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# Regression Toward the Mean in Neighborhood Effects Research: A Geographic Perspective

Yinhua Tao,[a] Ana Petrović,[b] Mei-Po Kwan,[c,d] and Maarten van Ham[b]

[a]*School of Transportation, Southeast University, China;* [b]*Faculty of Architecture and the Built Environment, Delft University of Technology, The Netherlands;* [c]*Institute of Space and Earth Information Science, The Chinese University of Hong Kong, China;* [d]*Department of Geography and Resource Management, The Chinese University of Hong Kong, China*

Neighborhood effects research focuses on the residential neighborhood, assuming it as the main spatial context relevant to individual outcomes. Individuals, however, are mobile and visit various spatial contexts other than the residential neighborhoods. This article conceptualizes contextual exposures to socioenvironmental factors in daily activity spaces and their relationship with residential exposures. By introducing regression toward the mean, we argue that mobility-based contextual exposures are, on average, less extreme than residential exposures. Previous neighborhood effects studies therefore tend to underestimate actual spatial contextual effects when they misrepresent residential neighborhood effects as the total contextual effects. Despite improved measurement accuracy with the transition from residence- to mobility-based exposures, we suggest the complexities remaining in the estimation of spatial contextual effects from a geographic perspective. These complexities include a possibly limited extent of neighborhood effects regression across neighborhoods and asymmetrical dispersion of between-individual contextual exposures within each neighborhood. *Key Words: daily mobility, environmental exposure, neighborhood effects averaging, residential segregation, spatial context.*

Human geographers have a long interest in studying the structural role of residential neighborhoods in (re)shaping individual outcomes, such as individuals' socioeconomic position, daily activity-travel behavior, and long-term health and well-being (Sampson, Morenoff, and Gannon-Rowley 2002; Van Ham et al. 2011; Tao, Petrović, and Van Ham 2023). These neighborhood effects studies are based on the notion that where people live to some extent determines their life chances and choices, over and above the influence of individual-level characteristics. More recently, an increasing number of studies suggest that residential neighborhoods, often operationalized as home-based administrative areas, are not a good proxy for the spatial context to which people are exposed in their daily lives (Kwan 2012; Morris, Manley, and Sabel 2018). This is because residents travel to other neighborhoods to work, shop and perform other routine activities. It is therefore important to employ a mobility-based approach to measure spatial context, taking into account all the places that individuals visit within daily activity space.

Despite the call for incorporating daily mobility into neighborhood effects research (Cummins 2007; Kwan 2018a; Petrović, Manley, and van Ham 2020), it is not clear to what extent the measurement of a sociospatial context (e.g., population socioeconomic composition or greenspace) in residential neighborhoods differs from measures taking into account the mobility outside residential neighborhoods. This leads to follow-up questions of how to incorporate and operationalize a mobility-based sociospatial context in the study of neighborhood effects, and how such a mobility-based approach will change our understanding of neighborhood effects. We argue that focusing more explicitly on mobility-based contextual exposure and its relationship with static residence-based exposure will contribute to a better understanding of the structural and behavioral mechanisms underlying spatial contextual effects, in and beyond the influence of residential neighborhoods.

A transition from residence-based to mobility-based exposure will introduce measurement problems related to scale attenuation effects; both ceiling and floor effects (Vogt and Johnson 2011). For example,

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CORRESPONDING AUTHOR Yinhua Tao yh.tao@hotmail.com

when studying changes in individual socioeconomic position over time, ceiling effects occur when the highest income groups are more likely to experience a decrease rather than an increase in their income because they have hit the ceiling of the income distribution (Piketty 2014). In contrast, the floor effect explains why the poorest people have a greater chance to increase their income than others over time because they are already at the bottom of the income distribution. These scale attenuation effects can also be observed when comparing exposure to some environmental factors in residential neighborhoods and daily activity spaces. The neighborhood effect averaging problem (NEAP), for example, indicates that a person from a residential neighborhood with low levels of a mobility-dependent environmental factor (e.g., greenspace) is likely to visit other neighborhoods with greater exposure to that factor in the course of a day, and vice versa (Kwan 2018b; Cai and Kwan 2024).

By introducing regression toward the mean (RTM), a concept that originates from biology and statistics, into neighborhood effects research, this study aims to conceptualize mobility-based contextual exposure, including exposure to both socioeconomic and environmental factors, in relation to static residential exposure within a more generic framework. RTM points to a statistical phenomenon that when investigating changes in measures, such as residence-based versus mobility-based socioenvironmental exposure, those located at or close to both ends of a normal distribution tend to leave the former position and revert closer to the population mean level (Galton 1877, 1886; Stigler 1997; Campell and Kenny 1999). Beyond the statistical definition of RTM, this article discusses the complexities involved in the estimation of spatial contextual effects from a geographic perspective. These complexities include a possibly limited extent of neighborhood effects averaging across neighborhoods and varying levels of mobility-based contextual exposure among residents from the same neighborhood. Without taking into account neighborhood effects averaging and the counterprocess of between-individual dispersion collectively, neighborhood effects research is likely to misunderstand the relationship between static residence-based exposure and mobility-based contextual exposure, and therefore produces biased results when assessing actual spatial contextual effects.

The next section of this article presents an overview of recent studies that compare socioenvironmental exposure in residential neighborhoods and daily activity spaces. Having critically reviewed the literature on the assessment of residential neighborhood effects versus spatial contextual effects, we introduce the concept of RTM, which leads the following discussion on the application of RTM in neighborhood effects research. The discussion section highlights an important lesson learned from this study; that is, progress in the accuracy of exposure measurement might not necessarily lead to more definite estimation of spatial contextual effects. The article ends with a call for integrating the epistemological thinking of RTM to advance the understanding of spatial contextual effects from a geographic perspective and to reflect on the efficacy of people-centered mobility interventions in alleviating residence-based socioenvironmental inequalities.

## Spatial Contextual Effects in and Beyond Residential Neighborhoods

### From Residence-Based to Mobility-Based Exposure Assessment

From a geographic perspective, neighborhood effects research has a place-based tradition in defining a neighborhood unit. In its definition, neighborhoods are the living spaces with social and cultural similarities among a group of people residing in proximity to one another (R. E. Park 1915; McKenzie 1922; Sampson, Morenoff, and Gannon-Rowley 2002). Classic works of neighborhood effects assume that the influence of residential neighborhoods operates through *exposure to geographic contexts*, including exposure to population socioeconomic composition and physical environments in neighborhoods, among other social and institutional processes (Galster 2012; Browning and Soller 2014). For the influence of neighborhood socioeconomic exposure, the geographic concentration of poverty demonstrates that low-income residents have been exposed to other socioeconomically disadvantaged populations and have endured persistent social problems (e.g., high crime rates) over decades, despite substantial population turnover in these neighborhoods (Massey, Gross, and Shibuya 1994; Sampson, Morenoff, and Gannon-Rowley 2002). For the effects of neighborhood environmental exposure, health geographers take the forefront in studying the spatial patterns of health-related outcomes in relation to the distribution of physical environmental factors, such as environmental pollutants, greenspace and built environments, across residential neighborhoods (Jones and Moon 1993; Parr 2002).

When delineating the neighborhood unit for socioenvironmental exposure assessment, neighborhood effects research often regards the *residential neighborhood* as the only contextual unit relevant to individual outcomes. Residential neighborhoods are operationalized as fixed administrative areas where the residence is located, such as home census tracts, block groups and postcode areas, considering the availability of data from population and administrative registers (Kwan 2018a). Notably, this place-centered approach overlooks the fact that individuals often travel outside the boundary of administration-defined residential neighborhoods to conduct daily activities. The sole focus on the local context of residential neighborhoods therefore cannot represent all the lived experiences that individuals have in their daily life.

For this reason, researchers have been searching for more accurate approaches to conceptualize exposure to *spatial contexts*, by placing individuals at the center of their potential daily activity spaces. These approaches include visualizing individual space–time paths and associated sociospatial contexts under the framework of space–time geography (Hägerstrand 1970; J. Y. Lee and Kwan 2011; Ellegård 2018), recognizing the lack of knowledge about "true causally relevant" contexts of individual behaviors and outcomes (Kwan 2012), developing a domains approach to incorporate experiences of socioeconomic segregation in different domains of daily life (Van Ham and Tammaru 2016), and calling for a turn from static administrative neighborhoods to a multiscale representation of spatial contexts (Petrović, Manley, and van Ham 2020). Acknowledging that neighborhoods cannot take any form of standardization, these people-centered approaches foreground human mobility as producing and produced by the microgeography of daily life (Sheller and Urry 2006; Kwan 2009; Cresswell 2011). Through daily mobility, activities, and social interactions, individuals become active agents who connect different neighborhoods and construct idiosyncratic spatial contexts (Kwan 2018a; Petrović, Manley, and van Ham 2020).

With the increasing availability of daily activity and mobility data, such as Global Positioning System (GPS) tracking data, mobile phone data, and geotagged social media data, a growing body of research has employed the activity space approach to capture the different neighborhoods in which individuals conduct routine activities and to encompass a full array of spatial contexts to which individuals are exposed in daily life (Chaix et al. 2012; Krivo et al. 2013; Cagney et al. 2020; Abbiasov et al. 2024; Liu, Kwan, and Yu 2024; Silm et al. 2024; Zheng et al. 2024). The studied socioenvironmental factors within activity spaces include populations of different racial and ethnic compositions (Y. A. Kim, Hipp, and Kubrin 2019; Candipan et al. 2021), income levels (Q. Wang et al. 2018), and education levels (Zhang et al. 2022); a composite index of neighborhood socioeconomic deprivation (Levy, Phillips, and Sampson 2020); and physical environment factors including greenspace (Wu et al. 2023), air pollution (Y. M. Park and Kwan 2017), service density (Chaix et al. 2017), and food environment (Sharp and Kimbro 2021). Findings from these activity space studies consistently show that using residential neighborhoods as the analytical contextual unit will result in exposure misclassification, as individuals are exposed to diverse socioenvironmental factors when traveling beyond the area of residential neighborhoods. Exposure misclassification is a methodologically important issue. It could lead to a mixture of residential neighborhood effects with actual spatial contextual effects, and furthermore, obstruct epistemological understanding of how geography and contexts of daily life matter for individual behaviors and behavior-related outcomes.

## From Residential Neighborhood Effects to Spatial Contextual Effects

There are two potential biases in neighborhood effects assessment resulting from the exposure misclassification. First, studies are subject to the "residential effects fallacy" when they regard the effects of socioenvironmental exposures in any spatial context as truly residential neighborhood effects (Chaix et al. 2017); that is, residential context is treated as the only context that matters for individuals. In this case, the observed associations between residential exposures and individual outcomes capture some of the effects caused by other neighborhoods that individuals visit in daily life. This could thus lead to overestimation on the impact of any place-based interventions taken in the residential neighborhoods. The second form of contextual effects misestimation appears when residential neighborhood effects are interpreted as total spatial contextual effects (Cummins 2007; Basta, Richmond, and Wiebe 2010). This contextual effects misestimation is less studied under the very notion of residential neighborhood effects. Following this notion, studies tend to treat contextual exposure in other neighborhoods as a measurement error of the exposure in residential neighborhoods, even though they do acknowledge static residential exposure as an imperfect proxy of mobility-based contextual exposure in residents' daily activity spaces (Cummins 2007; Basta, Richmond, and Wiebe 2010).

To understand the mobility-induced exposure misclassification, the first and foremost question is whether there are systematic differences in socioenvironmental exposures in and beyond residential neighborhoods. This question points to whether nonresidential exposure is a random measurement variance of residential exposure as assumed in previous neighborhood effects studies. Having reviewed research on within-individual variances of residence- and mobility-based environmental exposures, Kwan (2013, 2018b) summarized a specific form of exposure misclassification, termed the NEAP. The NEAP specifies that "[t]aking people's daily mobility into account will lead to an overall tendency toward the mean exposure (of the general population)," so "characteristics of the nonresidential neighborhoods people visit in their everyday lives could mitigate the disadvantage they experience in their residential neighborhood" (Kwan 2013, 1081).

Recent empirical analyses have substantiated the existence of the NEAP by comparing within-individual differences in residential and nonresidential exposures to air pollution (J. Kim and Kwan 2021), greenspace (Xu et al. 2023; J. Wang et al. 2024), COVID-19 risk (Huang and Kwan 2022), and population of different racial and ethnic and socioeconomic statuses (Levy, Phillips, and Sampson 2020; Tan, Kwan, and Chen 2020; Mennis et al. 2022; Zhang et al. 2022) in daily life. For example, J. Kim and Kwan (2021) mapped activity-travel trajectories of around 3,000 participants onto the air pollutant surface in the Los Angeles metropolitan statistical area. The results show that ozone levels approximated a bell-shaped distribution across participants' residential locations, whereas the distribution of mobility-based ozone exposures was less deviated and closer to the population mean level. Simply put, participants from a highly polluted residential neighborhood tend to be exposed to lower levels of ozone when they navigate the city in daily life, whereas participants living in a less polluted neighborhood tend to experience higher mobility-based ozone exposures, indicating the phenomenon of neighborhood effects averaging.

In contrast, some recent studies on air pollution and greenspace exposures argue that neighborhood effects averaging is not a universal phenomenon. Integrating air pollutant surface data and smartphone-recorded GPS data for more than 5,000 participants in Montreal, Canada, Fallah-Shorshani et al. (2018) observed that residence- and mobility-based exposures to air pollutants, including $NO_2$, $PM_{2.5}$, and ultrafine particles (UFPs), followed a similar statistical distribution, with little difference in the range of variances. Another two studies from a street area of suburban Beijing, China, even found that the variance of mobility-based greenspace exposures was greater than that of residential exposures (B. Wang et al. 2021; Wu et al. 2023). Wu et al. (2023) summarized this result as the neighborhood effect polarization problem (NEPP), suggesting that residents living in a neighborhood with low greenspace accessibility were exposed to even lower levels of greenspace in other neighborhoods visited in daily life, and vice versa. As a result, the overall distribution of mobility-based exposures was more polarized than that of residential exposures.

If neighborhood effects averaging is an important source of exposure misclassification, previous neighborhood effects studies are subject to underestimating the real effects of living in a neighborhood when they interpret residential neighborhood effects as total contextual effects. This contextual effects underestimation can be understood from a thought experiment: Imagine a city with neighborhoods of different levels of socioeconomic deprivation, with level 1 representing the least and level 10 representing the most deprived neighborhoods. Individuals who reside in an extremely deprived neighborhood, say at level 9, are likely to visit other neighborhoods with lower deprivation levels, say the mean level of 7, because of neighborhood effects averaging. In this case, previous neighborhood effects research could misassign the effect of deprivation level 7, which is often unobserved across all neighborhoods visited in daily life, as the effect of the observed deprivation level 9 at residential neighborhoods, leading to the underestimation of actual contextual effects. In other words, there would have been a stronger contextual impact of socioeconomic deprivation if individuals did experience the deprivation level 9 during the day.

The contextual effects underestimation resulting from neighborhood effects averaging can also be examined based on a counterfactual framework. If individuals choose to stay in residential neighborhoods throughout the day (i.e., static residential exposure similar to mobility-based contextual exposure), residence-based exposure would have a larger impact on individual outcomes compared to the situation when they move around and visit many other neighborhoods. As evidenced by Vallée et al. (2011) and Letellier et al. (2019), living in a neighborhood with high levels of socioeconomic deprivation had the most negative impact on the risks of depression and incident dementia, respectively, for residents whose activity spaces were within the area of residential neighborhoods. In contrast, limited activity spaces within residential neighborhoods showed protective health benefits for residents from the least deprived neighborhoods. Notably, these research findings might be biased from between-individual differences in selective daily mobility; that is, individuals who chose to leave or stay in the residential neighborhoods in daily life might have preexisting sociopsychological conditions that also contributed to their health problems.

In empirical settings, the contextual effects underestimation can be tested by including both residence- and mobility-based socioenvironmental exposures in the analysis. Because of neighborhood effects averaging, the analysis adjusting for differences in residential exposures between individuals (and thus keeping their residential exposures at a similar level) would amplify the actual contextual influence of mobility-based exposures. This approach has been used in studies on the associations of neighborhood socioenvironmental disadvantages with individual self-rated health (Inagami, Cohen, and Finch 2007), individual nonwork travel distances (Li, Kim, and Sang 2018), neighborhood crime rate (Y. A. Kim, Hipp, and Kubrin 2019; Graif et al. 2021; Zhang et al. 2022), and neighborhood COVID-19 infection rate (Levy et al. 2022). Findings from these studies consistently show a stronger influence of mobility-based socioenvironmental exposures, in terms of the effect size and the level of significance, after adjustment for corresponding socioenvironmental characteristics in residential neighborhoods.

## Introducing Regression Toward the Mean and Its Counterprocess

Neighborhood effects averaging is not a new problem exclusive to neighborhood effects research, but it represents a ubiquitous statistical phenomenon of any two correlated measures, in this study, individual socioenvironmental exposures in the residential neighborhood and in the daily activity space. The record of this averaging phenomenon dates from Galton's (1865) finding for regression toward mediocrity. Comparing the height of 930 adult children to that of their parents, Galton (1865, 1877) found that these adult children were more mediocre than their parents. They tended to be shorter than their parents if the parents were very tall, and to be taller than their parents if the parents were short in height. A biological explanation is that children inherit some part of height from their parents and the other part from their ancestry, whose height tends toward the average height of the population. In Galton's (1886, 1889) later works of natural inheritance, he reframed regression toward mediocrity as a statistical phenomenon, arising from the instability of variants deviating from the mean. As a result, the offspring of parents whose height deviated significantly from the population mean level would on average deviate less from the mean than their parents. This is the initial notion of RTM.

To observe RTM in a wider population over generations, Galton (1886) designed a pea-breeding experiment. He separated the seeds of sweet peas into seven packets, each packet consisting of pea seeds of the same size. Seeds from different packets were then cultivated in similar climatic and soil conditions. Just as suggested by RTM, for parent seeds from the packet of a large size, the offspring seeds were smaller on average than their parents, even though they were still larger than the mean size of the parent population as a whole. Oppositely, for parent seeds from the packet of a small size, the offspring seeds were larger on average than their parents and reverted toward the mean size of the parent population. This regression process results in decreases in variability of offspring seeds compared to that of parent seeds.

When Galton looked at the overall distribution of offspring seeds, however, he found it quite similar to that of parent seeds. This implies another dispersion process at work to counteract decreases in variability caused by RTM. Specific to the dispersion process, Galton observed that parent seeds from each packet produced offspring seeds with the size of a bell-shaped distribution, leading to increases in variability. The law of deviation describes the mathematical property of this bell-shaped distribution as a host of accidental causes acting indifferently in any directions and creating a distribution of values centered around the mean value (Hilts 1973). Altogether, dispersion for each subgroup of the population (e.g., each pocket including the same size of parent seeds) is always proportionate to regression toward the mean value of the general population (e.g., the mean size of all parent seeds), contributing to the stability of biological and human groups over generations (see the counterbalance between regression and dispersion as visualized in Appendix A of the Supplemental Material).

Modern statistical terminology properly defines RTM as follows. There are two normally distributed measures, $x$ and $y$, with an imperfect linear correlation between them. For each value of $x$, the predicted value of $y$ will deviate less from the mean of the distribution of $y$ than the value of $x$ from the mean of the distribution of $x$ (Bland and Altman 1994; Krashniak and Lamm 2021). The extent of RTM depends on two parameters, namely the degree of extremity of $x$ and the correlation coefficient between $x$ and $y$. The more extreme the value of $x$ (i.e., closer to the tails of the normal distribution of $x$) or the weaker the correlation between $x$ and $y$ is, the greater the predicted value of $y$ will regress toward the mean (see detailed formulas and explanation in Appendix B of the Supplemental Material).

Importantly, the statistical phenomenon of RTM does not infer any causal mechanism. Reframing RTM the other way around, we can similarly find that the predicted value of $x$, based on the value of $y$, would tend closer to the mean value of the $x$ distribution than that of the $y$ distribution (Stigler 1997). Because of the imperfect correlation between two measures, RTM would take place when predictions are made from either direction. For this reason, statisticians regard RTM as an observer phenomenon (Tweney 2013), a regression fallacy (Friedman 1992; Maraun, Gabriel, and Martin 2011), a statistical artifact (Campell and Kenny 1999), or an unavoidable statistical effect resulting from the distribution of the data (Stigler 2016). In empirical research, the construct of interest is often measured with random variances (or errors), which prevents researchers from isolating the existence of any genuine pattern from RTM. Essentially, RTM is a statistical phenomenon that has no effects in itself.

## Application of RTM in Neighborhood Effects Research

As described in the earlier literature review, residential neighborhoods are a poor proxy for the spatial contexts to which individuals are exposed in daily life. Moving from neighborhood effects to spatial contextual effects, geographers have strived for the last decade to define contextual units and measure contextual exposures that capture individual experiences of places more accurately. In their sense, the uncertainty of measurement of spatial contexts is a problem to be corrected and mitigated (Fusco et al. 2017; Schwanen 2018). With refined spatial and behavioral data, recent studies have compared individual socioenvironmental exposures in the residential neighborhood and in the daily activity space (e.g., J. Kim and Kwan 2021; Wu et al. 2023). These studies aim to understand how socioenvironmental inequalities situated in residential neighborhoods are represented in other neighborhoods visited in daily life. Neighborhood effects averaging is a representation of such geographic patterns, indicating that when individuals move outside the area of residential neighborhoods, their contextual exposures to some socioenvironmental factors (e.g., population socioeconomic composition and greenspace) would converge to the population mean level and thus be less extreme than residential exposures. This averaging phenomenon leads to an attractive but misleading implication that increasing residents' daily mobility would automatically alleviate socioenvironmental inequalities established at the place of residence.

To avoid this regression fallacy, it is time for geographers to take a step forward from addressing measurement uncertainty of exposure assessment to understanding spatial contextual effects from the perspective of daily mobility. The previous section introduced RTM based on knowledge from biology and statistics. RTM represents a static property of bivariate distribution and provides no causal explanation for two correlated measures (Maraun, Gabriel, and Martin 2011; Tweney 2013). When comparing residence- and mobility-based socioenvironmental exposures, therefore, researchers need to be cautious that neighborhood effects averaging is just an observer phenomenon of statistical analysis, and that improving daily mobility might not contribute to addressing residence-based socioenvironmental inequalities. Quantitative geography research has a tradition of summarizing some certainty from a myriad of uncertainties in the complex empirical world, as indicated by the NEAP (Kwan 2018b) or NEPP (Wu et al. 2023) in neighborhood effects research. We argue that when applying the concept of RTM to representing empirical settings, we need to acknowledge the uncertainty of understanding as "an intrinsic property of complex knowledge" (Couclelis 2003, 166). From a geographical way of thinking, the following two subsections elaborate on the uncertainty in the estimation of spatial contextual effects, including the extent of neighborhood effects averaging and the (a)symmetry of between-individual dispersion.

### The Extent of Neighborhood Effects Averaging

Neighborhood effects averaging identifies a geographic pattern showing that people from a residential neighborhood with a high level of a certain socioenvironmental factor are on average exposed to other neighborhoods visited in daily life with lower levels of that factor, and vice versa. The statistical definition of RTM indicates that the extent of neighborhood effects averaging depends on the extremity of socioenvironmental exposures in residential neighborhoods and the correlation of socioenvironmental distribution between residential neighborhoods and other visited neighborhoods. For this reason, neighborhoods located closer to either tail of the distribution of a socioenvironmental factor show greater potential for neighborhood effects averaging, as residents can easily travel to other nonresidential contexts with less extreme exposures (J. Kim and Kwan 2021; J. Wang et al. 2024).

From a geographic perspective, the analysis of neighborhood effects averaging should account for the spatial dependency of socioenvironmental factors and temporal dynamics in population movement patterns, which could result in a lesser extent of neighborhood effects averaging than expected by the statistical definition of RTM (Figure 1). According to RTM, a precondition for neighborhood effects averaging is that the studied socioenvironmental factor follows a normal distribution across neighborhoods, with more neighborhoods exposed to that socioenvironmental factor around the mean level than extreme levels. When developing the idea of NEAP, geographic research noticed that "the NEAP largely operates for mobility-dependent exposures," whereas it "does not operate when there is little or no spatiotemporal variation in the environmental factor being examined" (J. Kim and Kwan 2021, 136; Cai and Kwan 2024). Some social processes, particularly those related to the accumulation of social capital and collective efficacy, develop primarily in areas of sufficient socioeconomic resources and stable residential populations (Forrest and Kearns 2001; Sampson, Morenoff, and Gannon-Rowley 2002). The distribution of these social factors tends to be locally dependent on the place where people live. Once people move outside their residential neighborhoods, they will not be exposed to any contextual influences of these mobility-independent factors, so it is irrelevant to discuss the extent of neighborhood effects averaging.

Many socioenvironmental factors, including population socioeconomic composition, and some physical environment factors (e.g., greenspace and air pollution), approximate a bell-shaped curve across neighborhoods (Y. A. Kim, Hipp, and Kubrin 2019; J. Kim and Kwan 2021; J. Wang et al. 2024), but their local distribution shows spatial dependence, which violates the assumption of independent observations in a normal distribution. The spatial dependence determines the extent to which the socioenvironmental factor in a neighborhood is similar to or different from that in surrounding areas (Getis 1996; Sampson, Morenoff, and Gannon-Rowley 2002). To account for this spatial dependence, recent research has refined the operation of so-called egocentric neighborhoods or bespoke neighborhoods (Chaix et al. 2009; B. A. Lee et al. 2019; Petrović, Manley, and van Ham 2020). Different from the administration-defined neighborhoods, egocentric neighborhoods place individuals at the center of their own residential neighborhoods. Neighborhoods are therefore not treated as mutually exclusive territories with bounded spatial areas but as scalable contextual units with overlaps for residents living in proximity to each other (Hipp and Boessen 2013). By creating neighborhoods of different spatial scales centered at the place of residence (based on distances ranging from a home-centered 100 by 100-m grid to a much larger spatial scale over a 10-km radius), Petrović, van Ham, and

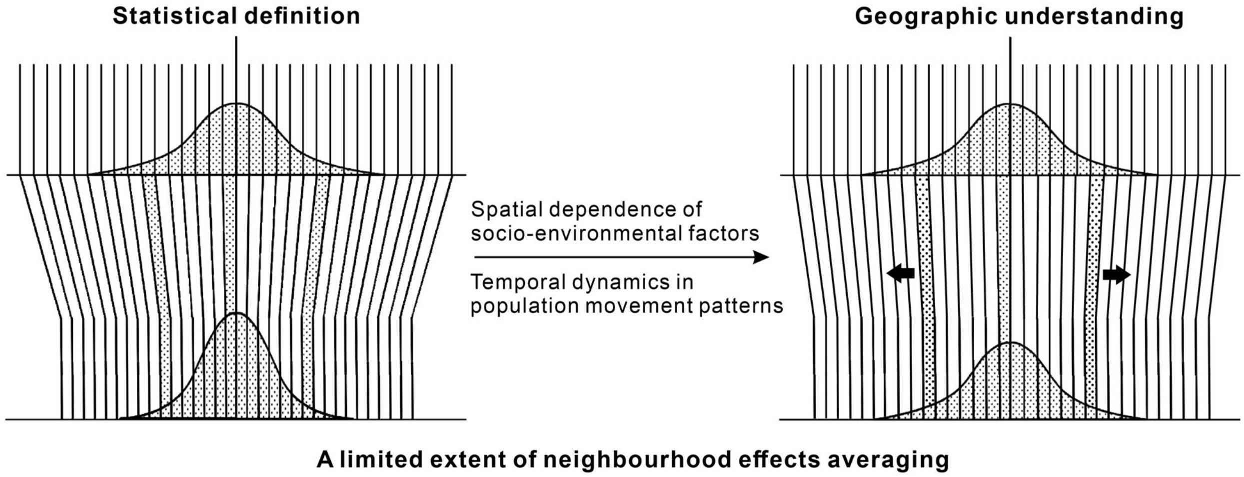


**Figure 1.** Statistical definition versus geographic understanding of neighborhood effects averaging.

Manley (2018, 2022) found that individual contextual exposure to different socioeconomic populations varied to a great extent in bespoke neighborhoods, depending on the spatial dependence of population distribution and spatial scale of neighborhood units. This scalar logic contributes to delineating complex social and geographic landscapes within multiscale neighborhoods and exploring how each residential neighborhood is embedded in an extralocal neighborhood context.

A common type of spatial dependence, spatial autocorrelation, is particularly relevant to the extent of neighborhood effects averaging. Spatial autocorrelation describes the pattern of geographic data as those nearby observations more similar than distant ones (Tobler 1970; Getis 2008). For a socioenvironmental factor, spatial autocorrelation outlines its interdependent distribution in and beyond residential neighborhoods. For example, racial or ethnic minority and low-income neighborhoods tend to cluster in certain areas of a city, due to housing affordability, discrimination from the housing market, and sociocultural intimacy of the same social group (Massey 1990; Ellis, Wright, and Parks 2004). Physical environment factors, such as air pollutants, often spread continuously over space with a strong spatial autocorrelation (Turner 1994). Given the fact that the probability of activity occurrence declines as activity locations are further away from residential locations (Wei et al. 2023), residents are likely to be exposed to a sociospatial context in nearby neighborhoods similar to that in residential neighborhoods. A growing body of studies has evidenced the spatial dependence of physical environmental exposures at different places visited and traversed for daily activities. Specifically, their results show a moderate-to-strong correlation between residence- and mobility-based exposures to greenspace (Wu et al. 2023; J. Wang et al. 2024), air pollution (Y. M. Park and Kwan 2017), service density (Chaix et al. 2017), and food environment (Sharp and Kimbro 2021). Compared to residents who live in an environmentally advantaged neighborhood, those from a disadvantaged residential neighborhood are exposed to fewer environmental benefits (e.g., greenspace) but more environmental harms (e.g., air pollutants) in other experienced neighborhoods of daily life. A moderate-to-strong correlation between residential and nonresidential environmental exposures would therefore lead to a limited extent of neighborhood effects averaging.

Besides the spatial dependence of physical environments across neighborhoods, neighborhoods themselves present temporal dynamics related to different combinations of resident and nonresident populations on a daily basis. Concepts of "places of movement" and "the daycourse of place" reveal that neighborhoods are not static spatial entities, but their social profiles follow a daily rhythm and trajectory (Hetherington 1998; Vallée 2017). Social geographers have conceptualized the time-varying nature of neighborhoods from a network perspective (Cummins et al. 2007; Sampson 2012). In the network of neighborhoods, each neighborhood node is connected with other nodes through population movement and exchanges. It receives inbound populations from other neighborhoods and sends outbound populations to other neighborhoods around the clock. Using geotagged social media data in the largest fifty U.S. cities, for example, Q. Wang et al. (2018) and Candipan et al. (2021) estimated around 400,000 users' residential neighborhoods and analyzed their daily movement from and to other neighborhoods visited in daily life. After aggregation of individual movement trajectories into the neighborhood network, the results indicate that population daily movement is not a random process, but is determined by spatial proximity, as well as social homophily, among neighborhoods. Particularly, the daily exchange of populations among socially proximal neighborhoods (e.g., neighborhoods of racial or ethnic minorities) would result in mobility-based socioeconomic (dis)advantages correlated with, but different from, socioeconomic segregation based on residential and spatially proximal neighborhoods.

Moreover, the idiosyncratic characteristic of population movement patterns for each neighborhood would limit the extent of neighborhood effects averaging. Recent neighborhood network analyses have uncovered significant differences in the socioeconomic composition of the neighborhoods visited across residential neighborhoods of different race or ethnic and income characteristics. Compared to socioeconomically advantaged neighborhoods, disadvantaged neighborhoods dominated by low-income residents and racial or ethnic minorities were less likely to receive inbound populations with a high socioeconomic position, but more likely to send outbound populations with a low socioeconomic position (Q. Wang et al. 2018; Y. A. Kim, Hipp, and Kubrin 2019; Levy, Phillips, and Sampson 2020; Candipan et al. 2021; Zhang et al. 2022). The convergence (i.e., a strong correlation) between residential and nonresidential socioeconomic segregation would result in the extent of neighborhood effects averaging less than expected by the statistical definition of RTM. The geography of crime summarizes these mobility-induced segregation patterns as triple neighborhood disadvantages, which jointly contribute to the criminal landscape within a city (Levy, Phillips, and Sampson 2020; Graif et al. 2021).

## The (A)symmetry of Between-Individual Dispersion

Neighborhood effects averaging indicates a convergence in mobility-based exposures to socioenvironmental factors compared to residential exposures across neighborhoods. Obsession for summarizing this averaging and regression tendency points to an important lesson that prioritizes methodological reductionism and emphasizes general rules over specific circumstances underpinning human mobility in daily life (Schwanen 2018). In this way, policymakers can turn to a mobility-based approach, such as increasing car ownership for socioenvironmentally disadvantaged populations and enhancing access to public transportation in socioenvironmentally disadvantaged neighborhoods, to enable the mobility-induced neighborhood effects averaging and tackle entrenched inequalities established at the place of residence. Notwithstanding a possibly limited extent of neighborhood effects averaging as discussed earlier, the sole focus on neighborhood effects averaging cannot capture the full picture underlying the relationship between residence- and mobility-based socioenvironmental exposures. The counterprocess of RTM—dispersion—specifies how individuals are exposed to varying levels of socioenvironmental factors in daily activity spaces even though they live in the same residential neighborhood. The between-individual dispersion would attenuate, or even reverse, the decrease in variability of socioenvironmental exposures caused by RTM, which complicates the understanding of spatial contextual effects in and beyond the influence of residential neighborhoods.

In the estimation of spatial contextual effects, for example, a disregard for between-individual dispersion in mobility-based socioenvironmental exposures would lead to the statistical artifact of the NEPP. Contrary to what neighborhood effects averaging has observed, B. Wang et al. (2021) and Wu et al. (2023) demonstrated how exposure to greenspace exhibits greater variations in other nonresidential contexts than in residential neighborhoods for participants residing in several suburban neighborhoods of a city. Notably, the observed phenomenon of neighborhood effects polarization should not be regarded as a counterevidence to neighborhood effects averaging. Averaging does occur across neighborhoods, but the extent of averaging is limited. This is because the studied neighborhoods, drawn from a subset of all city neighborhoods, have few variations in the distribution of greenspace. In contrast, residents from these neighborhoods can visit other city neighborhoods where they are exposed to a wider range of greenspace. In this case, between-individual dispersion contributes to greater variations of mobility-based greenspace exposures and overtakes the decrease in variations resulting from a limited extent of neighborhood effects averaging. As a result, the statistical artifact of neighborhood effects polarization would appear when between-individual dispersion within each neighborhood is aggregated to an overall distribution across neighborhoods.

Specific to the process of between-individual dispersion, it is not clear to what extent mobility-based socioenvironmental exposures are symmetrical in distribution within each neighborhood. According to the statistical definition of dispersion, individuals from the same residential neighborhood have an equal chance to visit other neighborhoods with socioenvironmental factors of either higher or lower levels than those in their residential neighborhood. In statistical terms, socioenvironmental factors distributed in the residential neighborhood represent a stable property for individuals' true level of exposure. From a geographic way of thinking, however, nonresidential exposures are unlikely to be random variances (or errors) around the mean level of residential exposures. Inequalities based on race or ethnicity, class, gender, disabilities, and other socioeconomic characteristics are (re)productive of uneven mobilities and accessibility (Cresswell 2011; Sheller 2018). In daily life, individuals' activity-travel patterns are thus manifested as a selection process, reflecting their mobility-related preference structure based on sociopsychological characteristics, as well as the constraints imposed by socioeconomic resources and environmental opportunities (Hedman and Van Ham 2011; Chaix et al. 2012). This selective daily mobility, or lack thereof, is likely to result in an asymmetrical distribution of mobility-based socioenvironmental exposures across individuals, even among those residing in the same neighborhoods (Figure 2).

On the one hand, asymmetrical socioenvironmental exposures could arise from individuals' mobility preferences. Extensive research has evidenced selective residential mobility, where individuals sort them out into different residential neighborhoods based on socioeconomic and psychological characteristics (Hedman and Van Ham 2011; Coulter, Ham, and Findlay 2016). Selective daily mobility, however, is less discussed in neighborhood effects research. Compared to long-term residential locations, daily activity locations are a matter of more immediate and flexible choices (Chaix et al. 2012). Residents who are inclined to live together in the same residential neighborhood might also tend to stay together in neighborhoods of work, leisure, and so on. A recent national study in the United States has substantiated that large cities do not encourage socioeconomic mixing through increased diversity of everyday encounters. Residents living in affluent neighborhoods tend to self-segregate in out-of-home activity locations because large cities "enable people to seek out and find others who are similar to themselves" (Nilforoshan et al. 2023). Regarding mobility-based exposure to physical environments, existing evidence is mixed for the tendency of convergence versus compensation compared to residential exposure. The psychology of convergence would gravitate individuals toward places similar to their residential environments (Maat and de Vries 2006). The compensation mechanism, however, indicates that individuals have a basic demand for environmental benefits and a maximum threshold for exposure to environmental harm (Hall and Page 2014). When residing in a disadvantaged neighborhood with few environmental benefits (or much environmental harm), individuals might proactively approach (or avoid) these environmental factors in other nonresidential contexts.

On the other hand, individuals' daily mobility and choices of activity locations are not always a manifestation of preferences. Constraints from the lack of socioeconomic resources and environmental opportunities could also contribute to an asymmetrical distribution of mobility-based socioenvironmental exposures within the neighborhoods. As discussed earlier, socioenvironmentally disadvantaged neighborhoods tend to lie in proximity to each other (e.g., concentrated poverty of neighborhoods; Wilson 2012). On this basis, residents of these disadvantaged neighborhoods—such as older, unemployed, and low-income residents—are likely to face mobility constraints from physical impairment and disabilities, low levels of car ownership, and poor access to public transportation (Thrift and Pred 1981; Kwan and Schwanen 2016; J. Kim and Kwan 2021). These constraints of daily mobility reduce the possibility of alleviating socioenvironmental disadvantages surrounding the place of residence, thereby resulting in mobility-based contextual exposures leaning toward disadvantaged residential circumstances. As suggested by the spatial entrapment hypothesis, low-income residents who live in a socioeconomically deprived neighborhood tend to stay in

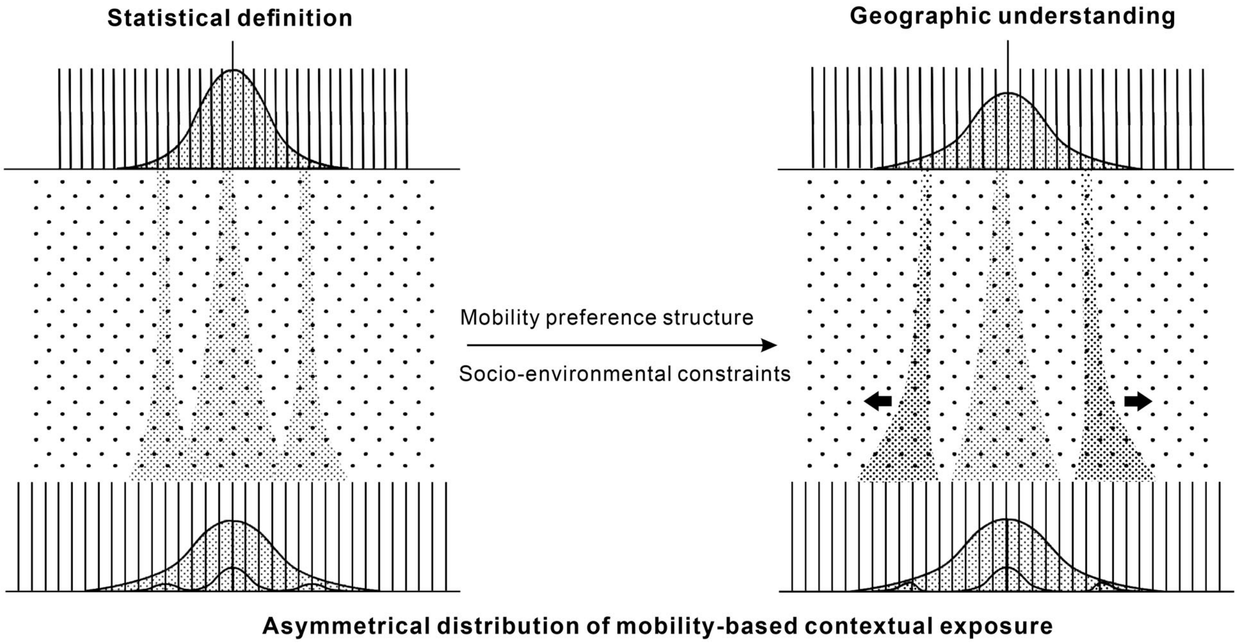


**Figure 2.** Statistical definition versus geographic understanding of between-individual dispersion in mobility-based contextual exposure.

their residential neighborhoods, or visit nearby neighborhoods with similar levels of deprivation, indicating double socioeconomic disadvantages exposed in residential neighborhoods and nonresidential contexts (McPherson, Smith-Lovin, and Cook 2001; Rapino and Cooke 2011; J. Kim and Kwan 2021; Tao 2024).

For residents from a socioenvironmentally advantaged neighborhood, however, a narrow extent of daily activity space does not often result from socioeconomic and environmental constraints. They spend much time in their neighborhoods due to an attachment to pleasant residential circumstances. Residents in high socioeconomic positions even deliberately promote the establishment of gated communities to increase neighborhood safety and retreat from public space (Atkinson and Flint 2004; Zhang et al. 2022). From this, we can learn that stasis or immobility has different meanings and represents different practices for individuals at two ends of a social hierarchy (Cresswell 2012; Nikolaeva et al. 2019). The politics of mobility underscores the fact that both movement and stasis are a representation of asymmetrical power relations among individuals (Hannam, Sheller, and Urry 2006; Cresswell 2011). The control over (im)mobility is exercised in the power geometry of daily life, which contributes to the asymmetry in exposures to sociospatial contexts between individuals beyond their residential neighborhoods.

## Conclusions

There is an a-mobile tradition in neighborhood effects research where the residential neighborhood is regarded as the sole contextual unit representing daily socioenvironmental exposures and relevant to individual behavior-related outcomes (Hannam, Sheller, and Urry 2006; Van Ham et al. 2011). By conceptually investigating the relationship between static residence-based exposure and mobility-based contextual exposure, this study contributes to understanding how we would misestimate the spatial contextual effects when disregarding the fact that residents move beyond the area of residential neighborhoods in daily life. Because of RTM, we argue that the population distribution of mobility-based socioenvironmental exposures will be less extreme on average than that of residential exposures. Previous neighborhood effects studies therefore tend to underestimate actual spatial contextual effects when they misinterpret residential neighborhood effects as the total contextual effects. Future research needs to take a step forward from improving the measurement accuracy of exposure assessment to understanding the spatial contextual effects in and beyond the influence of residential neighborhoods. As yet, it remains unclear to what extent neighborhood effects regression takes place for each neighborhood and how residents of each neighborhood deviate in their mobility-based contextual exposures, resulting in uncertainty in the estimation of spatial contextual effects.

Introducing the notion of RTM originating from biology and statistics, this study has conceptually elucidated the phenomenon of neighborhood effects averaging as observed in recent daily mobility research (J. Kim and Kwan 2021; Mennis et al. 2022; Zhang et al. 2022; Xu et al. 2023; J. Wang et al. 2024). Inherently, neighborhood effects averaging is a statistical phenomenon, which lends little causal inference on the relationship between residence-based and mobility-based socioenvironmental exposures. It is therefore overoptimistic to assume that individuals will alleviate socioenvironmental disadvantages situated at the place of residence once they move outside their residential neighborhoods for daily activities. From a geographic perspective, this study further indicates a lesser extent of neighborhood effects averaging than expected by the statistical definition of RTM, because of localized socioenvironmental distribution and idiosyncratic population movement patterns across neighborhoods. As introduced earlier, bespoke neighborhoods delineate the multiscale nature of socioenvironmental distribution over space (Petrović, Manley, and van Ham 2020), and neighborhood network analysis accounts for the dynamics in neighborhood population composition and exchanges on a daily basis (Sampson 2012; Graif et al. 2021). Future studies are welcome for using these ego-centered and mobility-based approaches to examine the extent of neighborhood effects averaging in empirical settings.

Besides neighborhood effects averaging, this study calls for equal attention being paid to between-individual dispersion in mobility-based socioenvironmental exposures within each neighborhood. Otherwise, some statistical artifacts would be observed and attributed to the explanation at the neighborhood level, such as neighborhood effects polarization (Wu et al. 2023) and environmental injustice exclusive to the place of residence (Tao et al. 2021). More important, the distribution of individual socioenvironmental exposures in daily activity space is likely to be asymmetrical around the level of residential exposure. The asymmetrical distribution of mobility-based socioenvironmental exposures is a manifestation of individuals' selective daily mobility, resulting from mobility preferences based on their sociopsychological characteristics and mobility constraints imposed by limited socioeconomic resources and environmental opportunities. Furthermore, understanding mobility-based contextual exposures in daily life should not be independent of long-term residential context and history. Neighborhood socioenvironmental contexts and individual socioeconomic composition interact with each other over time (Cummins et al. 2007; Diez Roux and Mair 2010). Besides the neighborhood effects on individual outcomes, individuals proactively (re)shape the sociospatial contexts of neighborhoods through daily mobility, activities, and social interactions.

By virtue of large-scale population movement data and advanced computational capacity, there is a growing body of studies transitioning from residence-based to mobility-based exposure assessment (e.g., Q. Wang et al. 2018; Levy, Phillips, and Sampson 2020; Levy et al. 2022; J. Kim and Kwan 2021; Cai and Kwan 2024; Silm et al. 2024). These studies aim to accurately identify spatial contextual units relevant to individual experiences of places and measure contextual exposures to socioenvironmental factors from the perspective of daily mobility. Advanced accuracy of exposure assessment will not automatically translate into better epistemological understanding of spatial contextual effects in and beyond the influence of residential neighborhoods, however. The analysis of empirical mobilities needs to evolve hand in hand with the development of mobile theorization and mobile methodologies (Sheller and Urry 2006; Shaw and Hesse 2010; Cresswell 2011). Derived from this dialogue, this study has conceptually investigated how the sole focus on residential neighborhoods will lead to the misestimation of actual spatial context effects. By understanding RTM, as well as the opposite tendency of dispersion, in neighborhood effects research from a geographic perspective, we have shown a myriad of complexities involved in obtaining a full understanding of spatial contextual effects, including a possibly limited extent of neighborhood effects averaging across neighborhoods and asymmetrical distribution of mobility-based contextual exposures around residential exposures across individuals.

An important takeaway from this study is that expanding the geographic scope of population daily movement will not automatically address socioenvironmental inequalities situated at the place of residence. As suggested by RTM, neighborhood effects averaging simply represents a statistical phenomenon where the distribution of residents' socio-environmental exposures across neighborhoods tends toward the population mean level after their daily mobility and resultant contextual exposures are taken into account. Besides a possibly limited extent of neighborhood effects averaging, there might be an asymmetrical distribution of individuals' mobility-based exposures leaning toward their residential exposures, due to the selective (im)mobility of daily activity locations and long-term residential locations. In an era of mobility turn, therefore, places and contexts still matter for neighborhood effects research (Sheller and Urry 2006; Kwan and Schwanen 2016). Extending the knowledge to implications for policy and practice, we advocate that place-based interventions, including place enhancement (e.g., the fifteen-minute city) and mobility infrastructure fix (e.g., multimodal mobility hubs), are still crucial for redistributing uneven environmental opportunities and mobility resources across neighborhoods. Whenever neighborhood effects research calls for more attention to human mobility in daily life, we suggest one step further from investigating the structural influence of residential neighborhoods to understanding the spatial contextual effects of residents on the move.

## Supplemental Material

Supplemental data for this article can be accessed on the publisher's site at: https://doi.org/10.1080/24694452.2025.2504533

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## ORCID

Yinhua Tao http://orcid.org/0000-0002-4018-9915
Ana Petrović http://orcid.org/0000-0002-6337-964X
Mei-Po Kwan http://orcid.org/0000-0001-8602-9258

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YINHUA TAO is an Associate Professor in the School of Transportation at Southeast University, Nanjing, China. E-mail: yh.tao@hotmail.com. He is an urban and transport geographer whose research focuses on the longitudinal analysis of neighborhood effects and activity-travel behaviors.

ANA PETROVIĆ is an Assistant Professor in the Department of Urbanism, Faculty of Architecture and the Built Environment at Delft University of Technology, 2628 BL Delft, The Netherlands. E-mail: A.Petrovic@tudelft.nl. Her research interests include sociospatial inequalities, segregation, and the interaction between people and their urban environment at multiple spatial scales.

MEI-PO KWAN is Head of Chung Chi College, Choh-Ming Li Professor of Geography and Resource Management, and Director of the Institute of Space and Earth Information Science at the Chinese University of Hong Kong, Hong Kong, China. E-mail: mpk654@gmail.com. Her research interests include environmental health, human mobility, sustainable cities, transport and health issues in cities, and GIScience.

MAARTEN VAN HAM is a Professor of Urban Geography in the Department of Urbanism, Faculty of Architecture and the Built Environment at Delft University of Technology, 2628BL Delft, The Netherlands. E-mail: M.vanHam@tudelft.nl. His main research interests are in urban inequality, segregation, and neighborhood effects.