Neighbourhood greenspace quantity, quality and socioeconomic inequalities in mental health

Citation for published version:
Wang, R & Pearce, J 2022, 'Neighbourhood greenspace quantity, quality and socioeconomic inequalities in mental health ', *Cities*, vol. 129, 103815. https://doi.org/10.1016/j.cities.2022.103815

Digital Object Identifier (DOI):
10.1016/j.cities.2022.103815

Published In:
Cities

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Abstract

There is tentative evidence suggesting that socioeconomically disadvantaged groups may benefit more from access to neighbourhood greenspace and therefore could be a lever for narrowing socioeconomic inequalities ('equigenesis') in mental health, although studies are equivocal. One potential explanation for this inconsistency is differences in study designs, particularly how greenspace is measured. Most previous studies are from high income countries, and there has been no investigations into equigenic environments in China. Using survey data collected from 26 neighbourhoods in Guangzhou, China, this study examines whether local greenspaces may narrow socioeconomic inequalities in health (i.e. equigenesis) in the Chinese context. The study is the first to explore the contribution of greenspace in reducing socioeconomic inequalities in mental health in the Chinese context. It uses Normalized Difference Vegetation Index (NDVI), Street View Greenness (SVG) and self-reported neighbourhood greenness quality as estimates of residential greenness exposure Results show that SVG-quantity, SVG-quality and self-reported greenspace quality narrow the neighbourhood socioeconomic inequalities in mental health. Our findings demonstrate the importance of improving equity in local green infrastructure for promoting health equity through urban planning and design, including improving access to green spaces, and providing more street trees in socioeconomically disadvantaged neighbourhoods.

Keywords

Greenspace quantity; Greenspace quality; Socioeconomic inequalities; Mental health; 'Equigenesis' theory

1. Introduction

The increase in the prevalence of mental health problems has become a major policy concern across the world, with huge financial implications for many countries (Frankish et al., 2018; Wu et al., 2021). Mental health problems can cost the global economy as much as $16 trillion from 2010 to 2030 if it does not get enough attention (Frankish et al., 2018). Socio-economic inequalities in mental health have become a global public health issue for a long time (Marmot and Bell, 2012). Although great efforts have been made to reduce inequalities in mental health (Ngui et al., 2010), people with low SES are still more likely to have worse mental health, since they are often unable to access sufficient health-related resources (e.g., psychological counseling) (Lorant et al., 2003). One opportunity for helping to narrow the socioeconomic inequalities in mental health is enhancing the provision of neighbourhood greenspace (Mitchell et al., 2015; Pearce et al., 2016). 'equigenesis' theory indicates that the health of people with low socio-economic status (SES) or living in socioeconomically disadvantaged neighbourhood may disproportionately benefit from key social, physical or service environments (Mitchell et al., 2015; Pearce et al., 2016). However, existing evidence for 'equigenesis' theory is inconsistent (Feng and Astell-Burt, 2017; Maas et al., 2006; McEachan et al., 2016; Sugiyama et al., 2016). Some studies find evidence to support it (Maas et al., 2006; McEachan et al., 2016), while others do not (Feng and Astell-Burt, 2017; Sugiyama et al., 2016). Some scholars further argued that the inconsistency of existing evidence may be partly due to the measurement of greenspace (e.g., greenspace quantity v.s greenspace quality) (Feng and Astell-Burt, 2017). Such hypothesis has not be fully confirmed and needs to be further investigated.

This study aims to explore whether neighborhood greenspace quantity and quality have stronger associations with mental health for socioeconomic disadvantaged groups ('equigenesis') in China using street view data and survey data collected from 26 neighbourhoods of Guangzhou. It particularly focuses on the extent to which greenspace quantity and quality moderate the association between residents' SES and mental health. This study extends previous research in several respects. First, it enhances our knowledge of the 'equigenesis' theory in developing countries. Existing evidence from 'equigenesis' related studies in China and other developing countries is inconsistent (Hong et al., 2021; Wu et al., 2021), which indicates that different findings are found in different parts of the world. One possible explanation for such inconsistency may be due to the different ways in which the analyses have been operationalized, including the various ways in which SES has been measured (e.g. educational-level, income) and greenspace exposure captured (e.g. distance to nearest greenspace, % greenness of area). Second, and related, previous studies have tended to evaluate socioeconomic circumstances at the area level which may be a weak proxy for individual-level SES, and unsurprisingly the results are mixed (Feng and Astell-Burt, 2017; Sugiyama et al., 2016). In this study, socioeconomic circumstances are measured at both individual and neighbourhood levels which improves our understanding of socioeconomic inequalities in health. Third, the current study uses a range of theoretically-driven metrics to measure the level of neighbourhood greenspace exposure, thereby enabling the comparison between greenspace quantity and quality.

2. Literature review

2.1 Greenspace and health inequalities

'Equigenesis' theory suggests that people with low SES or living in socioeconomically disadvantaged neighbourhood may benefit more from key social, physical or service environments such as greenspace (Mitchell et al., 2015; Pearce et al., 2016), which indicates that greenspace may narrow the SES inequalities in health. Evidence of equigenesis comes mostly from European studies, most notably work on greenspace and mental health (Mitchell et al., 2015; Pearce et al., 2016). Mitchell et al. (2015) pointed out that people with low SES or living in SES disadvantaged areas can benefit more from greenspace than those who live in higher SES areas, because people living in higher SES areas can benefit their health through different health-related resources and greenspace is only one of them. However, public greenspace is shared by all residents, so even people with low SES or living in SES disadvantaged areas can still benefit from local greenspace (Mitchell, 2013) which promotes greater health equity. There are further empirical studies support the 'equigenesis' theory for mental health (Maas et al., 2006; McEachan et al., 2016). For example, Mass et al. (2006) found that people with low SES benefit more from greenspace exposure for their mental health. However, other studies did not report any supportive evidence for this theory (Feng and Astell-Burt, 2017; Sugiyama et al., 2016). For instance, Sugiyama et al. (2016) did not find evidence to support that greenspace can narrow the psychological distress inequalities for people with different SES.

2.2 Measurement of greenspace and equigenesis

Some scholars argued that the inconsistency of the moderating role of greenspace may be partly due to the measurement of greenspace (Feng and Astell-Burt, 2017). In some places, greenspace is with high quantity but low quality (i.e unsafe) and local residents may reduce their access to it (Jiang et al., 2019; Weimann et al., 2017; Zhong et al., 2020). Under such circumstance, people with low SES or living in socioeconomically disadvantaged neighbourhood can not benefit more from greenspace exposure. Previous studies mainly focus on the effect of greenspace quantity and greenspace quality has been largely ignored (Van Dillen et al., 2012). Thus few studies have investigated the 'equigenesis' theory based on greenspace quality (Feng and Astell-Burt, 2017). The lack of attention on greenspace quality for most previous studies is mainly due to methodological limitations (Brindley et al., 2019). Traditional methods for assessing greenspace quality include two approaches: one is survey questionnaire which asks respondents a single question about their perception of their neighbourhood greenspace (Feng and Astell-Burt, 2017); the other is field audit which requires human auditors to walk through the neighbourhood and rate quality score based on a rating scale (Van Dillen et al., 2012). However, both of these approaches have limitations including self-reported bias, inefficient, human-intensive and expensive, so they may be not applicable to large scale studies. In recent years, some scholars begin to use street view images for field audit, because it can help investigators save more time and provide them with plenty of field scenery in research areas (Rundle et al., 2011). For example, Lu (2019) assessed greenspace quality based on street view data and found its results are similar to that from actual field audit. Thus, further combining street view data with machine learning method can proceed the application of greenspace quality for large scale health studies.

3. Methodology

Data

This study used the survey data to explore whether greenspace has an equigenic impact on mental health association in China. The survey data were collected in Guangzhou by a research team from Sun Yat-Sen University between March and August in 2017. The survey respondents were selected based on a multi-stage stratified PPS (probability proportionate to population size) sampling technique. First, 26 residential neighbourhoods (she qu) were selected randomly from seven districts (qu) (Fig S1). Second, 39 households from each sampled neighbourhood were chosen randomly. Last, one adult member from each household was chosen to answer the questionnaire based on the Kish Grid. The questionnaire has a filter section which aims to exclude participants who are under 18, do not live in the targeted neighbourhood, or are students. The survey yielded a total of 1003 valid respondents. The demographic characteristics of the participants are consistent with the general population based on census data in Guangzhou (Table S1), which indicates that the study samples are representative. The questionnaire survey was approved by Sun Yat-sen University and all participants gave informed consent.

Measures

Outcome

SCL-90 Depression and Anxiety

We used the SCL-90 (Symptom Checklist-90) to evaluate participants' depression and anxiety (Morgan et al., 1998). Depression was measured by thirteen-item depression subscale of SCL-90 (Symptom Check List-90) (Morgan et al., 1998) while anxiety was measured by eight-item depression subscale of SCL-90 (Morgan et al., 1998). The SCL-90-Depression scale is related to depressive symptoms over the past week while the SCL-90-Anxiety scale is related to anxious symptoms over the same period. Each item is rated on a five-point Likert scale, ranging from "never" to "serious." We calculated the sum score of SCL-90-Deprssion (13-65) and SCL-90-Anxiety (8-40). The higher the score, the more depressive (anxious) symptoms. The SCL-90 has been shown to have good validity and reliability across many countries (Kim et al., 1992). Cronbach's alpha indicates a high internal consistency among the five items (both>0.80).

Exposure to neighbourhood greenness

Since the inconsistent findings of 'equigenesis' theory may be partly due to the measurement of greenspace (Feng and Astell-Burt, 2017), we used both greenspace quantity and quality in this study.

NDVI

We used remote sensing data at a 30 m spatial resolution to calculate the normalized difference vegetation index (NDVI) (Tucker, 1979). These data were obtained for the year 2016 from the USGS EarthExplorer (https://earthexplorer.usgs.gov/). We used cloud-free data in the greenest season (August) to avoid distortions. Also, following previous studies (Markevych et al., 2017), we omitted pixels with a negative NDVI value for this study. NDVI for each neighbourhood was calculated by averaging NDVI value of all pixels within the neighbourhood buffer (1000-m circular buffer).

SVG-quantity

We used street view data to calculate street view greenness quantity (SVG-quantity). The street view images were collected from Tencent Map[https://map.qq.com/] which is the most comprehensive online map in China (Deng et al., 2019). We collected images from each sampling point constructed along the road network based on OpenStreetMap (Haklay and Weber, 2008) at 100m intervals. The sampling points were randomly selected throughout the research area. In total, 71286 sampling points were constructed and four images from four main cardinal directions (0, 90,180, and 270 degrees) were collected for each sampling point. Following previous studies (Wang et al., 2021b, c), we calculated SVG-quantity based on the ADE20K training data (https://groups.csail.mit.edu/vision/datasets/ADE20K/) (Zhou et al., 2019) and a fully convolutional neural network for semantic image segmentation (FCN-8s) (Long et al., 2015).. This method has been proven to achieve high accuracy for identifying greenspace (trees and grasses) from street view images (Wang et al., 2021b, c). Then, SVG-quantity per sampling point was calculated by the proportion of greenspace pixels per image summed over the four cardinal directions to the total number of pixels per image summed over the four cardinal directions. Last, SVG-quantity for each neighbourhood was calculated by averaging SVG-quantity of all sampling points within the neighbourhood buffer (1000-m circular buffer).

SVG-quality

We also used street view data to assess street view greenspace quality (SVG-quality). We randomly selected two thousand images for data training which were scored (0-10) based on ten attributes including accessibility, maintenance, variation, naturalness, colourfulness, clear arrangement, shelter, absence of litter, safety and general impression (Cronbach's alpha=0.85) (Van Dillen et al., 2012). Then, we used a random forest model (Breiman, 2001) for automatic rating training and it was trained by fitting each greenspace quality attribute score with the proportion of 151 elements from the image segmentations. After training the random forest model, we used it to score ten attributes of greenspace quality for all images in 71286 sampling points. More details can be found in the supplementary file. Following existing studies (Van Dillen et al., 2012), greenspace quality score in each image was assessed by the mean score of all ten attributes. For each neighbourhood, the SVG-quality was calculated by the mean score of all sampling points within the 1000-m buffer. More details of this approach can be found in Wang et al. (2021a).

Self-reported greenspace quality

Following Feng and Astell-Burt (2017), we evaluated self-reported neighbourhood greenspace quality through a single question included in the questionnaire. Respondents were asked "Do you agree that you feel comfortable in the greenspace or park in this neighbourhood". Responses to the statement ranges from "1=strongly disagree" to "5=strongly agree". Existing studies pointed out that people's sense of comfort in urban greenspace is an important indicator of general greenspace quality (Brindley et al., 2019; Gidlow et al., 2012). Therefore, the proposed self-reported question aims to evaluate participants' general impression of the neighbourhood greenspace quality.

SES indicators

We used three SES indicators (extracted from the questionnaire) including income, education attainment and neighbourhood deprivation index (NDI) (Sampson et al., 2002). First income was assessed by gross monthly household income (Chinese Yuan) reported by respondents. Second, educational attainment was assessed based on self reported highest qualifications. Last, following Sampson et al. (2002) and Liu et al. (2017), NDI was developed based on four census indicators at the neighbourhood level including homeownership rates, unemployment rates, low levels of education, and low status occupation. The homeownership rate was the proportion of residents living on their own property in the neighbourhood. The unemployment rate was the proportion of unemployed residents in the neighbourhood. The low level of education referred to the proportion of residents with education attainment level lower than high school. The low-status occupation represented the proportion of residents working in the unskilled occupations. We used principal component analysis to combine neighbourhood deprivation index from the above four indicators.

Covariates

Following previous studies (Wang et al., 2019b,c), we controlled for individual sociodemographic covariates: gender, age, marital status, hukou status (registered permanent residence vs registered temporary residence), current smoking status and current drinking status. As for neighbourhood-level covariates, we adjusted for population density, street intersection density and land use mix following Frank et al. (2006). The summary of descriptive statistics was shown in Table 1.

Methods

We used multilevel linear regressions to examine the associations between greenspace exposure and mental health as well as the moderating effect of greenspace exposure for SES-mental health association due to the hierarchical structure of our data (individuals are in level 1 while neighbourhoods are in level 2). First, we estimated the association between greenspace exposure, SES indicators and mental health outcomes (Models 1 and 2). Second, we estimated the moderating effect of greenspace indicators on NDI-mental health association (Models 3 and 6). Third, we estimated the moderating effect of greenspace indicators on education-mental health association (Models 4 and 7). Last, we estimated the moderating effect of greenspace indicators on income-mental health association (Models 5 and 8). As for the moderation analysis, we mainly focused on the interaction terms. If the interaction terms are significant and the direction is opposite to SES indicators, then it indicates that greenspace exposure mitigates SES disparities in mental health and 'equigenesis' theory is supported by our findings. The analyses were performed by Stata 15.1 (StataCorp., College Station, TX, USA) using the ‘mixed’ command.

Table 1

Descriptive statistics.

Variables	Proportion/Mean (Standard Deviation)
Outcome	

SCL-Depression	21.1(8.1)
SCL-Anxiety	17.0(6.7)
Predictors	
NDVI [median (IQR)]	0.1(0.0)
SVG-quantity [median (IQR)]	0.2(0.1)
SVG-quality	5.6(0.4)
Self-reported greenspace quality	3.119(0.9)
SES indicators	
NDI	0.2(0.169)
Education (%)	
Junior high school or below	6.4
Senior high school	27.5
College or above	66.1
Gross monthly household income (Chinese Yuan)	15637.2(8488.5)
Individual covariates	
Gender (%)	
Male	50.0
Female	50.0
Age	36.4(9.7)
Marital status (%)	
Cohabiting	5.4
Married	80.1
Single, divorced or widowed	14.6
Hukou status (%)	
Local hukou	81.0
Non-local hukou	19.0
Current smoking status (%)	
Current smoker	39.4
Non-smoker	60.6
Current drinking status (%)	
Drinker	42.1
Non-drinker	57.9
Built environment covariates	
Population density (person/km^2)	46687.3(30383.0)
Intersection density (number of intersections/km^2)	89.8(66.2)
Land use mix	0.1(0.0)

4. Results

Model 1 (Table2) presents the baseline model for SCL-Depression scores. SVG-quality (Coef.=-4.9, SE=1.9) and self-reported greenspace quality (Coef.=-0.1, SE=0.1) were both negatively associated with SCL-Depression scores, but neither NDVI (Coef.=2.3, SE=2.2) nor

SVG-quantity (Coef.=-2.2, SE=1.2) is found to be associated with SCL-Depression scores. Compared with respondents with junior high school or below educational attainment, respondents with college or above educational attainment had lower SCL-Depression scores (Coef.=-1.4, SE=0.5). Hence, gross monthly household income was negatively associated with SCL-Depression scores (Coef.=-0.1, SE=0.1), while NDI was positively associated with SCL-Depression scores (Coef.=15.5, SE=6.0)..

Model 2 (Table2) presents the baseline model for SCL-Anxiety scores. SVG-quality (Coef.=-5.1, SE=2.4) and self-reported greenspace quality (Coef.=-0.1, SE=0.0) were both negatively associated with SCL-Anxiety scores, but no evidence is supportive of that NDVI (Coef.=2.1, SE=3.2) or SVG-quantity (Coef.=-2.4, SE=1.5) is associated with SCL-Anxiety scores. Compared with respondents with a junior high school or below education, respondents with a college or above education had lower SCL-Anxiety scores (Coef.=-1.4, SE=0.7). Similarly to results for depression , gross monthly household income was negatively associated with SCL-Anxiety scores (Coef.=-1.8, SE=0.8), while NDI was positively associated with SCL-Anxiety scores (Coef.=22.7, SE=8.6).

Table 2. The multilevel models for the association between greenspace exposure and SCL-Depression scores.

	Model 1 Coef. (SE)	Model 2 Coef. (SE)
Fixed part		
NDVI	2.3(2.2)	2.1(3.2)
SVG-quantity	-2.2*(1.2)	-2.4(1.5)
SVG-quality	-4.9**(1.9)	-5.1**(2.4)
Self-reported greenspace quality	-0.1**(0.1)	-0.1**(0.0)
NDI	15.5***(6.0)	22.7***(8.6)
Senior high school (referenced group= Junior high school or below)	-0.7(0.5)	-0.7(0.6)
College or above (referenced group= Junior high school or below)	-1.4**(0.5)	-1.4**(0.7)
Gross monthly household income	-0.1**(0.1)	-1.8**(0.8)
Individual covariates		
Male (referenced group= Female)	-0.3(0.3)	-0.2(0.4)
Age	-0.0(0.0)	0.0(0.0)
Local hukou (referenced group= Non-local hukou)	-0.0(0.3)	-0.1(0.4)
Married (referenced group= Cohabiting)	0.4(0.4)	-0.3(0.4)
Single and not cohabiting, divorced or widowed (referenced group= Cohabiting)	0.2(0.3)	-0.1(0.1)
Drinker (referenced group= Non-drinker)	-0.2(0.3)	-0.0(0.4)
Current smoker (referenced group= Non-smoker)	-0.2(0.4)	-0.5(0.5)
Built environment covariates		
Population density	0.8(3.5)	0.5(4.9)
Intersection density	-0.0(0.0)	-0.0(0.0)
Land use mix	-83.7(59.8)	-98.4(84.6)

Constant	46.6**(23.2)	63.0*(32.6)
Random part		
Var (Neighbourhoods)	15.4***	31.2***
Var (Individuals)	13.0***	18.5***
Number of individuals	1003	1003
Number of neighbourhoods	26	26
Log likelihood	-2753.1	-2935.0
AIC	5546.3	5910.0

Note: Coef. = coefficient; SE = standard error; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 3 shows the moderating effect of greenspace exposure on the association between SES and SCL-Depression scores. Model 3 indicates that SVG-quantity, SVG-quality and self-reported greenspace quality negatively moderate the association between NDI and SCL-Depression scores especially showing that SVG-quantity, SVG-quality and self-reported greenspace quality weaken the positive effect of NDI on SCL-Depression scores. Model 4 shows that SVG-quality and self-reported greenspace quality moderate the association between educational attainment and SCL-Depression scores in that SVG-quality and self-reported greenspace quality weaken the negative effect of higher educational attainment on SCL-Depression scores. Model 5 indicates that SVG-quality and self-reported greenspace quality moderate the association between gross monthly household income and SCL-Depression scores and shows that SVG-quality and self-reported greenspace quality weaken the negative effect of gross monthly household income on SCL-Depression scores.

Table 3. The multilevel models for the association between greenspace exposure and SCL-Depression scores.

	Model 3	Model 4	Model 5
	Coef. (SE)	Coef. (SE)	Coef. (SE)
Fixed part			
NDVI	2.7(2.6)	2.6(2.5)	2.3(2.2)
SVG-quantity	-2.5*(1.2)	-1.9*(1.1)	-2.2*(1.2)
SVG-quality	-5.2***(1.9)	-5.4***(2.0)	-4.9**(1.9)
Self-reported greenspace quality	-0.1**(0.1)	-0.5**(0.2)	-0.1**(0.1)
NDI	15.2**(6.2)	15.5***(6.0)	15.2**(6.0)
Senior high school (referenced group= Junior high school or below)	-0.8(0.5)	-0.7(0.6)	-0.7(0.5)
College or above (referenced group= Junior high school or below)	-1.4***(0.5)	-1.4**(0.6)	-1.4***(0.5)
Gross monthly household income	-0.2**(0.1)	-0.1**(0.1)	-0.2***(0.1)
Interaction term			
NDVI×NDI	-2.2(9.8)		
SVG-quantity×NDI	-13.1**(6.2)		
SVG-quality×NDI	-20.5**(9.5)		

Self-reported greenspace quality×NDI	-3.0***(0.7)		
NDVI×Senior high school		-0.2(1.2)	
SVG-quantity×Senior high school		0.4(1.6)	
SVG-quality×Senior high school		0.6(0.8)	
Self-reported greenspace quality×Senior high school		0.1(0.6)	
NDVI×College or above		-0.3(1.1)	
SVG-quantity×College or above		0.1(1.5)	
SVG-quality×College or above		0.6**(0.3)	
Self-reported greenspace quality×College or above		0.7***(0.2)	
NDVI×Gross monthly household income			-0.5(1.0)
SVG-quantity×Gross monthly household income			-2.0(1.4)
SVG-quality×Gross monthly household income			1.4**(0.6)
Self-reported greenspace quality×Gross monthly household income			1.5**(0.7)

Note: Models adjusted for covariates. Coef. = coefficient; SE = standard error; *p < 0.10, **p < 0.05, ***p < 0.01.

Table 4 shows the moderating effect of greenspace exposure on the association between SES and SCL-Anxiety scores. Model 6 indicates that SVG-quality and self-reported greenspace quality negatively moderate the association between NDI and SCL-Anxiety scores in that SVG-quality and self-reported greenspace quality weaken the positive effect of NDI on SCL-Anxiety scores. Model 7 indicates that SVG-quality and self-reported greenspace quality moderate the association between educational attainment and SCL-Anxiety scores since SVG-quality and self-reported greenspace quality weaken the negative effect of higher educational attainment on SCL-Anxiety scores. Model 8 shows that SVG-quality and self-reported greenspace quality moderate the association between gross monthly household income and SCL-Anxiety scores which means SVG-quality and self-reported greenspace quality weaken the negative effect of gross monthly household income on SCL-Anxiety scores.

Table 4. The multilevel models for the association between greenspace exposure and SCL-Anxiety scores.

	Model 6 Coef. (SE)	Model 7 Coef. (SE)	Model 8 Coef. (SE)
Fixed part			
NDVI	1.6(3.8)	1.0(3.4)	2.2(3.2)
SVG-quantity	-2.4(1.6)	-2.5(2.3)	-2.2(1.5)
SVG-quality	-5.8**(2.8)	-4.6**(2.1)	-5.3**(2.5)
Self-reported greenspace quality	-0.1**(0.0)	-0.2**(0.1)	-0.2**(0.1)
NDI	21.3**(9.0)	22.7***(8.5)	22.8***(8.6)
Senior high school (referenced group= Junior high school or below)	-0.8(0.6)	-0.2(0.7)	-0.6(0.6)
College or above (referenced group= Junior high school or below)	-1.5**(0.7)	-1.9***(0.7)	-1.4**(0.7)
Gross monthly household income	-1.9**(0.8)	-1.8**(0.8)	-1.8**(0.8)

Interaction term			
NDVI×NDI	-0.3(14.1)		
SVG-quantity×NDI	5.1(7.5)		
SVG-quality×NDI	-16.9**(8.2)		
Self-reported greenspace quality×NDI	-3.1***(0.9)		
NDVI×Senior high school		1.2(1.4)	
SVG-quantity×Senior high school		2.4(1.9)	
SVG-quality×Senior high school		1.5*(0.9)	
Self-reported greenspace quality×Senior high school		1.0(0.8)	
NDVI×College or above		1.2(1.3)	
SVG-quantity×College or above		3.0*(1.8)	
SVG-quality×College or above		0.2***(0.1)	
Self-reported greenspace quality×College or above		0.1**(0.1)	
NDVI×Gross monthly household income			-0.1(1.2)
SVG-quantity×Gross monthly household income			-0.2(1.7)
SVG-quality×Gross monthly household income			2.3**(1.1)
Self-reported greenspace quality×Gross monthly household income			1.1**(0.4)

Note: Models adjusted for covariates. Coef. = coefficient; SE = standard error; *p < 0.10, **p < 0.05, ***p < 0.01.

5. Discussion

This study extends previous research on the modification effects of greenspace quantity and quality on socioeconomic inequalities in mental health ('equigenesis'). First, this is amongst the first studies to systematically explore the moderation effects of greenspace exposure on the association between SES and mental health in a densely populated Chinese context. This is important because it provides novel theoretical insights into the generalizability of 'equigenesis' beyond a high income country context, and in particular whether it offers explanatory power in an urban Chinese context where the demographic, social and health profiles of the local population differ markedly from previous studies. Second, it makes a novel methodological contribution to the 'equigenesis' theory by considering different measurements of greenspace quantity and quality. This also contributes to existing knowledge by integrating green justice into 'equigenesis' theory. Third, this study also measures SES at both the individual and neighbourhood levels which enhances our understanding of 'equigenesis' pathways and theory. Such analysis highlights that 'equigenesis' may not be consistent across different scales.

Our findings suggest that greenspace quality moderates the association between SES indicators and mental health. This finding can be explained by the restoration and instoration mechanisms through which greenspace quality influences mental health. First, greenspace quality may benefit mental health through attention restoration and stress recovery (Douglas et al., 2017; Markevych et al., 2017). Stress reduction theory (SRT) highlights the role of greenspace quality in restoring attention from an adaptive evolutionary perspective (Ulrich et al., 1991), while attention restoration theory (ART) highlights the role of greenspace quality in buffering stress through its restorative features (i.e fascination) (Kaplan, 1995). In comparison with their more advantaged counterparts, people in socioeconomically disadvantaged circumstances may disproportionately benefit through attention restoration and stress recovery through two pathways: (1) the restorative effect of greenspace quality depends on duration of greenspace exposure (Shanahan et al., 2015). Hence, higher SES groups are less constrained in the nature and location of their recreational activities, which may result in these groups spending less time in their local greenspaces with less overall exposure to greenspace in dense urban areas of China (Dipeolu et al., 2021; Jim and Shan, 2013); (2) ART indicates greenspaces have four types of restorative quality features such as fascination, being away, extension and compatibility (Kaplan, 1995). However, higher SES individuals are more likely to have a greater range of options for accessing greenspaces beyond their locale, potentially with higher restorative quality and therefore these groups are less reliant on their local greenspace (Jim and Shan, 2013). This assertion is supported by previous work, including for example, Cao et al. (2020) who found that residents with higher SES in China are more able or willing to spend more resources on visiting national parks which can provide them with a sense of tranquility, despite residing in an otherwise sparse suburban area. Therefore, it is plausible that given the unevenness in opportunities and exposures between higher and lower SES groups, the restorative qualities of local greenspaces may be more beneficial to lower SES populations.

The instoration mechanism is associated with building capacities for mental health, and relevant studies have mainly focused on the mediating role of physical activity and social cohesion (Kruize et al., 2020; Markevych et al., 2017). Greenspace quality may influence people's engagement in outdoor physical activity including walking and cycling because higher greenspace quality may provide further motivation to utilize these resources (de Vries et al., 2013; Lu et al., 2019; Qin et al., 2021; Yang et al., 2021). Hence, higher quality greenspaces provide a more attractive environment for residents to socialize with each other, often enhancing local social cohesion (de Vries et al., 2013). However, people in socioeconomically disadvantaged circumstances may benefit disproportionately through the above two mechanisms due to several reasons: (1) people with higher SES have more choices for physical activity (i.e indoor fitness), so they may take less greenspace-related physical activity such as walking for recreation (Cohen et al., 2013); (2) people in socioeconomically disadvantaged circumstances in China often have poorer social networks, so they are more likely to regard local greenspace as preferred options for social interaction (Jim and Shan, 2013); (3) people with higher SES tend to have greater access to more health-related resources that can enhance mental health (e.g., access to psychological counseling) (Huang et al., 2020), so they may depend less on local greenspace. For example, people living in neighbourhoods with higher social cohesion can benefit from the health-related knowledge of their neighbors and are better supported in their mental health (Elgar et al., 2010). However, people with higher SES have more options for other health-related resource and do not necessarily rely on local greenspace.

However, whereas SVG-quantity moderates the association between NDI and mental health, no evidence was found to suggest that NDVI moderates the association between SES indicators and mental health. It is important to acknowledge that this study cannot provide definitive evidence that NDVI and SVG-quantity do not stimulate greater health equity in mental health. There are some potential reasons why evidence of 'equigenesis' was not found for greenspace quantity in this research. First, we used different SES (both individual and neighbourhood level) and mental health indicators which may have influenced the findings. The narrowing of inequities may not be observed for some indicators of SES (e.g., individual SES), but perhaps in other dimensions (e.g., neighbourhood SES). In this study, the moderation effect of SVG-quantity was only observed with the neighbourhood SES indicator (NDI) which is consistent with previous studies. For example, Dadvand et al., (2014) found that 'equigenesis' was observed for neighbourhood SES indicator (i.e Index of Multiple Deprivation) but not for individual indicator (i.e educational attainment). A possible explanation is that NDI may capture the multidimensionality of disadvantage and a wider set of underlying factors (e.g. lack of local health-related resources) than an individual indicator. This may also apply to different measures of mental health (e.g., depression v.s anxiety). Second, although they have been used widely in previous research, NDVI and SVG-quantity both have limitations in assessing greenspace quantity. NDVI measures greenspace quantity from an over-head perspective and may not account for smaller pockets of vegetation, and therefore not fully capture all visible greenspace (Liu et al., 2021; Wang et al., 2021b; Wu et al., 2021). While SVG-quantity can more comprehensively reflect visible greenspace quantity, there remain limitations. For example, this measure would be less likely to capture greenery in private gardens. It would also be difficult to capture other aspects of balcony greening, especially in areas where buildings tend to be high. Finally, it is also crucial to acknowledge that the effect of greenspace quantity may vary across the lifecourse (Astell-Burt et al., 2014). Astell-Burt et al. (2014) noted that younger and older adults benefit more from greenspace quantity than middle-aged adults, so the narrowing of SES inequities for greenspace quantity may not manifest in our sample which consisted of mostly middle-aged adults.

The following limitations should be noted. First, we used a cross-sectional study design which prevents us from inferring causation between greenspace exposure and mental health. Second, duration of greenspace exposure was not accounted for which may cause bias. For example, Jiang et al. (2016) found that duration of greenspace exposure is positively associated with mental health. Therefore, without the information of duration of greenspace exposure, we were not able to quantify the effect of greenspace exposure accurately. Third, we measured greenspace exposure without detailed information of the participants' daily activity spaces which may result in the Uncertain Geographic Context Problem (UGCoP) leading to exposure misclassification (Kwan, 2012). Hence, we were not able to consider the variation of different greenspace metrics within the neighbourhoods, which may lead to overestimation or underestimation of greenspace exposure for different participants. Fourth, mental health outcomes were self-reported which may lead to some bias since participants may overestimate or underestimate their health status. Fifth, the data were collected from March to August, which has the potential to cause bias due to seasonal changes in mental health status. Last, our self-report greenspace quality metric is assessed based on a single question, so it may not be sufficiently comprehensive to reflect participants' general impression of neighbourhood greenspace quality.

6. Conclusion

This study shows that greater greenspace provision may help to narrow neighbourhood socioeconomic inequalities in mental health. Further studies that elucidate causal relationships between greenspace, and socioeconomic inequalities in mental health are urgently needed. With the increase of conditions including depression, anxiety and suicide, addressing the rise and inequalities in mental health should become a key policy priority in urban China. To achieve the goal of promoting mental health and reducing inequalities through urban planning and design in Chinese cities, policymakers and planners should consider enhancing the provision of neighbourhood green infrastructure, which can better fulfil the requirement of "Healthy China 2030" plan (The CPC Central Committee and the State Council, 2016). Also, as the World Health Organization has called for attention on equitable healthier cities for sustainable development (World Health Organization, 2016), policy makers around the world should pay attention not only to greenspace quantity, but also quality, since greenspace quality may be more important to narrow SES disparities in health than quantity.

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