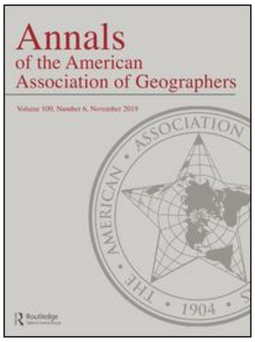

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# Where Do Neighborhood Effects End? Moving to Multiscale Spatial Contextual Effects

Ana Petrović,[*] Maarten van Ham,[*,†] and David Manley[‡,*]

[*]Department of Urbanism, Faculty of Architecture and the Build Environment, Delft University of Technology, The Netherlands
[†]School of Geography and Sustainable Development, University of St. Andrews, UK
[‡]School of Geographical Sciences, University of Bristol, UK

There is no theoretical reason to assume that neighborhood effects operate at a constant single spatial scale across multiple urban settings or over different periods of time. Despite this, many studies use large, single-scale, predefined spatial units as proxies for neighborhoods. Recently, the use of bespoke neighborhoods has challenged the predominant approach to neighborhood as a single static unit. This article argues that we need to move away from neighborhood effects and study multiscale context effects. The article systematically examines how estimates of spatial contextual effects vary when altering the spatial scale of context, how this translates across urban space, and what the consequences are when using an inappropriate scale, in the absence of theory. Using individual-level geocoded data from The Netherlands, we created 101 bespoke areas around each individual. We ran 101 models of personal income to examine the effect of living in a low-income spatial context, focusing on four distinct regions. We found that contextual effects vary over both scales and urban settings, with the largest effects not necessarily present at the smallest spatial scale. Ultimately, the magnitude of contextual effects is determined by various spatial processes, along with the variability in urban structure. Therefore, using an inappropriate spatial scale can considerably bias (upward or downward) spatial context effects. *Key Words: bespoke neighborhoods, distance decay, neighborhood effects, socioeconomic status, spatial scale.*

Sociospatial inequalities have been increasing in many European cities (Tammaru et al. 2016), which, in turn, results in spatial concentrations of low-income households. Governments have a long history of developing area-based policies to target neighborhoods with concentrations of poverty, and such policies are partially based on the belief that living in a deprived area has a negative impact on individual outcomes (for reviews, see Ellen and Turner 1997; Dietz 2002). These impacts are usually referred to as neighborhood effects, although from a theoretical perspective they involve various processes that are not bounded to a single spatial scale (Sampson, Morenoff, and Gannon-Rowley 2002; Galster 2012), so that it is more appropriate to use the term *spatial contextual effects* (Petrović, van Ham, and Manley 2018). Fundamentally, neighborhood effects research asks whether there is a causal association between the spatial context in which someone lives and their life outcomes. Although the definition of neighborhood has been identified as a major challenge in the neighborhood effects research (see, e.g., Galster 2008), Diez Roux (2001) noted that it is "more precisely, definition of the geographic area whose characteristics may be relevant to the specific … outcome being studied" (1784). Therefore, the size and definition of the relevant geographic area might vary according to both the spatial contextual process and the individual outcome being studied—from small to large areas with different geographic boundaries, many of which might not conform to the idea of "neighborhood" at all. Because we expect causal processes to operate at various spatial scales, we need a multiscale approach to represent them (Petrović, van Ham, and Manley 2018).

Existing studies on neighborhood effects use one of three main approaches when considering the spatial scale of context. First, most studies use a single spatial scale, usually administrative units, treating neighborhood as a static single-scale entity (Manley, Flowerdew, and Steel 2006), and without exploring



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the consequences of this choice. This is somewhat surprising, because the importance of spatial scale is well known in the methodological literature on the modifiable areal unit problem (see Openshaw and Taylor 1979), which suggests that using a different scale of spatial context could yield different results.

The second approach is to compare neighborhood effects measured at different spatial scales. Such studies found statistically significant relationships between residential context at various spatial scales and personal health (Lebel, Pampalon, and Villeneuve 2007; Duncan et al. 2014), political attitudes and voting behavior (MacAllister et al. 2001; Johnston et al. 2005), educational achievement (E. K. Andersson and Malmberg 2014), and labor market outcomes (R. Andersson and Musterd 2010; Hedman et al. 2015). Since the early 2000s, neighborhood effects research has been enhanced by the use of "bespoke neighborhoods" (Johnston et al. 2000), which are constructed around the residential location of an individual (ideally using geographic coordinates, but often small areas) to represent the neighborhood of that individual, at various spatial scales (see also Hipp and Boessen 2013; Clark et al. 2015). One common result in studies that compare the effects of different spatial scales is the stronger effects at smaller scales (see, e.g., Bolster et al. 2007): In other words, localized neighborhoods appear to matter more for individual outcomes, although this is not universally the case (Buck 2001). Crucially, it is difficult to compare different studies, because they use a variety of scales to depict "neighborhood"—from the micro (R. Andersson and Musterd 2010) to large administrative units such as U.S. counties (Chetty and Hendren 2018), which are much bigger than what people would normally consider as "their neighborhood" or where the processes of socialization and peer group effects would occur.

Finally, the third way of dealing with the issue of spatial scale is to systematically examine its effect, varying only scale while everything else remains constant. Spielman, Yoo, and Linkletter (2013) did so using simulated data and demonstrated that the misrepresentation of spatial scale of the neighborhood systematically biased estimates of neighborhood effects. To simulate the common research practice, they assumed that there was a "true" neighborhood and an associated effect present at one specific spatial scale. In reality, there are a multitude of spatial processes that take place simultaneously at various scales (Dietz 2002; Sampson, Morenoff, and Gannon-Rowley 2002; Galster 2012). Furthermore, these scales are unlikely to be constant over space or time: The same process could occur at several scales even in one location and might vary over time, perhaps depending on the moment in an economic cycle. The scale(s) at which spatial contextual effects operate are driven (in part) by the mechanism that is being investigated: Smaller neighborhoods could be important to understand social interactive mechanisms, whereas processes such as area stigmatization might operate at a much larger spatial scale (Manley, Flowerdew, and Steel 2006; van Ham and Manley 2012). The systematic examination of spatial scale should also involve the urban structure (Spielman and Yoo 2009). This is important, for example, because deprivation and affluence concentrate at different spatial scales between places, so that stigmatized areas might be relatively large in big cities, whereas smaller cities or towns might experience the same processes confined to smaller locales.

This article takes the third (systematic) approach to spatial scale, combining it with the theoretical guidelines about the multitude of spatial processes. Our aim is to better understand how the estimates of spatial contextual effects on individual income vary as that context is measured at different spatial scales, how this translates across urban space, and what the consequences are when using an inappropriate scale, in the absence of theory. We used individual-level register data for the whole population of The Netherlands (1999–2014), which includes a low level of geocoding of each individual's place of residence (100 m × 100 m grid cells) annually. We created bespoke areas, centered on each person's location, at 101 spatial scales (see Petrović, van Ham, and Manley 2018), and measured the share of low-income people in these areas, across all urban regions in The Netherlands, highlighting the four regions of Amsterdam, Rotterdam, Utrecht, and Groningen. For every scale, we modeled individual income based on people's residential context characteristics, applying a distance decay function, thus generating parameter estimates of spatial contextual effects at the entire range of spatial scales. In doing so, we explored the fallacies and potential risks of isolating specific spatial scales from a wider spatial context.

## Spatial Scale of Contextual Effects on Socioeconomic Status

### Multiscale and Bespoke Nature of Sociospatial Context

For almost a century researchers have observed the effects of spatial scale on the results of statistical analyses (see, e.g., Gehlke and Biehl 1934). The modifiable areal unit problem has prompted many authors to think about the sociospatial context of people beyond standard administrative units at a single spatial scale (see, e.g., Flowerdew, Manley, and Sabel 2008; Kwan 2009). Various spatial contexts with no regard to administrative boundaries are especially important for studying potential exposure to, and interaction with, other people. For example, Grannis (1998) used street networks, whereas Coulton et al. (2001) mapped residents' perceptions of neighborhood boundaries. One important finding is that residents had various, noncoterminous perceptions; another one is that they commonly placed themselves in the middle of the neighborhood. This matches earlier ideas that individuals place themselves in the center rather than on the edge of a neighborhood (Hunter 1974; Galster 1986). Accordingly, neighborhood boundaries are not fixed but "sliding," depending on residents' individual locations, personal characteristics, and perceptions, and the geographical setting. Sliding boundaries do not only reflect not only the differences between people but also the multiscale nature of spatial context of a single person. As early as 1972, Suttles (1972) argued that one person belongs to spatial contexts at multiple scales, starting with the close surrounding of their home and expanding to larger areas.

Combining the ideas of the multiscale and bespoke nature of spatial context, the introduction of "bespoke neighborhoods" (Johnston et al. 2000) into neighborhood effects research is understandable. This approach allows the use of areas with varying scale, so that studies using bespoke neighborhoods have greater possibilities to explore the spatial scale of context (see, e.g., Chaix et al. 2005; Bolster et al. 2007). The bespoke neighborhood approach also tackles edge issues that arise when a person lives close to the boundary of an administrative area, meaning that his or her context might be better represented by adjacent administrative areas rather than the more distant parts of his or her "own" neighborhood. Small-scale spatial contexts are then more individual specific (different for people in different locations), and as scale increases bespoke contexts become increasingly shared. Thus, spatial contexts of (increasingly distant) individuals overlap, which represents the social landscape of the city more closely than nonoverlapping areas (Hipp and Boessen 2013). Bespoke neighborhoods therefore reflect an individual's location and distances within the context of one person, as well as the overlapping contexts of multiple people. They can be generated by starting from very small spatial units, increasing to very large areas, thus allowing a multiscale investigation of contextual effects, not bounded to a single neighborhood. This is more in line with the theoretical insights into the variety of mechanisms through which spatial context might affect individual socioeconomic status.

### Multiscale Contextual Effects on Socioeconomic Status of People

Authors such as Galster (2012) and Sampson, Morenoff, and Gannon-Rowley (2002) have systematized a vast variety of processes arising from spatial contextual characteristics that might affect individual outcomes, including those related to socioeconomic status. These processes are often jointly termed *neighborhood effects*, but the variety of spatial extents at which they operate suggests that various spatial contexts are relevant for individual outcomes rather than a single neighborhood. This involves scales that might be larger or smaller than what is often invoked under the term *neighborhood* but might influence individuals through different mechanisms. For example, role models or personal social networks can influence job search behavior and efficacy (Bala and Goyal 1998; Topa 2001; Dietz 2002). These mechanisms belong to a wider group of social-interactive mechanisms (Sampson, Morenoff, and Gannon-Rowley 2002; Galster 2012), which depend on the individual characteristics of people and their activity spaces. They generally operate within the local neighborhood, often smaller than administrative units, and require exposure, if not contact, to other people, however.

The effect of the micro spatial context cannot be understood in isolation from the macro framework, which represents the "context of context" for the small-scale neighborhoods (Petrović, van Ham, and Manley 2018). Using an example from Auckland, New Zealand, Manley et al. (2015) demonstrated that the microscale residential mosaic is framed by a relatively permanent macroscale structure of the city, where changes occur at a slower rate than in the microcontext. External (large-scale) contextual mechanisms result from a neighborhood's location relative to economic and political structures, so that jobs or public services remain less accessible for some people than for others (Kain 1968). Between the micro and macro spatial contexts exist various mesocontexts, representing particular segments within the city (Manley et al. 2015; Petrović, van Ham, and Manley 2018), that could earn reputations based on demographics, housing types, or other (historical or current) characteristics. This reputation might influence people's decision to move in or out of the neighborhood (Sampson 2012) but also cause stigmatization of their residents by, for example, potential employers (White 1998).

Many studies have examined spatial contextual effects on personal income as a proxy for socioeconomic status (see, e.g., Brännström 2005; Bolster et al. 2007; Hedman et al. 2015). Although crucial for understanding contextual effects, the place in which someone lives is often operationalized pragmatically—using a single, predefined scale and sometimes comparing a handful of scales. Frequently, this means using spatial units constructed for administrative purposes to represent neighborhoods. Given the variety of possible spatial contextual effects, using a single scale could capture some of the processes, but it is very likely to miss many others (Petrović, Manley, and van Ham 2020), despite representing the predominant approach in the estimation of neighborhood effects, particularly those related to socioeconomic outcomes. Because different studies use different data sets, from different countries and cities, studying contextual effects on different outcomes, and at different spatial scales, consensus on the importance and impact of scale for contextual effects is difficult to find.

## The Impacts of Spatial Scale and Urban Structure on Modeling Contextual Effects

One challenge of addressing the issue of spatial scale in modeling contextual effects is to demonstrate how the coefficient estimates vary with spatial scale; another challenge is how to include different scales in the models so that they represent the impact of various residential contexts, from the micro to macro. Although neighborhood effects studies have, to date, generally found bigger effects at smaller spatial scales, we should not forget that the urban landscape is highly variable across small distances (Fowler 2015; Johnston, Poulsen, and Forrest 2015; Catney 2016). This was explored by Chaix et al. (2005), who assessed the spatial scale of variability in the prevalence of mental disorders using the parameter that quantifies the rate of correlation decay with increasing distance between neighborhoods. After applying this parameter, larger areas resulted in smaller neighborhood effects. Besides reflecting the urban structure, the correlation decay supports the idea that an individual's residential context cannot simply be captured in a neighborhood but is a continuous field whose influence decays with distance (Spielman, Yoo, and Linkletter 2013), as opposed to a single, fixed geographic area. Although social interactions are not just a function of distance, distance is an important factor and indicator of spatial interactions, whereby nearby zones have a greater importance than those further away—the so-called distance-decay effect. Reardon et al. (2008) argued that applying a distance decay function "more plausibly corresponds to patterns of social interaction" (511).

Through a series of simulations, Spielman and Yoo (2009) illustrated the importance of considering the issue of spatial scale and the urban structure of a specific setting for understanding the relationship between individuals and their spatial context. Petrović, van Ham, and Manley (2018) used multiscale measures of population in bespoke neighborhoods to show the effects of scale on measuring spatial context within and between cities. In this study, the effect of scale became particularly apparent when comparing cities with different urban forms, demonstrating that both inter- and intraurban polycentricity are reflected in spatial context measures at various scales. This also highlights that one of the reasons for the limited understanding of spatial scale of contextual effects is the focus in the neighborhood effects literature on single cities.

Spielman, Yoo, and Linkletter (2013) analyzed the effects of urban structure and the definition of neighborhood on the assessment of neighborhood effects by using synthetic data in a simulated environment. Although urban structure was not associated with a systematic bias of the contextual effects estimates across spatial scale, the authors found that misspecifying the spatial extent of the neighborhood systematically biased the effect estimates. Simulating the common practice in the neighborhood effects research that assumes that there is one "true" neighborhood, the authors demonstrated that when overstating the extent of neighborhood, the effect is underestimated, whereas when using neighborhood below the scale of the effect, an overestimation resulted. This experiment therefore demonstrated the impact of varying spatial scale on modeling the contextual effect of one spatial process operating in a specific area on individual outcomes. When the spatial scale of this process of a contextual effect is misrepresented, the researcher engages in a spurious statistical inference. Therefore, it is important to hypothesize the spatial scale at which each mechanism would operate based on theory and operationalize the spatial context accordingly (see also Petrović, Manley, and van Ham 2020).

The systematic investigation using synthetic data and simulations has taught us a lot about the impact of spatial scale on assessing contextual effects, starting from the assumption that there is one "true" neighborhood. In the real world, there are a vast variety of contextual effects mechanisms at different spatial scales, and therefore it is difficult to isolate a single spatial process and to identify a single area where this process operates in the continuous space of contexts to which a person belongs. Models using real data include multiple potential effects on individuals and therefore the systematic investigation of the impact of spatial scale becomes even more difficult. To capture the uncertainty around contextual effects, studies should stop searching not only for one "true" effect from the model with the best fit (Spielman and Yoo 2009) but also for one "true" neighborhood that affects individuals, given the multitude of contextual effects at different spatial scales.

This article systematically investigates in which way the estimates of contextual effects on individual income vary when using detailed multiscale measures of spatial context. We do so by characterizing contextual space using bespoke, overlapping areas at increasingly large spatial scales, in all twenty-two urban regions of The Netherlands. To examine the effect of various urban forms, the study then compares four distinct urban regions, each of them including the main city with a few surrounding municipalities. Those regions are Amsterdam, Rotterdam, and Utrecht, as parts of Randstad, the largest conurbation in The Netherlands, as well as Groningen, a relatively isolated northern city in a rural environment.[1] The article uses the multiscale measures of population at 101 spatial scales as independent spatial context variables in models of personal income. This generated an array of 101 parameter estimates for all urban regions combined, as well as for each of the four selected urban regions, allowing us to assess the variability in the contextual effects at a range of spatial scales.

## Data and Methods

We used register data containing the entire population of The Netherlands recorded in the Social Statistical Database (Sociaal Statistisch Bestand; see Bakker 2002; Houbiers 2004). The longitudinal nature of the data allows us to follow individual residential histories for fifteen years (from 1999 to 2014). Crucially, each person's place of residence is georeferenced to a 100 m × 100 m grid cell each year, allowing the construction of multiple bespoke areas. Controlling for personal and household characteristics, we modeled spatial contextual effects on personal income from work, corrected for inflation, for all men who were of working age (twenty to sixty-five) throughout the whole period (i.e., twenty to fifty-one in 1999 and then thirty-four to sixty-five in 2014). We include men only to avoid gender interactions, because, for example, women in The Netherlands work part-time more often than men, and the register data do not include information about hours worked (although important, the gender effect is not of primary interest in this investigation and we want to be able to isolate the impact of scale as clearly as possible). We also excluded men for whom education data were not available, because the previous literature has shown that education is a major predictor of wages.

Besides education (defined as low, medium, or high), we identified the following individual characteristics at time *t:* age (regular and quadratic terms), ethnicity as belonging to either Western or non-Western backgrounds, type of household (couples, and single and other household types), and whether the individual has dependent children. To define ethnicity, we adopted the Statistics Netherlands ethnic classification, because their definition of the non-Western group[2] reflects the use of "ethnic minorities" within social policy in The Netherlands (Alders 2001). The non-Western minorities in The Netherlands originate from Africa, South America, and Asia, including Turkey and excluding Indonesia and Japan.[3] The other major group in our ethnic classification is that of Dutch and other Western ethnicities together.

Our contextual variable is the proportion of individuals in the neighborhood who have a low income. Here, income includes not only income from work but also from social welfare payments received by the working-age population. To measure low income, we use the International Labor Organization definition adjusted for the Dutch context. Thus, an individual has a low income if he or she is in receipt of less than 40 percent of the median income in The Netherlands.[4] We measured the share of people with a low income in the area at time $t-1$ to allow for the time lag of exposure to context. Of course, the length of exposure required to result in a change to the individual is also an issue of scale and temporality, but to concentrate on the spatial scale effect, we assume, in line with much of the literature, that a one-year lag is sufficient to lead to an alteration of outcome. The smallest neighborhood scale is represented by the 100 m × 100 m cell in which an individual lives, and we constructed 100 further bespoke neighborhoods by increasing the radii by 100-m increments to create a range of spatial contexts from 100 m up to 10 km (see Petrović, van Ham, and Manley 2018). The purpose of varying the bandwidth so extensively is to examine the (in)stability of the models and to observe changes in the contextual effect over distance.

We modeled the contextual effects for men from all twenty-two urban regions in The Netherlands, controlling for whether or not they lived in one of the four largest cities (Amsterdam, Rotterdam, The Hague, and Utrecht), which are considered to be distinct from the rest of the country in terms of economic and urban development. To investigate the potentially differential effect of scale in multiple urban regions in The Netherlands, we then focused on four selected urban regions of Amsterdam, Rotterdam, Utrecht, and Groningen, restricting the sample to men who never moved from the region they were located in 1999 (although they could move within that region, thus changing neighborhood), to isolate the effect of each region. This allows us to keep as much of the analytical design the same over time, and although there might be biases as a result, the impact of scale will not be differentially confounded as a result of changing exposure to different contexts in other cities. To assess the impact of scale over time, we ran 101 fixed effects models (one for each scale) for each of the four urban regions, keeping everything else constant, except the spatial scale of the residential context. The fixed effects model estimates the within (time) effect, controlling for the time-invariant variables (observed and unobserved). Although the ethnic background is time invariant, the models also include the interaction between this individual and the time-variant contextual characteristic (the share of low-income neighbors). We adopted a fixed effects approach, because it is commonly used in the literature for modeling contextual effects.

Although individual characteristics are the same in the models at all spatial scales, the contextual characteristic was measured separately for each scale $s \in \{0, \ldots, 101\}$, which gave 101 estimates of each coefficient. To account for the conceptual meaning of residential contexts at various spatial scales, specifically the diminishing possibility for meaningful spatial interactions as scale increases, we have transformed the spatial context variable: The share of low-income people is multiplied by the "bespoke scale term" (the squared distance in kilometers $d \in \{0, 0.1, \ldots, 10\}$), which formulates the diminishing potential exposure with increasing distance, based on Tobler's first law of geography (Tobler 1970). Squared distance belongs to a family of distance decay functions, widely studied in geography to find an appropriate measure of interaction intensity over distance, and it was a default applied in the original measures of multiscale spatial segregation by Reardon and O'Sullivan (2004). Besides the distance decay of potential exposure, our "bespoke scale term" takes into account the spatial structure (see Fotheringham 1981). At the smallest scale, the model uses the raw measure of the share of low-income people, because $d^2 = 0$. With increasing spatial scale, the bespoke residential contexts both increase in size and increasingly overlap with each other. This is formulated with the quadratic growth of $d^2$, which is proportional to the size of the area ($A = \pi r^2$). The so-constructed models are represented in the following equation:

$$y_{it} = \alpha_{i,s} + \beta_s X_{it} + \beta_s X_{it-1,s}\ (1 + d^2) + u_{it,s},$$

**Table 1.** Descriptive statistics for all twenty-two urban regions: Individual characteristics and contextual characteristics at the spatial scale of 100 m × 100 m grid cells

| Variable | M | SD | Minimum | Maximum |
|---|---|---|---|---|
| Year at time *t* | 2007 | 4.32 | 2000 | 2014 |
| Log income in 1,000 euros | 3.59 | 0.72 | — | — |
| Medium education (reference = low) | 0.34 | 0.47 | 0 | 1 |
| High education (reference = low) | 0.63 | 0.48 | 0 | 1 |
| Age | 38.99 | 8.58 | 21 | 65 |
| Age$^2$ | 1,593.93 | 703.76 | 441 | 4,225 |
| Non-Western background | 0.06 | 0.24 | 0 | 1 |
| Children | 0.54 | 0.50 | 0 | 1 |
| Single or other household type (reference = couple) | 0.27 | 0.45 | 0 | 1 |
| Living in one of the four largest cities | 0.25 | 0.43 | 0 | 1 |
| Share of low-income people | 14.52 | 9.92 | 0 | 100 |
| Non-Western background × Share of low-income people | 0.96 | 4.52 | 0 | 100 |
| Living in one of the four largest cities × Share of low-income people | 3.85 | 8.14 | 0 | 100 |

*Note:* All twenty-two urban regions, $N = 289{,}711$; observations = 4,345,665. Shaded fields indicate contextual characteristics.

where $y_{it}$ is log income in 1,000 euros of individual $i$ at time $t$; $\alpha_{i,s}$ is the unobserved time-invariant individual-specific effect in the model for spatial scale $s$; $\beta_s$ is the matrix of parameters for spatial scale $s$; $X$ is the regressor matrix of individual characteristics; $X_{it-1,s}$ is the share of low-income people in the residential context of individual $i$, measured at time $t-1$ at spatial scale $s$; and $u_{it,s}$ is the error term in the model for spatial scale $s$.

## Results

We begin by describing individual characteristics of people from our study area (twenty-two urban regions in The Netherlands), focusing on the four distinct regions of Amsterdam, Rotterdam, Utrecht, and Groningen. After that, the analysis of contextual effects is presented in three steps: First, we explore how the share of low-income people in the residential context varies with spatial scale, between people and over time. We then present the linear relationship between contextual poverty and the income of individuals at four sample scales. Finally, we analyze the estimates of spatial contextual effects from 101 fixed effects models for all urban regions, as well as for each of the four selected regions—presenting spatial profiles of the effects of the share of low-income people at 101 scales on personal income. Our main point of interest is how these effects vary with increasing scale, how the variability in urban structure affects the results, and whether there are differences between the four urban regions.

Table 1 shows a descriptive overview of the individual characteristics from the models for all twenty-two urban regions (the white cells); these are constant for all 101 models. The table also contains the records of spatial context (the light gray cells) that are used in the lowest scale models. Table 2 shows the same overview but for each of the four selected urban regions. Among them, Rotterdam is distinct with the lowest education levels, Amsterdam has a greater proportion of single households without children, and both of these regions have more non-Western people than Utrecht and Groningen. The mean and standard deviation[5] values of income show that Utrecht and Rotterdam have similar average income levels but Utrecht exhibits greater inequality in income. Groningen has the lowest average income and Amsterdam the greatest inequality (measured as standard deviation).

The spatial context characteristics at the lowest spatial scale (see Tables 1 and 2) show that in the immediate neighborhood the potential exposure to low income ranges from 0 to 100 percent. In Groningen, however, 100 m × 100 m neighborhoods have the highest average share of low-income people (18 percent) as well as the highest inequality ($SD = 15$). The other three regions are more similar (14 percent low-income people in Amsterdam and Rotterdam, 15 percent in Utrecht), which is also around the average level for all twenty-two urban regions. The inequality in exposure, however, varies more: Utrecht has a of standard deviation of 11, compared to 8 in both Amsterdam and Rotterdam.

**Table 2.** Descriptive statistics for the four urban regions (Amsterdam, Rotterdam, Utrecht, and Groningen): Individual characteristics and contextual characteristics at the spatial scale of 100 m × 100 m grid cells

| Amsterdam[a] | | | | | Rotterdam[b] | | | |
|---|---|---|---|---|---|---|---|---|
| *M* | *SD* | Minimum | Maximum | Variable | *M* | *SD* | Minimum | Maximum |
| 2007 | 4.32 | 2000 | 2014 | Year at time *t* | 2007 | 4.32 | 2000 | 2014 |
| 3.58 | 0.75 | — | — | Log income in 1,000 euros | 3.62 | 0.68 | — | — |
| 0.36 | 0.48 | 0 | 1 | Medium education (reference = low) | 0.39 | 0.49 | 0 | 1 |
| 0.61 | 0.49 | 0 | 1 | High education (reference = low) | 0.56 | 0.50 | 0 | 1 |
| 39.41 | 8.35 | 21 | 65 | Age | 39.52 | 8.77 | 21 | 65 |
| 1,622.60 | 687.71 | 441 | 4,225 | Age$^2$ | 1,638.42 | 725.65 | 441 | 4,225 |
| 0.12 | 0.33 | 0 | 1 | Non-Western background | 0.11 | 0.32 | 0 | 1 |
| 0.48 | 0.50 | 0 | 1 | Children | 0.56 | 0.50 | 0 | 1 |
| 0.34 | 0.47 | 0 | 1 | Single or other household type (reference = couple) | 0.27 | 0.45 | 0 | 1 |
| 14.06 | 7.57 | 0 | 100 | Share of low-income people | 13.92 | 8.10 | 0 | 100 |
| 1.85 | 5.72 | 0 | 87.89 | Non-Western background × Share of low-income people | 1.88 | 5.99 | 0 | 81.40 |

| Utrecht[c] | | | | | Groningen[d] | | | |
|---|---|---|---|---|---|---|---|---|
| *M* | *SD* | Minimum | Maximum | Variable | *M* | *SD* | Minimum | Maximum |
| 2007 | 4.32 | 2000 | 2014 | Year at time *t* | 2007 | 4.32 | 2000 | 2014 |
| 3.62 | 0.72 | — | — | Log income in 1,000 euros | 3.47 | 0.70 | — | — |
| 0.31 | 0.46 | 0 | 1 | Medium education (reference = low) | 0.33 | 0.47 | 0 | 1 |
| 0.66 | 0.47 | 0 | 1 | High education (reference = low) | 0.64 | 0.48 | 0 | 1 |
| 39.48 | 8.42 | 21 | 65 | Age | 40.13 | 8.80 | 21 | 65 |
| 1,629.36 | 695.91 | 441 | 4,225 | Age$^2$ | 1,687.65 | 735.97 | 441 | 4,225 |
| 0.06 | 0.23 | 0 | 1 | Non-Western background | 0.02 | 0.15 | 0 | 1 |
| 0.54 | 0.50 | 0 | 1 | Children | 0.53 | 0.50 | 0 | 1 |
| 0.26 | 0.44 | 0 | 1 | Single or other household type (reference = couple) | 0.26 | 0.44 | 0 | 1 |
| 14.97 | 10.73 | 0 | 100 | Share of low-income people | 18.06 | 14.72 | 0 | 100 |
| 0.95 | 4.61 | 0 | 89.62 | Non-Western background × Share of low-income people | 0.49 | 3.95 | 0 | 89.47 |

*Note:* Shaded fields indicate contextual characteristics.
[a]*N* = 36,594; observations = 548,910.
[b]*N* = 23,443; observations = 351,645.
[c]*N* = 18,409; observations = 276,135.
[d]*N* = 10,094; observations = 151,410.

## Multiscale Residential Context: The Variability in Urban Structure

Tables 1 and 2 only include the spatial context parameters (share of low-income people) at the lowest spatial scale. Figure 1 shows the same variable for all 101 spatial scales, depicted using variance, and for each of the four selected urban regions (see Appendix for the figure for all urban regions). From the variance we can derive more information by decomposing it into two components that reveal different origins of inequality in exposure to contextual poverty. Firstly, there is the variance *between* people (which denotes differences between contexts of different people for the entire examined period) and, secondly, is the *within*-person variance (over time, averaged for all people in the urban region).

The between-people variance shows that different people were (potentially) exposed to different spatial contexts at multiple scales over the entire time period (1999–2013). These differences are the greatest in Groningen but also substantial in Utrecht, where distinct types of context in terms of income levels have a radius of a few kilometers (the scale after which the between variance drops). The within (people) variance shows how much the context of people changes over time, either because they moved or because the area around them changed (perhaps due to mobility of others or the changing characteristics of the residents within those areas). These temporal changes are the greatest in the immediate area surrounding an individual's home

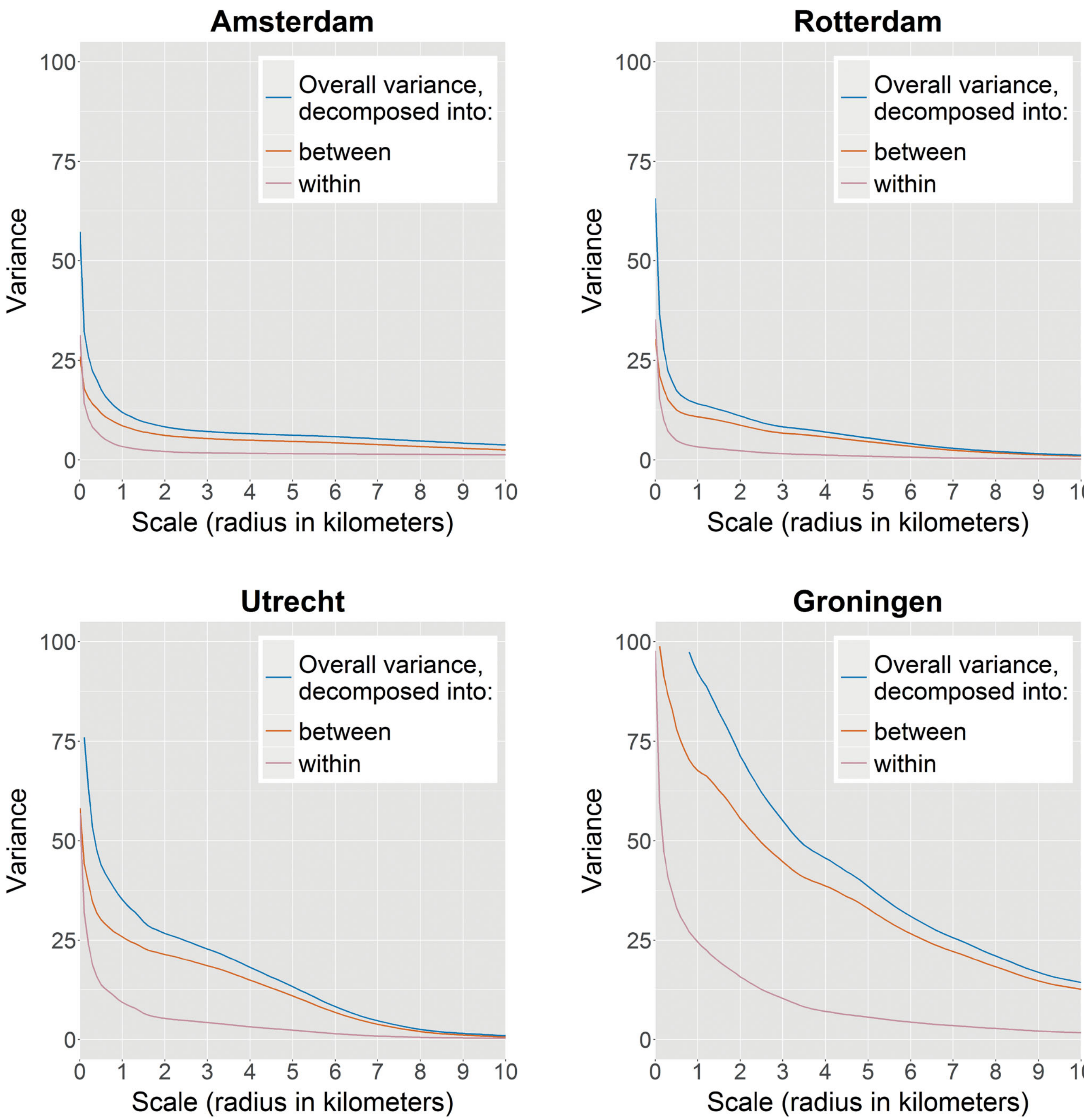


**Figure 1.** Variance of the share of low-income people in spatial contexts measured at 101 spatial scales for the four selected urban regions.

(the smallest spatial scale). In Amsterdam and Rotterdam, they are greater than the variance between people, reflecting the fact that in these cities the residents are generally exposed to a wide variety of immediate neighborhoods during their life. As scale increases, however, there are more permanent differences between contexts, rather than the temporal changes (the between variance is much bigger than the within variance). This is the evidence of temporal segregation: Different people remain living in different spatial contexts over the entire study, never or rarely mixing with other types of places (although they may have moved). In this study, we focus on the effects of changes in potential exposure to contextual poverty over time (here described by the within variance), and this is captured by the fixed effects model.

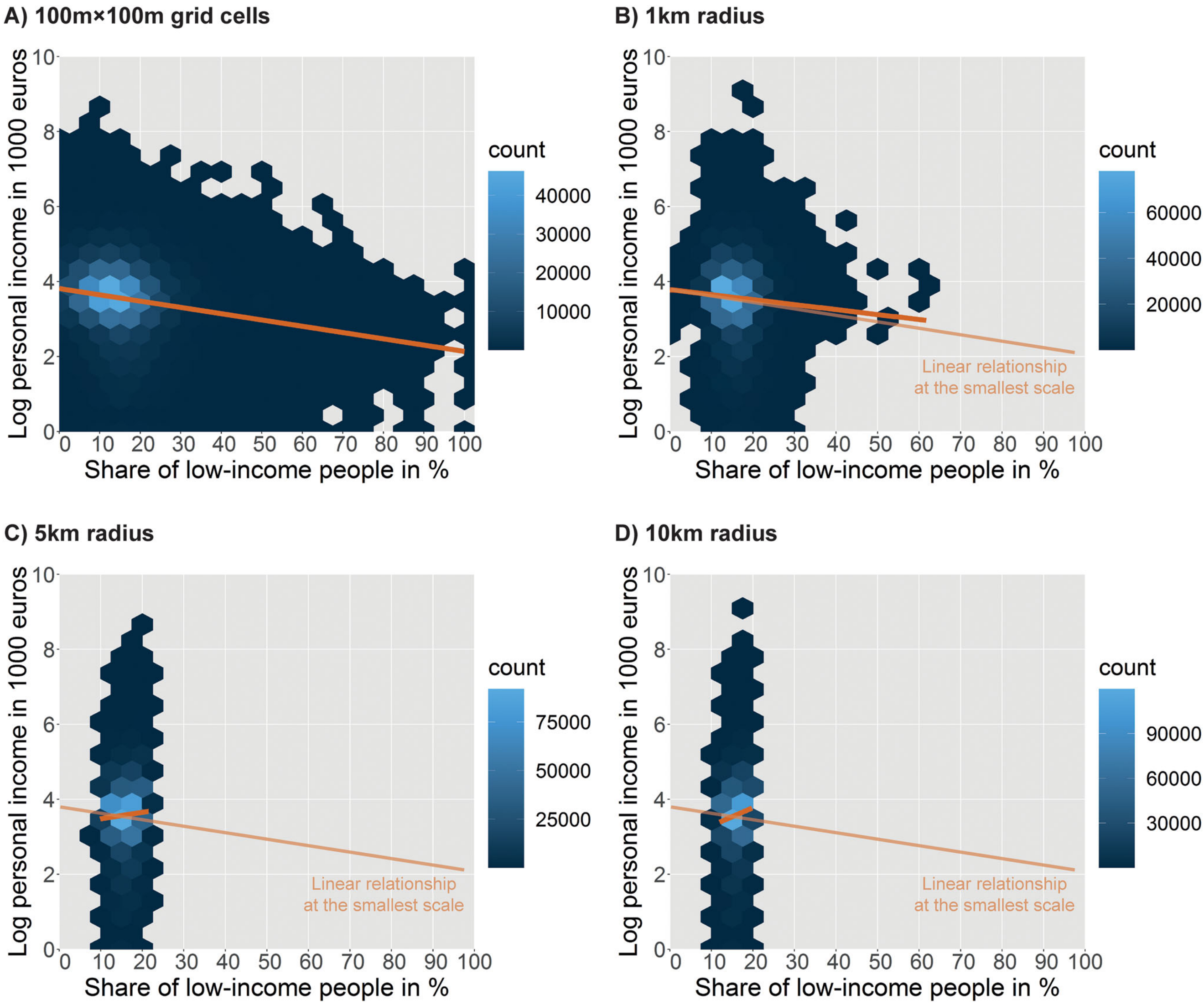


**Figure 2.** Relationship between personal income and the share of low-income people for four sample scales in Amsterdam: (A) 100 m × 100 m grid cells; (B) areas with 1-km radius; (C) areas with 5-km radius; (D) areas with 10-km radius.

## Relationship between Multiscale Context and Individual Income: The Consequences of the Choice of Scale

Figure 1 reports the diminishing variance in contextual poverty across spatial scale, with particularly small variance at the scales of a few kilometers. Because our primary interest is the effect of the residential context on individual income, we next explore how the decreasing variance in urban structure affects the linear relationship between contextual poverty and individual income. Figure 2 demonstrates this for four sample scales in the Amsterdam urban region. The graph contains all of the data points for all people and for all years; although the individual observations have been blurred to maintain privacy, the properties of the relationship remain intact. When comparing the four panels, it is clear that as scale increases, the range of the share of low-income people (shown on the *x* axis) decreases (confirming the observation from the variance graphs). This is a natural artifact of increasing the scale: Thus, at the smallest scale, individuals in the Amsterdam region are potentially exposed to the full range of the share of low-income neighbors (0–100 percent). By contrast, at the highest spatial scale (10 km radius), this range of potential exposures in Amsterdam decreased to between 10 and 20 percent. This is a consequence of the larger areas containing a greater proportion of the population of the region, so that the differences

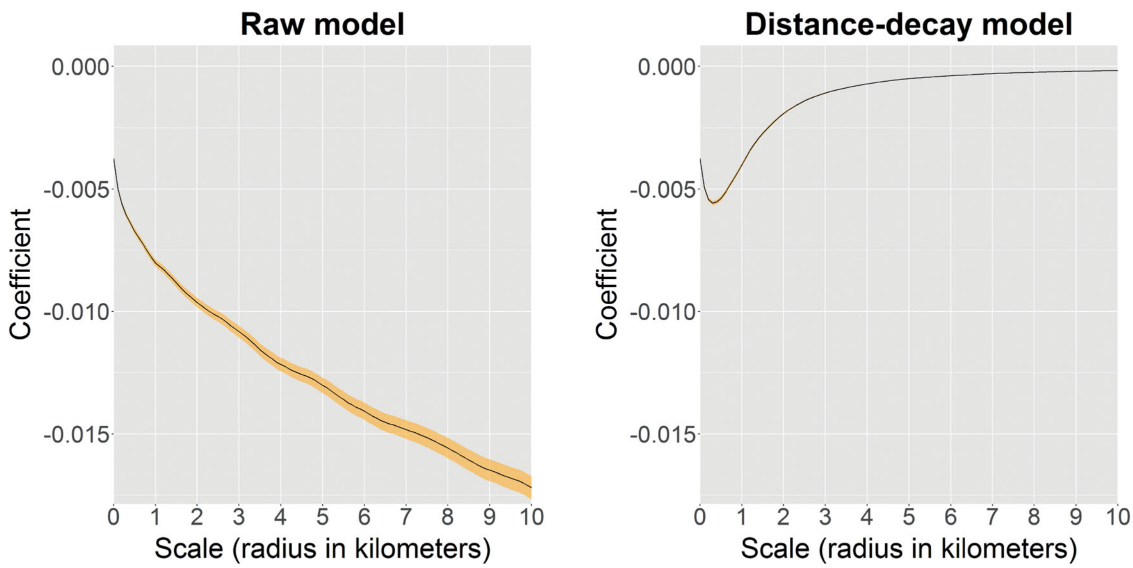


**Figure 3.** Fixed effects coefficient estimates of the share of low-income people, measured at 101 spatial scales, on personal income from work for people in all urban regions in The Netherlands.

exhibited at the finer spatial scales are "smoothed out" at the higher scales. For the lower two spatial scales (100 m × 100 m and 1-km radius), the more low-income people are in the residential context, the lower an individual's income becomes (Figure 2A and Figure 2B). This negative relationship becomes weaker as scale increases (with 1-km radius being weaker than the 100 m × 100 m).

By contrast, the figures for the two largest spatial scales report a positive relationship between individual incomes and contextual poverty (Figure 2C and Figure 2D). Because the same analysis for single years[6] shows negative relationships, it is the addition of time (using the full period 1999–2014) that results in the positive relationship at the larger scales. This indicates that, as personal income, shown on the *y* axis, increases over time—which would be expected as individuals progress through their career—the share of low-income people in larger areas, shown on the *x* axis, also increases. A possible explanation is that sociospatial inequalities are growing in the Amsterdam region (see Tammaru et al. 2016). Differences between large-scale contexts, both over time and for different people within the same region, are, however, not that large, as can be seen from the small ranges of the share of low-income people in Figure 2C and Figure 2D, which do not expand over the entire *x* axis, as was the case in Figure 2A. Although the larger spatial context in which someone lives is important, its characteristics are very stable over time—much more so than at the lower scales. This is a consequence of the size of the area, where any individual altering his or her location or income cannot have a substantial impact on area characteristics. By comparison, at smaller scales, individuals, as part of a smaller population, can exert much more influence on that local average, the characteristics of which are then much noisier. Ultimately, this leads to the question of how the variability in urban structure, ranging from small local areas to the shared context of the city, affects the estimation of contextual effects in common research practice and in a more theoretically informed framework.

## From the Localized to the Shared Context: Where Do Neighborhood Effects End?

Our overarching question is how the effect of contextual poverty on individual income varies across a large range of spatial scales. We estimated 101 within-people (fixed) effects models of individual income (one for each spatial scale) for all twenty-two urban regions in The Netherlands (Figure 3), as well as for each of the four selected urban regions (Figure 4). It is not possible to present all parameters of these models here, so we present the main results of interest: the parameter estimates of the effect of low-income people in the spatial context at all the scales. (See Appendix Tables A.1 and A.2 to get an idea of the full models, including all variables, with the spatial context at the lowest

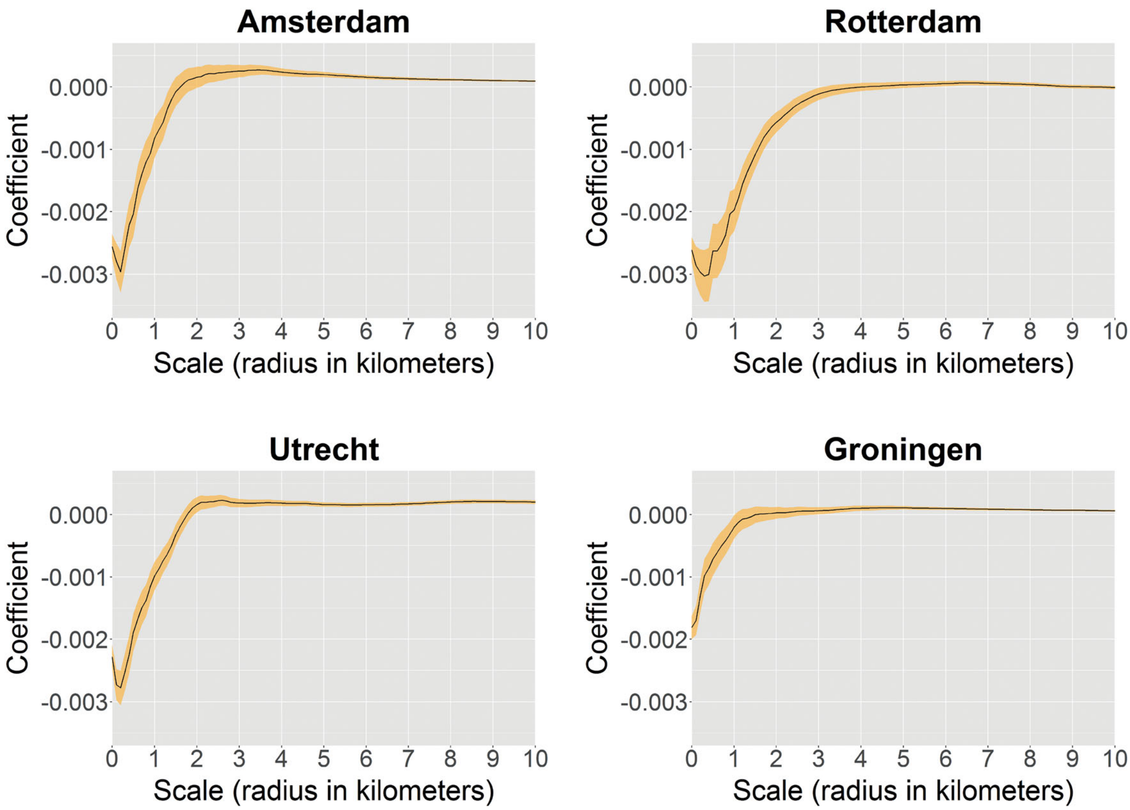


**Figure 4.** Fixed effects coefficient estimates of the share of low-income people, for 101 spatial scales, on personal income from work for people in the four selected urban regions.

spatial scale.) In both figures, the black lines follow the changes of the coefficient estimates over scale and the shaded areas surrounding the lines show the confidence intervals.

Exploring the relationship between individual income and the spatial contexts across scale (in the previous section) suggested that if we model contextual effects without a theoretical approach, the results will be determined by the variance in urban structure. The left panel of Figure 3 displays the results of the raw models (without distance decay incorporated) for all urban regions, across 101 scales. This results in an increasing effect across scales. Notable, at the largest scales, the changes in the spatial context over time are so small that they appear to have a very large effect on individual income (that changes at the same rate in all models). For reference, the largest area in our study is almost ten times smaller than an average U.S. county, used as a "neighborhood" in other studies (Chetty and Hendren 2018). We suggest that these large effects at higher scales might be an artifact of the low variance at these scales, which we investigate further by using the distance decay model, shown in the right panel of Figure 3. In this theoretically instructed model, the distance decay function represents a diminishing potential for exposure and interaction with spatial scale. The model takes into account the effect of decreasing variance at higher scales and, as a result, avoids the issue that very small changes in the spatial context appear to have large effects on income. The comparison between the two models demonstrates how misleading results of neighborhood effects studies can be when using a single spatial scale, particularly really large areas as a proxy for neighborhood.

Because we log-transformed income from work (in thousands of euros), a relatively small coefficient of $-0.001$ results in each 1 percent increase in the share of low-income people being associated with a 0.1 percent decrease in an individual's annual income from work. In line with previous European evidence, we did not find very strong contextual effects, but they are significantly different from zero. Crucially, the effects vary across spatial scales and generally decrease with increasing scale. It is also important to note that to focus on temporal changes we used fixed effects models, which gave average effects for all of the people, although the between variance suggested that there were considerable differences between people, so that for some of them the contextual effect might well be stronger than for others.

In this study, we investigate differences between people from the four urban regions. Given the preceding findings, we continue to use the distance decay function. Figure 4 presents the within-people effect of contextual poverty at 101 scales on personal income from work; the four sections of the figure represent the four urban regions (Amsterdam, Rotterdam, Utrecht, and Groningen). In each of the four regions, the negative effect of living in a spatial context with a high proportion of low-income people is stronger at smaller spatial scales, falling as scale increases to a point where the effect is (almost) zero. This is in line with previous studies, which predict that negative neighborhood effects are stronger at smaller spatial scales, where the area represents localized contexts and within which people interact with their neighbors. The rate at which the negative spatial context effect diminishes and the point at which the effect becomes zero are, however, different in each of the four regions.

In contrast to the majority of existing studies dealing with spatial scale, the negative contextual effects are not the strongest at the very lowest scale, with the exception of Groningen. Most other studies, however, do not use this smallest spatial scale or this detailed range of scales. The smallest scales represent the more immediate neighborhood contexts that individuals experience when they leave the front door of their house. For our study, Amsterdam, Rotterdam, and Utrecht exhibit weaker spatial context effects at the smallest scale than at slightly larger scales (around 200–300 m), suggesting that it takes a few hundred meters to form a small-scale area that exerts the strongest effect on individual income. This reflects different and distinct urban structures of neighborhoods in the three regions within the Randstad conurbation, compared to Groningen, a monocentric city surrounded by more rural municipalities, relatively isolated from large urban centers.

The scale at which the localized context becomes a shared context (the point at which the contextual effect becomes zero) is different for each urban region. This switch from local to shared occurs at the largest scale (3 km) in Rotterdam, a city with the largest concentrations of poverty, compared to the other three regions, which potentially exerts a more scale-persistent negative effect on its residents' income from work. By contrast, Utrecht and Amsterdam show a switch at around 2 km, and Groningen, the smallest of our urban regions, has the earliest switch at 1.5 km. Before reaching this point, some contextual effects profiles also contain small positive effects. The small positive effect at meso- and macroscales indicates growing sociospatial inequalities not only in Amsterdam (see Tammaru et al. 2016) but also in Utrecht. Although people's income is increasing, they are simultaneously increasingly surrounded by low-income people. These results strongly suggest that at different scales we model different spatial processes. An arbitrarily chosen spatial scale somewhere along the distance profile would therefore capture only some of the processes. Critically, only slight changes in spatial scale can lead to different modeling outcomes. Returning to the issue of using administrative areas for contextual effects studies, the scale of the administrative would give us a result falling between −0.003 and 0, depending on the scale chosen, and would omit the other potential results we have observed.

## Discussion and Conclusions

This article argues for the need to move away from the concept of neighborhood effects and instead study multiscale spatial contextual effects. Spatial contextual effects operate at multiple spatial scales, and studying them at a single spatial scale is likely to bias the results. This article has systematically investigated the effect of spatial scale on modeling individual income. We have operationalized the residential context of individuals using 101 bespoke areas, from the immediate surrounding of the home (100 m $\times$ 100 m) up to areas extending over a 10-km radius—a context that is similar for all people within one city. For all twenty-two urban regions in The Netherlands, as well as the four selected regions we focused on (Amsterdam, Rotterdam, Utrecht, and Groningen), we ran 101 fixed effects models for 101 different spatial scales. Our results showed that the choice of spatial scale and the theoretical approach to various scales of context influenced the modeled outcomes considerably, particularly taking into account specific geographic settings with different urban structures. The study applied a distance decay function, which follows the theory of diminishing potential exposure of people to spatial context across distance, taking into account the relationship between spatial scale and variance in urban structure.

Three lines of discussion follow from our results. First, different spatial scales result in different estimates of contextual effects, because people belong to multiscale spatial contexts, which are related to various spatial processes, operating from micro- to macroscales. Spielman, Yoo, and Linkletter (2013) demonstrated in a series of simulation experiments that using the "wrong" scale can bias the estimated effect upward or downward, whereas the effect is correctly estimated when the "right" scale is used. The success of this approach must be related to the investigation of a very specific and known process. In this study, we used real data, which contain a wide variety of potential processes and effects. These effects vary, because different spatial scales capture different processes, reflecting the complexity of the residential context to which people are exposed, regardless of what is officially considered as their neighborhood.

From this follows our second line of discussion—that a theoretical approach to spatial context effects is necessary. This study suggested the approach of distance decay in potential exposure and interactions in urban space, which can certainly be further developed to capture more complexity in spatial interactions. Using small increments in radius from the hypermicro to hypermacro contexts revealed the differences between locations and changes over spatial scale at a finer resolution than is possible when using fixed administrative boundaries. The strongest evidence of a spatial context effect occurred at 200 m in both Amsterdam and Utrecht and 400 m in Rotterdam, whereas Groningen was the only urban region with the strongest effect at the very lowest scale (100 m × 100 m). Modeling the effect using a single-scale administrative area gives policymakers only limited, incomplete, or even misguided evidence. For example, inappropriately large administrative units obscure stronger effects from smaller spatial scales. Concomitantly, it should not automatically be assumed that the largest effect occurs at the smallest spatial scale, but scale should be examined with respect to theoretical approaches. Although this study did not directly examine social contagion or socio-interactive processes, it did examine small scales at which these mechanisms might occur, highlighting their incompatibility with larger spatial units. Increasingly large contexts can be used to show where the neighborhood effects "end" and other processes, such as growing regional inequalities, take over. As with the distance decay function, which operationalizes the diminishing effect of potential exposure to others as scale increases, processes such as stigma require mesoscales, and labor market spatial mismatch requires regional geographies—in a different theoretical approach. Talking about neighborhoods when using large (administrative) areas is theoretically confusing and technically problematic.

The latter argument is related to our third line of discussion—the variability in urban structure by spatial scale. The magnitude of contextual effects is, at least partially, determined by the mechanisms and the spatial scales at which they operate. There is also a deterministic relationship, however, between variance and regression coefficients, which explains why studies using very large spatial units as a proxy for neighborhoods find large "neighborhood effects." To demonstrate this, we first decomposed the variance of the share of low-income people into the between-people variance, which presents the more permanent spatial structure of the urban regions, and the within-people (temporal) variance, which is a combination of individual mobility and neighborhood change. The amounts of variance in these two components at multiple spatial scales suggest that different processes, such as residential sorting of people, long-term concentration of poverty, and neighborhood change (or stability), are likely to play different roles at different scales. Crucially, both of the variance components decrease with spatial scale. The decreasing variance is not just a consequence of using bespoke neighborhoods, because it occurs for all increasingly large spatial units. We demonstrated that "neighbourhood effects" are found for large spatial units when using the "raw" models, but when theory-driven distance decay models are used these effects disappear. This is because at larger scales there is little variance, especially when using a fixed effects model that is based on changes in area characteristics over time, and the temporal (within-people) variance was even smaller than the between-people variance. Not taking into account this relationship can lead to misleading results revealing a large "neighborhood" effect for large-scale areas, which might have been seen in studies using very large U.S. counties as neighborhood units (Chetty and Hendren 2018). Due to the smaller variance at larger scales, these larger spatial contexts appear to have large effects when they are used as neighborhoods. Our distance decay models, which are based on the theory of diminishing potential exposure and interaction, include the relationship between distance and variance in spatial structure. When using the "raw" models, this leads to potentially misleading large estimates of "neighborhood effects," and the size of the effect is in fact the result of low variance in these large spatial units.

Neighborhood effects are likely to be larger if we consider variability by person and place (Spielman and Yoo 2009). This article has addressed the latter (variability by urban region), along with the prior issue of spatial scale, showing that the impact of scale is place specific. Thus, there is no single de facto correct scale for measuring residential context, even within closely related places in the same country, such as the three regions within the Randstad conurbation (Amsterdam, Rotterdam, and Utrecht). Places in different countries might differ even more. The relationship between scale and geographic setting is a fundamental issue for national-level investigations into neighborhood effects or investigations taking in multiple urban areas, because measures of context at one scale possibly do not capture the same processes in different spaces, and the results of such projects can hardly be generalized. Variability in contextual exposure by person, which we only considered by looking at the between-people variance, is one of the most promising applications of bespoke neighborhoods. Multiscale bespoke areas can embrace a variety of spatial contexts starting from a location that is more specific to an individual's residential location than administrative units. In doing so, we recognize the multiplicity of spatial contexts, rather than search for one generic fixed area as a global proxy for neighborhood.

Although early research on sociospatial inequalities was largely driven by the availability of data for administrative units, individual-level microgeographic data are increasingly accessible. Distances between individuals are playing a more important role in measuring segregation (Wong 2016) and, according to this study, in assessing contextual effects. Our bespoke multiscale approach demonstrates the geographical uncertainty in modeling contextual effects and provides alternatives to predefined administrative units, usually adopted as a proxy for neighborhood. Within the study of neighborhood effects, there are multiple and substantial methodological challenges (see van Ham and Manley 2012), and the literature often highlights the issues of temporality or residential sorting, along with the endogeneity of neighborhood characteristics. As such, spatial scale has often been relegated to the sidelines in the empirical literature or, if discussed, was often limited to defining the neighborhood. Rather than giving a definitive answer for the definition of neighborhood, this article demonstrated that it is more useful to recognize that the multiple scales and the geographic setting of scale are fundamental for understanding spatial contextual effects. In short, it is time to put geography into the center of the neighborhood effects research debate.

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## ORCID

Ana Petrović http://orcid.org/0000-0002-6337-964X
Maarten van Ham http://orcid.org/0000-0002-2106-0702
David Manley http://orcid.org/0000-0003-1864-5141

## Notes

1. The regions and their municipalities are mapped in Figure A.1 in the Appendix, also showing the population and area sizes.
2. Statistics Netherlands defines foreign background as when someone is a first-generation migrant (i.e., they are born abroad, except when born abroad to Dutch parents) or when someone's parents belong to the first generation. People with a foreign background are further divided into Western and non-Western backgrounds.

3. People from Indonesia and Japan are categorized as Western based on their social and economic position in Dutch society: Indonesians because of the historical linkages between The Netherlands and the former Dutch East Indies and Japanese because they or their family member work for a Japanese company in The Netherlands (Alders 2001).
4. The International Labor Organization definition is set at two thirds.
5. Minimum and maximum income values are not shown for privacy reasons because we work with full population data.
6. Not shown but available on request.

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ANA PETROVIĆ is a Postdoc Researcher in the Department of Urbanism, Faculty of Architecture and the Built Environment, 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.

MAARTEN VAN HAM is a Professor of Urban Geography and Head of the Department of Urbanism, Faculty of Architecture and the Built Environment, Delft University of Technology, 2628 BL Delft, The Netherlands, and a Professor of Geography at the School of Geography & Sustainable Development, University of St. Andrews, St. Andrews KY16 9AL Fife, UK. E-mail: M.vanHam@tudelft.nl. His main research interests are in urban inequality, segregation, and neighborhood effects.

DAVID MANLEY is a Professor of Human Geography at the School of Geographical Sciences, University of Bristol, Bristol BS8 1SS, UK. E-mail: D.Manley@bristol.ac.uk. His main research interests are in urban geography, in particular the development and measurement of urban segregation and the impact that residential neighborhood context can have on individual outcomes.

## Appendix

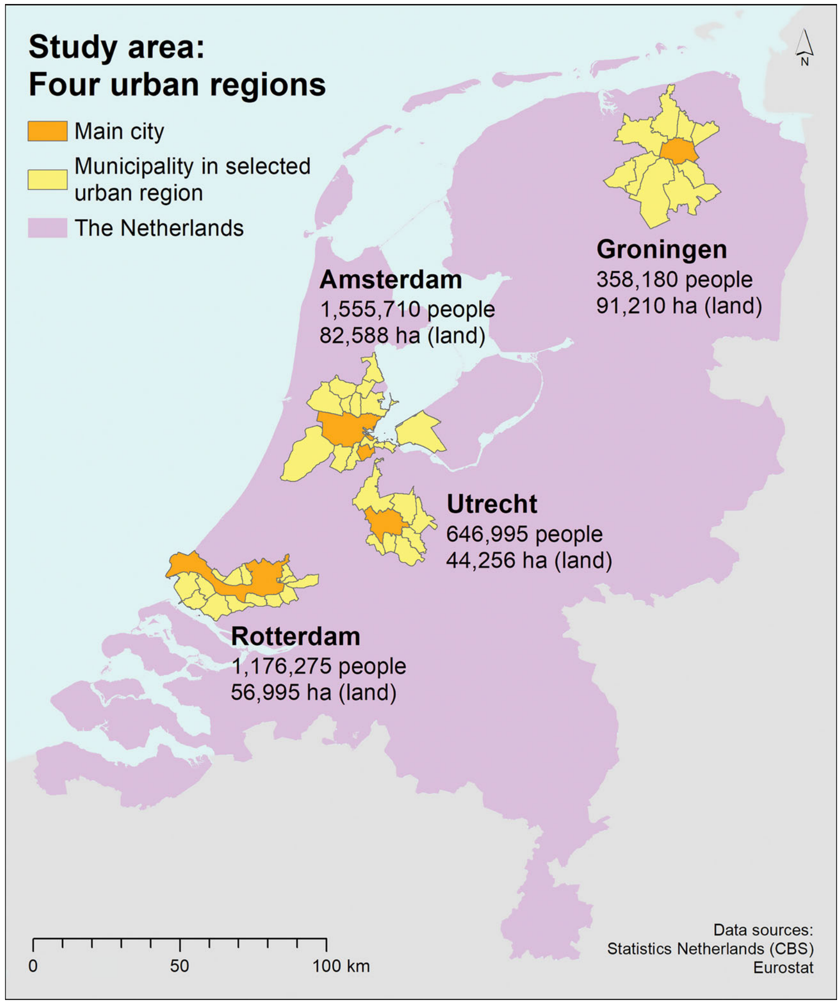


**Figure A.1.** Map of the four selected urban regions (Amsterdam, Rotterdam, Utrecht, and Groningen), with population and area sizes.

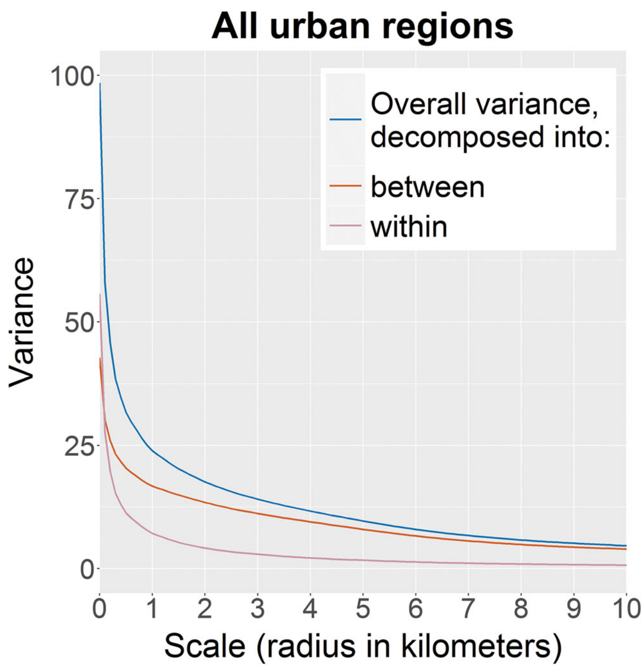


**Figure A.2.** Variance of the share of low-income people in spatial contexts measured at 101 spatial scales for all urban regions in The Netherlands.

**Table A.1.** Fixed effects model of the contextual effects of the share of low-income people, measured at the smallest spatial scale (100 m × 100 m grid cells), on personal income from work, for all urban regions in The Netherlands

| Variable | Coefficient | *SE* | *p* |
|---|---|---|---|
| Medium education (reference = low) | –0.0787888 | 0.0038986 | 0.000 |
| High education (reference = low) | 0.525983 | 0.0040262 | 0.000 |
| Age | 0.2228118 | 0.0002335 | 0.000 |
| Age$^2$ | –0.0019331 | 0.00000284 | 0.000 |
| Non-Western background | 0 | (Omitted) | |
| Children | –0.0541454 | 0.0005376 | 0.000 |
| Single or other household type (reference = couple) | –0.0608013 | 0.0006394 | 0.000 |
| Living in one of the four largest cities | 0.0482651 | 0.0013277 | 0.000 |
| Share of low-income people | –0.0037505 | 0.0000265 | 0.000 |
| Non-Western background × Share of low-income people | –0.000159 | 0.0001014 | 0.117 |
| Living in one of the four largest cities × Share of low-income people | 0.0004442 | 0.0000569 | 0.000 |
| Intercept | –2.234973 | 0.0059191 | 0.000 |

*Note:* Shaded fields indicate contextual characteristics.

**Table A.2.** Fixed effects models of the contextual effects of the share of low-income people, measured at the smallest spatial scale (100 m × 100 m grid cells), on personal income from work, for the four selected urban regions

| Amsterdam | | | | Rotterdam | | |
|---|---|---|---|---|---|---|
| Coefficient | *SE* | *p* | Variable | Coefficient | *SE* | *p* |
| 0.0688013 | 0.0120734 | 0.000 | Medium education (reference = low) | –0.0503765 | 0.0110403 | 0.000 |
| 0.465917 | 0.0124698 | 0.000 | High education (reference = low) | 0.4196488 | 0.0114977 | 0.000 |
| 0.2171401 | 0.0007049 | 0.000 | Age | 0.2116035 | 0.0007436 | 0.000 |
| –0.0018626 | 0.00000856 | 0.000 | Age$^2$ | –0.0017873 | 0.00000898 | 0.000 |
| 0 | (Omitted) | | Non-Western background | 0 | (Omitted) | |
| –0.0449021 | 0.001704 | 0.000 | Children | –0.0612793 | 0.0017837 | 0.000 |
| –0.0487584 | 0.0018461 | 0.000 | Single or other household type (reference = couple) | –0.061382 | 0.0022013 | 0.000 |
| –0.0025581 | 0.0000989 | 0.000 | Share of low-income people | –0.0026096 | 0.0001025 | 0.000 |
| 0.0001918 | 0.0002749 | 0.485 | Non-Western background × Share of low-income people | –0.0008061 | 0.0002956 | 0.006 |
| –2.216017 | 0.0181207 | 0.000 | Intercept | –1.937667 | 0.0181289 | 0.000 |
| **Utrecht** | | | | **Groningen** | | |
| Coefficient | *SE* | *p* | Variable | Coefficient | *SE* | *p* |
| –0.0814482 | 0.0170857 | 0.000 | Medium education (reference = low) | –0.0022948 | 0.0216889 | 0.916 |
| 0.4778684 | 0.0175476 | 0.000 | High education (reference = low) | 0.5783847 | 0.0223782 | 0.000 |
| 0.2250712 | 0.00096 | 0.000 | Age | 0.2082554 | 0.0012274 | 0.000 |
| –0.0019524 | 0.0000115 | 0.000 | Age$^2$ | –0.0017526 | 0.0000145 | 0.000 |
| 0 | (Omitted) | | Non-Western background | 0 | (Omitted) | |
| –0.0591156 | 0.002212 | 0.000 | Children | –0.0666252 | 0.003073 | 0.000 |
| –0.0690865 | 0.002635 | 0.000 | Single or other household type (reference = couple) | –0.0512861 | 0.0035138 | 0.000 |
| –0.0022824 | 0.0000946 | 0.000 | Share of low-income people | –0.0018092 | 0.0000952 | 0.000 |
| –0.0005106 | 0.0003972 | 0.199 | Non-Western background × Share of low-income people | –0.0018694 | 0.0005846 | 0.001 |
| –2.289958 | 0.0251437 | 0.000 | Intercept | –2.216017 | 0.0322089 | 0.000 |

*Note:* Shaded fields indicate contextual characteristics.