity	−0.007 (0.002)***	−0.008 (0.002)***	−0.006 (0.001)***	−0.017 (0.008)* *	−0.011 (0.003)***	−0.039 (0.012)***
16	20 + days×Hispanic– White Dissimilarity	−0.005 (0.001)***	−0.007 (0.002)***	−0.007 (0.001)***	−0.022 (0.007)***	−0.009 (0.003)***	−0.033 (0.010)***
	Exposure of segregation						
17	0–5 days×Black-White interaction	0.028 (0.006)***	0.011 (0.002)***	0.037 (0.006)***	0.090 (0.020)***	0.038 (0.010)***	0.053 (0.018)***
18	6–14 days×Black-White interaction	0.021 (0.005)***	0.012 (0.002)***	0.057 (0.004)***	0.048 (0.022)* *	0.033 (0.011)***	0.043 (0.020)* *
19	15–19 days×Black-White interaction	0.032 (0.006)***	0.014 (0.003)***	0.062 (0.006)***	0.068 (0.023)***	0.033 (0.012)***	0.033 (0.010)***
20	20 + days×Black-White interaction	0.029 (0.004)***	0.008 (0.002)***	0.044 (0.003)***	0.107 (0.031)***	0.040 (0.008)***	0.032 (0.010)***
21	0–5 days×Hispanic-White interaction	0.017 (0.006)***	0.015 (0.007)* *	0.037 (0.005)***	0.093 (0.040)* *	0.058 (0.011)***	0.035 (0.017)* *
22	6–14 days×Hispanic-White interaction	0.016 (0.005)***	0.020 (0.005)***	0.049 (0.004)***	0.047 (0.010)***	0.035 (0.010)***	0.038 (0.019)* *
23	15–19 days×Hispanic-White interaction	0.024 (0.006)***	0.026 (0.007)***	0.049 (0.005)***	0.037 (0.011)***	0.050 (0.012)***	0.044 (0.020)* *
24	20 + days×Hispanic-White interaction	0.026 (0.004)***	0.022 (0.004)***	0.036 (0.003)***	0.087 (0.010)***	0.086 (0.016)***	0.035 (0.009)***
	Concentration of segregation						
25	0–5 days×Black concentration	−0.032 (0.007)***	0.018 (0.002)***	0.062 (0.006)***	−0.116 (0.016)***	0.024 (0.009)***	0.022 (0.004)***
26	6–14 days×Black concentration	−0.033 (0.006)***	0.010 (0.002)***	0.085 (0.005)***	−0.162 (0.016)***	0.030 (0.009)***	0.039 (0.009)***
27	15–19 days×Black concentration	−0.030 (0.008)***	0.014 (0.003)***	0.088 (0.006)***	−0.130 (0.010)***	0.036 (0.010)***	0.028 (0.008)***
28	20 + days×Black concentration	−0.035 (0.004)***	0.019 (0.004)***	0.055 (0.004)***	−0.134 (0.011)***	0.065 (0.011)***	0.035 (0.012)***

(continued)

Table 3. Continued

Row	Independent variables	Group 1: Metropolitan Statistical Areas			Group 2: Top 100 Largest Cities		
		(1) Work behaviour share	(2) Distance travelled	(3) Non-home time	(4) Work behaviour share	(5) Distance travelled	(6) Non-home time
29	0–5 days×Hispanic concentration	−0.036 (0.006)***	0.021 (0.007)***	0.042 (0.005)***	−0.205 (0.014)***	0.049 (0.012)***	0.025 (0.008)***
30	6–14 days×Hispanic concentration	−0.044 (0.005)***	0.028 (0.006)***	0.055 (0.005)***	−0.229 (0.016)***	0.051 (0.016)***	0.022 (0.006)***
31	15–19 days×Hispanic concentration	−0.041 (0.007)***	0.033 (0.008)***	0.054 (0.006)***	−0.221 (0.018)***	0.043 (0.015)***	0.022 (0.007)***
32	20 + days×Hispanic concentration	−0.042 (0.004)***	0.027 (0.004)***	0.040 (0.003)***	−0.207 (0.014)***	0.079 (0.012)***	0.024 (0.008)***
	Control variable						
33	0–5 days×Essential occupation rate	0.132 (0.006)***	0.013 (0.002)***	0.111 (0.002)***	0.201 (0.003)***	0.078 (0.002)***	0.082 (0.003)***
34	6–14 days×Essential occupation rate	0.121 (0.002)***	0.010 (0.002)***	0.123 (0.002)***	0.183 (0.002)***	0.023 (0.005)***	0.078 (0.002)***
35	15–19 days×Essential occupation rate	0.102 (0.003)***	0.011 (0.001)***	0.132 (0.003)***	0.174 (0.002)***	0.0.45 (0.006)***	0.093 (0.003)***
36	20 + days×Essential occupation rate	0.087 (0.002)***	0.013 (0.003)***	0.092 (0.004)***	0.147 (0.002)***	0.031 (0.004)***	0.102 (0.004)***
37	0–5 days×Poverty rate	0.164 (0.001)***	0.058 (0.002)***	0.182 (0.001)***	0.077 (0.012)***	0.036 (0.010)***	0.052 (0.011)***
38	6–14 days×Poverty rate	0.162 (0.001)***	0.050 (0.002)***	0.147 (0.001)***	0.115 (0.010)***	0.234 (0.012)***	0.212 (0.010)***
39	15–19 days×Poverty Rate	0.169 (0.003)***	0.038 (0.002)***	0.124 (0.001)***	0.101 (0.012)***	0.120 (0.016)***	0.186 (0.013)***
40	20 + days×Poverty rate	0.166 (0.002)***	0.008 (0.001)***	0.092 (0.001)***	0.125 (0.007)***	0.023 (0.009)***	0.106 (0.007)***
41	0–5 days×No-college-degree rate	0.041 (0.001)***	0.037 (0.001)***	0.055 (0.002)***	0.164 (0.011)***	0.108 (0.014)***	0.212 (0.010)***
42	6–14 days×No-college-degree rate	0.046 (0.001)***	0.042 (0.001)***	0.060 (0.001)***	0.179 (0.010)***	0.152 (0.012)***	0.287 (0.009)***
43	15–19 days×No-college-degree rate	0.037 (0.002)***	0.016 (0.002)***	0.073 (0.002)***	0.204 (0.012)***	0.139 (0.015)***	0.317 (0.012)***
44	20 + days×No-college-degree rate	0.047 (0.002)***	0.022 (0.001)***	0.059 (0.001)***	0.194 (0.007)***	0.091 (0.009)***	0.255 (0.007)***
45	0–5 days×Trump share	−0.009 (0.002)***	−0.008 (0.002)***	−0.040 (0.001)***	−0.018 (0.003)***	−0.137 (0.013)***	−0.058 (0.010)***
46	6–14 days×Trump share	−0.038 (0.003)***	−0.007 (0.001)***	−0.059 (0.001)***	−0.039 (0.009)***	−0.137 (0.011)***	−0.149 (0.009)***
47	15–19 days×Trump share	−0.033 (0.002)***	−0.007 (0.001)***	−0.065 (0.001)***	−0.024 (0.011)* *	−0.108 (0.013)***	−0.149 (0.011)***
48	20 + days×Trump share	−0.026 (0.003)***	0.003 (0.002)***	−0.028 (0.002)***	−0.026 (0.006)***	−0.245 (0.008)***	−0.048 (0.006)***
49	0–5 days×POI mix	−0.027 (0.003)***	−0.012 (0.001)***	−0.018 (0.001)***	−0.045 (0.009)***	−0.017 (0.003)***	−0.033 (0.009)***
50	6–14 days×POI mix	−0.034 (0.004)***	−0.016 (0.001)***	−0.016 (0.001)***	−0.041 (0.007)***	−0.019 (0.009)* *	−0.022 (0.007)***
51	15–19 days×POI Mix	−0.032 (0.002)***	−0.015 (0.002)***	−0.015 (0.002)***	−0.031 (0.009)***	−0.011 (0.005)* *	−0.029 (0.009)***
52	20 + days×POI mix	−0.034 (0.003)***	−0.014 (0.001)***	−0.017 (0.001)***	−0.010 (0.002)***	−0.018 (0.006)***	−0.015 (0.005)***
53	COVID-19 new cases	−0.013 (0.001)***	−0.028 (0.002)***	−0.015 (0.001)***	−0.013 (0.003)***	−0.016 (0.003)***	−0.011 (0.001)***
54	Census tract fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
55	Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
56	Observations	3,665,579	3,665,579	3,665,579	994,358	994,358	994,358
57	*R*-squared	0.64	0.56	0.74	0.75	0.61	0.76

Note: The number in parentheses is a standard error; Each column reports the standardised coefficient.
* *$p < 0.05$. ***$p < 0.01$.

higher in more ethnically diverse neighbourhoods. Interestingly, the magnitude of the coefficients is the greatest during the period of zero to five days after the enactment of the order. This might be due to the interplay between the high proportion of essential occupation workers in these neighbourhoods and the decreasing demand for such occupations over time because of the majority population starting to stay at home, thereby requiring less service and resulting in increasing unemployment. The coefficients of Black-White dissimilarity and Hispanic-White dissimilarity are all negative (row 9–16). That is, a higher dissimilarity between ethnic minorities and Whites, which represents more segregation, may be associated with a lower proportion of work behaviour.

The exposure variables indicate that both the Black-White and Hispanic-White interactions are positively associated with work behaviour in both groups (row 17–24). The higher value of the interaction index indicates that ethnic minorities have a higher chance to interact with non-Hispanic Whites. These finding indeed reinforces the theory of ethnic community that assumes that the isolated communities could, in turn, have a better performance in health behaviours.

From the concentration dimension (row 25–32), results indicate that both the Black and Hispanic concentration in a neighbourhood would reduce a neighbourhood's average percentage of work behaviours at an increasing rate over time after a public order. It generally suggests that people in neighbourhoods with a high Black and Hispanic concentration would be less likely to go to work after the issuance of the stay-at-home order. It aligns with the existing literature that minority populations like non-Hispanic Blacks and Hispanics have been suffering a high unemployment rate during this pandemic (Fairlie et al., 2020). Moreover, it could be because ethnic minorities were disproportionately doing part-time jobs from which they were laid-off during the early outbreak of the pandemic (Fairlie et al., 2020).

Travel distance

Without controlling for other variables, the average travel distance actually increased in both study groups (Table 2). This may be explained by the lack of immediate restriction of long-distance travel and the cross-state travel, yet, some states permitted it with varying degrees of quarantine. In the meantime, there were observed increases in visits of relatives and friends, long-distance shopping trips to secure essential items, and spring break vacations among students during spring break (Mangrum and Niekamp, 2020; Zhang et al., 2021). The increases in travel patterns after the stay-at-home order were also arguably due to quarantine fatigue when the order prolonged people to comply with the stay-at-home order, thereby making people travel longer distances outside their homes when seeking a break (Zhao et al., 2020).

From row 5–8 in both column 2 and 5 (Table 3), residents were more likely to take a longer trip in more ethnically diverse neighbourhoods. Additionally, the coefficients of ethnic diversity display an upward trend over the time windows in both groups, suggesting that the greater effects took time to materialise along with the continuing pandemic. Similar to the effects on work behaviour, the higher dissimilarity between ethnic minorities and non-Hispanic Whites, namely high segregation, could lead to less travel distance after the issuance of a stay-at-home order (row 9–16). Thus, both the ethnic diversity index and dissimilarity index show that more segregated neighbourhoods have less travel distance.

Interestingly, both the Black-White interaction and Hispanic-White interaction variable coefficients are positive following an order (row 17–24), but the magnitude of the coefficients for the Black-White interaction term appears to be less than those of the Hispanic-White interaction term. It implies that the greater interaction between ethnic minorities and non-Hispanic Whites would lead to additional travel distance during the early stage of the directive. This aligns with the preceding findings of work behaviour, which suggests that the isolation of ethnic minorities seems to be beneficial for altruistic behaviours. The results are quite consistent for MSAs and large cities.

Our model coefficients of the Black concentration and Hispanic concentration are positive in both groups (row 25–32). It demonstrates that if the ethnic minorities are more densely concentrated within a neighbourhood, the average trip distance generated from the corresponding neighbourhood would be greater. The coefficients of Black concentration are less than that of Hispanic concentration, indicating that the density of Hispanics may have a higher association with the travel distance during the early outbreak. It confirms some of the existing findings that Hispanics had higher rates of infection than non-Hispanic Blacks, driven by pre-existing health conditions and lower quality health care (Anyane-Yeboa et al., 2020). Another possible reason is that some public health outreach materials (related to the social-distancing guidance or vaccine roll-out) were not translated into Spanish and other languages at the same time as the English language materials were disseminated (Velasquez et al., 2020).

Non-home time

According to Table 2, we found that the order was generally effective in reducing non-home time, which suggests that people were more likely to stay at home after the issuance of the order. It implies that public health orders are generally effective on a macro level but they may not be as effective when we scrutinise the public health behaviours of minority populations.

Model results from row 5–8 in column 3 and column 6 on non-home time are generally consistent with our previous findings and discussions (Table 3). People in neighbourhoods with higher ethnic diversity were likely to spend more time outside of the home and they appeared to travel even more over time after the order. The Black-White dissimilarity and Hispanic-White dissimilarity are also negatively associated with non-home time (row 9–16), in line with preceding findings of work behaviour share and distance travelled. The Black-White interaction and Hispanic-White interaction are both positively associated with the percentage of non-home time in both groups (row 17–24), which implies that if ethnic minorities were more exposed to non-Hispanic Whites, the altruistic behaviour of the neighbourhood would decrease.

The model coefficients of Black concentration and Hispanic concentration are all positive (row 25–32). Again, the results suggest that ethnic minorities would exhibit less compliance with stay-at-home orders. It also, in part, confirms the findings from Yang et al. (2021), Millett et al. (2020) and Hu et al. (2020), which all found that segregated ethnic minorities had suffered the highest cases of COVID-19. It can be inferred that, due to the structural inequalities, ethnic minorities are more involved in essential occupations, requiring them to work outside of their home, sometimes even with more time, during the pandemic.

Discussion and conclusion

Revisiting the theoretical debate

Based on our empirical findings using the census tracts in MSAs and large cities, we found significant associations between ethnic segregation and social-distancing behaviours, but different dimensions of segregation may have varying findings of the association.

First, we found that individuals in a more ethnically diverse neighbourhood were less likely to practice social distancing following a stay-at-home order. One plausible reason is that ethnic diversity could be detrimental to public cooperation because individuals in a diverse neighbourhood would normally face difficulties in enforcing social norms across different ethnic lines (Winter and Zhang, 2018). Hence, informal social norms like practicing social distancing amid the pandemic can be more difficult to maintain in these neighbourhoods. Many have also argued that ethnic diversity would even lead to adverse collective outcomes such as low levels of mutual trust or a lack of social capital and civic engagement (e.g. Abascal and Baldassarri, 2015; Uslaner, 2012). Our findings indeed support such propositions. Even though Egorov et al. (2021) argue that ethnically diverse communities could actually exhibit higher stay-at-home behaviours based on the theory of *other-regarding preferences*, this theoretical mechanism would fail to explain the collective actions because people generally attach positive utility to the welfare of the same ethnic groups rather than to other ethnic groups (Habyarimana et al., 2007).

Additionally, our results show that the higher interaction index potential is, the lower compliance with social distancing orders would be, arguably because of the increased antisocial behaviours. This finding, in part, contradicts the perspective of ethnic stratification, which argues that more intergroup social connections would be beneficial to collective actions and altruistic behaviours (Ostrom and Ahn, 2009). Even though our research cannot substantiate this contradiction, this finding is intuitive for this pandemic because the choice of affluent people to distance themselves is on the pursuit of self-interest (Egorov et al., 2021). Furthermore, ethnic minorities are more willing to self-isolate within their neighbourhoods because of out-group distrust when considering the main risk of asymptomatic transmission (Egorov et al., 2021; van Bavel et al., 2020). Additionally, it also underscores the importance of mutual trust among ethnic groups because social-distancing behaviour is largely determined by people's willingness.

Lastly, the concentration dimension also shows varying effects on neighbourhood-level social distancing behaviours. On the one hand, the concentration dimension is positively associated with travel distance and non-home time. This finding is partly because many of the non-Hispanic Blacks were disproportionately involved in essential work, and therefore had to continue to go to their workplaces exposing themselves to the virus (Hawkins, 2020). On the other hand, we found that work behaviours decreased in neighbourhoods with a high Black or Hispanic concentration. This is because ethnic minorities have significantly suffered from the increasing unemployment rate since March 2020 with the ensuing related economic devastation (Fairlie et al., 2020).

Long-term trends

Although the focus of this research lies in the social-distancing behaviours during the early outbreak of COVID-19, the long-term trends are also attractive and important for future containment actions. Figure 2 shows the trends of three social distancing indicators in all MSAs and the top 100 largest cities. The overall trends of MSAs or cities are similar to each other, even though some outliers exist. Not surprisingly, the temporal variations of mean values are quite consistent with our findings in Table 2, suggesting that the mean of working rate and non-home

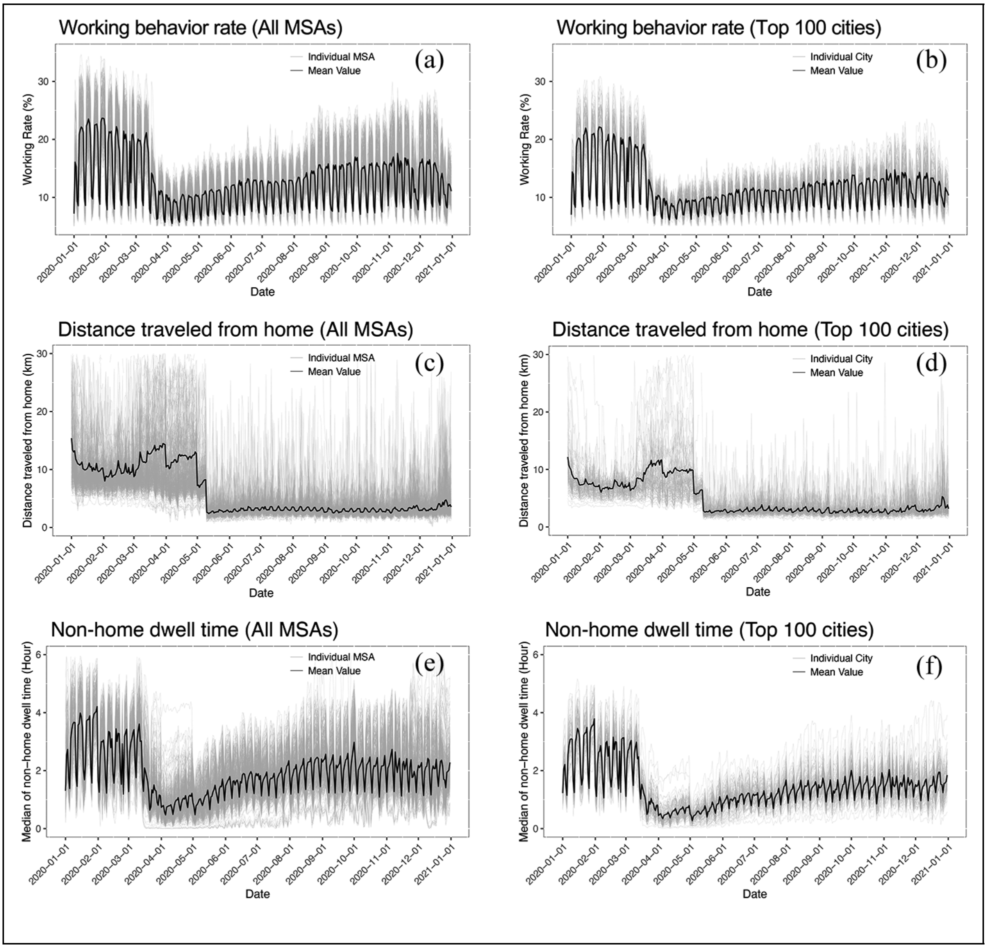

Figure 2. The temporal changes of social-distancing measures in 2020: (A) working behaviour rate (all MSAs), (B) working behaviour rate (top 100 cities), (C) distance travelled from home (all MSAs), (D) distance travelled from home (top 100 cities), (E) non-home dwell time (all MSAs) and (F) non-home dwell time (top 100 cities).

time decreased significantly and the mean of travel distance, in turn, increased between March and May 2020. Interestingly, with the reopening of many restaurants and public schools since the middle of May, the working rate and non-home dwell time gradually increased and then stabilised. On the contrary, there is a significant drop in travel distance since the middle of May, without a clear increasing trend. Despite the detected discrepancies, all the temporal trends of these metrics collectively show that new normal patterns emerge during the second half of 2020 yet they have so far failed to bounce back to their pre-pandemic state.

Limitations

Admittedly, there are limitations to this study. The first is related to the quality of this 'big' data. For example, the temporal definitions of home and work behaviours are not robustly validated. It is highly possible that some phones are owned by non-workers and not all workers work during the defined time period, especially night shift workers, and their workplaces may not be temporally bounded. However, due to the limited access to the raw data, we may not be able to perform the sensitivity analysis in the study by testing varying definitions of work behaviours.

Second, even though we applied the concept of the composite population to capture the spatial nature of ethnic segregation, the spatial dependence has not been specifically examined in the regression analysis. The main reason is that the study areas are the urban census tracts in different MSAs or big cities, which are spatially separated across the country. In addition, conventional spatial regression models (e.g. spatial lag model and the spatial error model) may not capture the impacts before and after the stay-at-home order, where the DID model shows advantages. Furthermore, our national study used the stay-at-home orders issued by states, counties and cities, which failed to consider local institution's COVID-19 policy, such as the closure of a university that may also significantly influence social-distancing behaviours. We suggest that future studies focus on one region, MSA or city for an in-depth analysis to examine local spatial dependence between census tracts (e.g. Hu et al., 2020) as well as to explore how local institutions have affected social-distancing behaviours.

Lastly, this study largely focussed on the early outbreak of COVID-19. Our preliminary analysis of the long-term variations of social-distancing behaviours shows that there is a new normal during the second half of 2020. However, the long-term effects of ethnic segregation on social distancing behaviours remain understudied and merit future research.

Conclusions

Based on this national empirical study, we find that people are less likely to stay at home in an ethnically diverse neighbourhood, the higher interaction between ethnic minorities and non-Hispanic Whites could lead to less compliance with stay-at-home orders, and a higher concentration of non-Hispanic Blacks or Hispanics could lead to more distance travelled and more non-home dwell time. Our empirical findings show that the use of an ethnic segregation dimension matters for the theoretical debate between ethnic stratification and ethnic community when it comes to people's health behaviours.

In conclusion, this study suggests that special attention needs to be paid to the varying groups of the population because people can exhibit very different behaviour changes in the face of health risks. We must admit that the socio-political complexity and the difficulty in adopting varying orders issued in different places, but the government could, at least, more efficiently and effectively allocate resources and enforce the orders by targeting more ethnically diverse neighbourhoods. Additionally, the stay-at-home order and related containment measures should also consider the public quarantine fatigue and its long-term effectiveness. The orders did meet their immediate public health needs, but not the long-run objective, with increasing out-of-home activities permitted in later orders, which consequently lead to subsequent waves of the viral outbreak. We finally would like to urge caution in rushing to ease the restrictive orders. Specifically, local government could incrementally ease the order in steps, for example, by prioritising industries that present the lowest risk of infection for customers and employees.

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