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Neighborhood socioeconomic deprivation and psychiatric medication purchases. Different neighborhood delineations, different results? A nationwide register-based multilevel study

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ABSTRACT

Previous studies of neighborhood socioeconomic deprivation and mental health treatment have shown mixed results. Multiple reviews have highlighted that the definition and measurement of neighborhoods can lead to different results, providing one explanation for these mixed findings. This study compares the use of micro-areas created using an automated redistricting algorithm and divided by physical barriers with the use of two administrative units, Danish parishes and postal codes. The geographical data are linked to Danish register data of the Danish population from age 16 in 2017, $N = 4{,}347{,}001$, to measure the association between the purchase of psychiatric medication and neighborhood socioeconomic deprivation using logistic multilevel models. Neighborhood socioeconomic deprivation is associated with a slightly increased probability of redeeming prescriptions for psychiatric medication after controlling for individual sociodemographic composition. However, this association was present only for micro-areas and not for parishes or postal codes. The results indicate that neighborhood effects on psychiatric medication purchases are affected by the neighborhood delineations used and that future studies should carefully consider how neighborhoods are defined and measured.

1. Introduction

Within the study of spatial variations in mental health conditions, neighborhood socioeconomic conditions and deprivation have received much attention (Ellen et al., 2001; Julien et al., 2012; Mair et al., 2008; March et al., 2008; Richardson et al., 2015; Silva et al., 2016).

While most studies in this area have relied on self-reported measures of various mental health conditions, which are subject to both responder and interviewer bias (Maguire et al., 2016), fewer studies have focused on the association between neighborhood socioeconomic deprivation (NSD) and mental health treatment. However, the findings of these studies are mixed, with some studies finding that higher neighborhood deprivation is linked with prescriptions and dispensations of psychiatric medication in general (Crump et al., 2011), ADHD medication (Jablonska et al., 2020) and anxiolytic and antidepressant medication (Maguire et al., 2016). Other studies have linked neighborhood deprivation to diagnoses of mental or behavioral disorders due to psychoactive substance use (Chaix et al., 2005) or in combination with neurotic, stress-related, and somatoform disorders (Chaix et al., 2006) and with hospitalization due to depression or psychosis (Lofors and Sundquist, 2007).

Contrary to these findings, other studies found no adjusted association between neighborhood socioeconomic conditions and antidepressants consumption or psychiatrist consultations (Annequin et al., 2015), psychiatric in- and outpatient care combined with dispensation of psychotropic medication (Ivert et al., 2013) and diagnoses of schizophrenia or depression in fully adjusted models (Sariaslan et al., 2015). Furthermore, two studies found that residing in deprived areas was associated with lower odds of prescriptions or purchases of antidepressant medication (Bocquier et al., 2013; Tarkiainen et al., 2021).

Finally, one study, focusing on persons aged 0–25 years in France, found that antipsychotic dispensing rates were higher in areas with a high rate of persons receiving welfare benefits but were lower in areas with a high rate of unemployment. However these associations were only present in the age group of 16–20 years, and not the full sample (Verdoux et al., 2015).

Several methodological approaches have been used to investigate these so called neighborhood effects, defined as independent effects of neighborhood context over and above individual factors (Arcaya et al., 2016), by addressing the hierarchical structure of neighborhood data and possible sources of selection bias, including the use of multilevel models (e.g., Annequin et al., 2015; Crump et al., 2011) and various

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experimental designs (e.g., Leventhal and Brooks-Gunn, 2003; Ludwig et al., 2013; White et al., 2017). Despite such approaches and the growing body of research covering this field, one of the weakest areas of current practice in health and environment research remains the conceptualization of place (Matthews, 2008). Multiple reviews highlight this problem and how the neighborhood definition and measurement process can lead to different analytical results, thus providing an explanation for the mixed findings beyond differences in samples, age groups under study, designs and variables across studies (Diez Roux, 2001; Ellen et al., 2001; Mair et al., 2008; March et al., 2008; Richardson et al., 2015; Truong and Ma, 2006; Visser et al., 2021). This issue, which is relevant to all fields working with spatial data, is also known as the modifiable areal unit problem (MAUP), which is composed of both a scaling problem depending on the number of areal units used and an aggregation problem depending on how the boundaries are drawn (Openshaw, 1983). Another problem related to the operationalization of neighborhoods is the uncertain geographic context problem (UGCoP), as articulated by Kwan (2012), which focuses on how neighborhood effects can be affected by the method used to delineate areas and the extent to which these areas deviate from the true, causally relevant geographic context of the outcomes under study.

When neighborhoods are chosen as the areal unit of interest, the first issue is that several competing definitions of 'neighborhood' exist (Galster, 2001). However, most definitions focus on either small geographical areas with social interaction among residents or small areas with similar attributes (Haynes et al., 2007). Despite this, existing administrative areas such as census tracts, wards or parishes are still often used as rough proxies for socially meaningful neighborhoods, as these areas may be the only practical alternative in many cases (Flowerdew et al., 2008). Nevertheless, the use of such areas is limited, as they rarely correspond to the theoretical definition of a neighborhood but instead are arbitrary units with no defined effect or meaning to the people living within them, which makes such areas problematic for the study of social processes (Sampson et al., 2002). To solve this issue, the use of perception-based neighborhoods may be an alternative for capturing socially meaningful areas (Coulton et al., 2001). However, the use of such techniques is challenged by the inconsistency among individuals' perceptions, which complicates the subsequent process of aggregation and delineation in larger quantitative studies (Deng, 2016). Another solution is to use an automated neighborhood design technique that automates the neighborhood delineation procedure according to user-specified criteria (Cockings and Martin, 2005; Flowerdew et al., 2008; Haynes et al., 2007; Riva et al., 2008). One possible criterion is the use of physical barriers, such as larger roads and railroad tracks, as dividers based on the understanding of neighborhoods as ecological contexts with social and psychological meaning (Chaskin, 1997) measured on a micro-level scale using factors such as the logic of neighborhood social interactions (Sampson et al., 2002). Such physical barriers may also function as social dividers and thereby promote or hinder social interaction (Feld, 1981; Grannis, 1998), thereby resulting in high within-group sociodemographic homogeneity (Foster and Aaron Hipp, 2011; Lund, 2018). Furthermore, residents may use such major physical barriers to help identify their neighborhoods (Campbell et al., 2009; Grannis, 2009; Lynch, 1971). As a result, using physical barriers rather than administrative areas to create neighborhood delineations may better capture the causally relevant geographical context.

In a recent study, Lund (2018) proposed a new method of spatial division based on an automated redistricting algorithm utilizing Danish georeferenced data on larger physical barriers such as large roads, rivers and forests. In addition, the division is limited by discretionary criteria by Statistics Denmark, and thus, each area contains at least 100 inhabitants. The study shows that compared to the administrative unit of Danish parishes and different modifications of the parishes, such as quartering them, the newly constructed areas greatly improved socioeconomic homogeneity. The areas were further compared with completely random clustering where the physical barriers were removed and the only considerations were areas with at least 100 inhabitants. Additionally, for these areas, the new micro-areas showed higher homogeneity. However, as Lund notes, arguing which method for measuring spatial units is best should always be done in the context of the problem at hand (Lund, 2018). Even though high homogeneity is often used as a criterion in neighborhood evaluation, this criterion should not in itself be used as an argument for potential contextual effects, as complete homogeneity within a neighborhood in fact precludes the study of contextual effects. As Pickett and Pearl point out, a neighborhood does not need to be homogenous to affect the lives of its inhabitants (Pickett and Pearl, 2001). The question is therefore whether these smaller areas lead to different results than administrative areas when looking not only at homogeneity but also at outcomes other than the one used by Lund and when looking at both the visual spatial patterns and the potential contextual effects of these areas.

Although previous reviews have highlighted the importance of studying mental health conditions among alternative methods for designating neighborhoods, several reviews also emphasize that the majority of published studies use only a single set of areas, and most rely on administrative areas (Jivraj et al., 2019; Mair et al., 2008; March et al., 2008; Richardson et al., 2015). Some previous studies have systematically compared the use of different area delineations for various health outcomes, with studies finding that changing the areal units affected the results (e.g., Chaix et al., 2006; 2005; Cockings and Martin, 2005; Flowerdew et al., 2008; Franzini and Spears, 2003; Jablonska et al., 2020; Messer et al., 2012; Parenteau and Sawada, 2011) and other studies finding no major differences between areas (e.g., Cabrera-Barona et al., 2018; Lovasi et al., 2008; Root, 2012; Tarkiainen et al., 2010). This difference may be explained by the fact that the studies examined different health outcomes and contextual factors and that some studies only compared different administrative areas, while other studies looked at alternative area delineations. While comparisons of different administrative boundaries are relevant to finding the most suitable option when these areas are the only alternative, there is still a need to test alternative area conceptualizations and measurements and compare these to the more widely available administrative areas to investigate whether neighborhood effects research can benefit from the development of such new methodological inventions.

Focusing on mental health conditions, the two studies by Chaix et al. (2006, 2005) found that the strength of the association between contextual deprivation and mental disorders increased with decreasing size of the examined areas when spatially adaptive areas that were centered on individual residences and were smaller in size than administrative areas were used.

This suggests that the type of delineation used can be of great importance and that areas beyond administrative boundaries can potentially affect the results. However, to my knowledge, no existing study has compared the use of automatically generated geographically fixed areas divided by physical barriers with different administrative areas for the study of NSD and psychiatric medication purchases.

Therefore, the aim of this study is to investigate the use of neighborhoods divided by physical barriers compared with administrative delineations in determining the relationship between NSD and psychiatric medication purchases. To do this, the following two types of analyses were conducted:

1) GIS-based geodemographic mapping to investigate the descriptive and visual spatial patterns of psychiatric medication purchases and NSD.
2) Multilevel regression analyses to investigate the potential association between NSD and psychiatric medication purchases.

2. Methods

2.1. Data sources

In this study, two different types of data were used: 1) Register data for the Danish population from age 16 in 2017 derived from various registers (Baadsgaard and Quitzau, 2011; Jensen and Rasmussen, 2011; Pedersen, 2011; Wallach Kildemoes et al., 2011) to measure psychiatric medication purchases, sociodemographic characteristics and NSD, and 2) geo-referenced register data dividing the Danish population into parishes and postal codes and geo-referenced micro-areas in 2017 developed by Lund (2018). Participants' unique personal identification numbers (CPR) were used as the key to link all data.

The study population consisted of the entire Danish population from age 16 in 2017 ($N = 4{,}787{,}201$).

The sample was restricted to respondents with full information on all variables used in the analyses, resulting in a final sample of $N = 4{,}347{,}001$.

Because of the large register-based sample and the absence of major differences between the sample and the study population in key demographic variables (gender, age and marital status), missing data were omitted from the analysis rather than being imputed.

2.2. Psychiatric medication purchases

To study the use of psychiatric medication by the full Danish population, a register-based indicator containing information on citizens who filled one or more prescriptions for psychiatric medication in the calendar year of 2017 was used. The following anatomical therapeutic chemical (ATC) code categories were included: N05 for antipsychotics, anxiolytics, hypnotics and sedatives and N06A for antidepressants. The variable was coded 1 for respondents who purchased one or more of the abovementioned medications in the given year and 0 for respondents who did not purchase any of these medications.

2.3. Neighborhood delineations

To analyze the use of different neighborhood delineations, three distinct measures of areal units were used: Automatically generated micro-areas, Danish parishes and Danish postal codes.

The micro-areas were created by Lund (2018) using an automated redistricting algorithm to form the smallest areas possible with at least 100 inhabitants and separated by large physical barriers. To run the algorithm, the National Square Grid assigning addresses in Denmark to 'hectare cells' (100 m x 100 m) in 2000, 2005, 2010, and 2015 was used as georeferenced data. The algorithm used to create the areas follows two overall steps. First, physical barriers in the form of highways, roads broader than 6 m, rivers and streams broader than 3 m, railways, lakes, forests, coastlines, and intakes are applied. Then, the square grid is applied, and the grids are dissolved into the areas where the largest part of the square is located with borders formed by the squares. As a result, the smooth borders are replaced by the borders of the squares in each area. This made it possible to calculate how the population is distributed within the areas. In this step, 20,940 new inhabited areas were created.

After this step, the created areas are further clustered to ensure that each area includes at least 100 inhabitants according to the discretionary criteria of Statistics Denmark and criteria established to ensure the smallest possible number of merges and the smallest possible number of inhabitants. This process results in 8043 new areas. Setting these criteria ensures that the algorithm will create the same mergers if the process is repeated (Lund, 2018). For more detailed descriptions of the algorithm, see Lund (2019, 2018).

In comparison, the Danish parishes and postal codes are two of the smallest administrative geographical units available in Danish registers and have no political purpose. Parishes have been used as a measure for neighborhoods or local areas in previous studies of various health outcomes in a Danish context (Bloomfield et al., 2018; Kjærulff et al., 2019; Meijer et al, 2012, 2013a; Osler et al., 2003). In addition, postal codes such as American zip codes have been used in several studies with a specific focus on NSD and mental health (Almeida et al., 2012; Ross, 2000; Stockdale et al., 2007; Wilson et al., 1999).

In Denmark, postal codes cover very small areas in the capital region; in many cases, they only cover a single street. These approximately 500 so-called street postal codes in Copenhagen were therefore merged into the following three areas according to the Danish Ministry of Environment: 1000–1499 Copenhagen K, 1500–1799 Copenhagen V and 1800–1999 Frederiksberg C (The Danish Ministry of Environment, 2010).

2.4. Neighborhood socioeconomic deprivation

To measure NSD, a composite index was created for each of the three types of areal units. In many countries, different composite deprivation indices have been developed, such as the English Indices of Deprivation (Noble et al., 2019) and the Carstairs index (Carstairs and Morris, 1989). Despite differences among various indices, most deprivation measures include domains related to income and employment, which reflect deprivation because they limit material resources, and education, because low levels of education create disadvantages in accessing various resources, such as better jobs (Allik et al., 2020).

Based on previous contextual socioeconomic deprivation scores, the indices were created with the following three key indicators: Proportion of the population between 30 and 64 years of age in the area who were unemployed at least half of the year, including recipients of sickness benefits, persons on leave and recipients of cash benefits (Bender et al., 2015; Juhász et al., 2010; Meijer et al., 2013b); proportion of the population between 30 and 64 years of age in the area with a total annual personal income in the lowest quartile (Bender et al., 2015; Meijer et al., 2013b); and proportion of the population between 30 and 64 years of age in the area with basic education (levels 0–2) based on the UNESCO International Standard Classification of Education (ISCED) (UNESCO Institute for Statistics, 2012) as the highest attained educational level (Bender et al., 2015; Juhász et al., 2010; Lund, 2020). The population between 30 and 64 was used to capture individuals who typically have graduated and are of working age.

All three indicators were standardized to z-scores and constructed to indices using unrotated principal component analysis (PCA) to determine the relative weight of each indicator. For all three areal units, only the first component, which loaded high on all three indicators, was used. This first component explained 82, 80 and 74% of the variation in micro-areas, parishes and postal codes, respectively, with scores ranging from -3.5 – 9.0. To investigate potential nonlinear associations, the indices were categorized into deciles, with the first decile containing the least deprived areas and the 10th decile containing the most deprived areas.

2.5. Individual-level variables

Individual-level variables included gender, age, marital status, education, personal income and occupation status. Age was grand mean centered by subtracting the sample mean (49.1 years) from the respondent's age. Marital status was collapsed into married, cohabiting or living alone. Education was measured as the highest attained education according to the ISCED collapsed into three categories, with levels 0–2 indicating 'basic education', levels 3–5 indicating 'medium education' and levels 6–8 indicating 'high education'. Income was measured as the total annual personal income (except for any rental income from one's own accommodation and before deducting labor-market contributions and pension contributions) and categorized into quartiles. Occupation status was collapsed into four basic categories: Employed, unemployed, student and pensioner/early retiree. For all level-1 categorical predictors, the reference group was coded as zero.

2.6. Statistical analysis

To analyze the spatial patterns of psychiatric medication purchases and NSD, these variables were aggregated to the areal unit levels and mapped focusing on the capital area of Denmark, showing the different patterns with the use of micro-areas, parishes and postal codes (Fig. 1). The spatial patterns of people redeeming psychiatric medication prescriptions were measured as percentage prevalence, and NSD was measured as the index score. Data were classified using deciles with the classification based on the micro-areas and used for the parishes and postal codes as well.

To analyze the statistical association between NSD and psychiatric medication purchases and compare the use of different neighborhood delineations, two-level logistic multilevel random intercept models were specified for the micro-areas, parishes and postal codes separately using the 'melogit' command in Stata Version 16 (StataCorp, 2019).

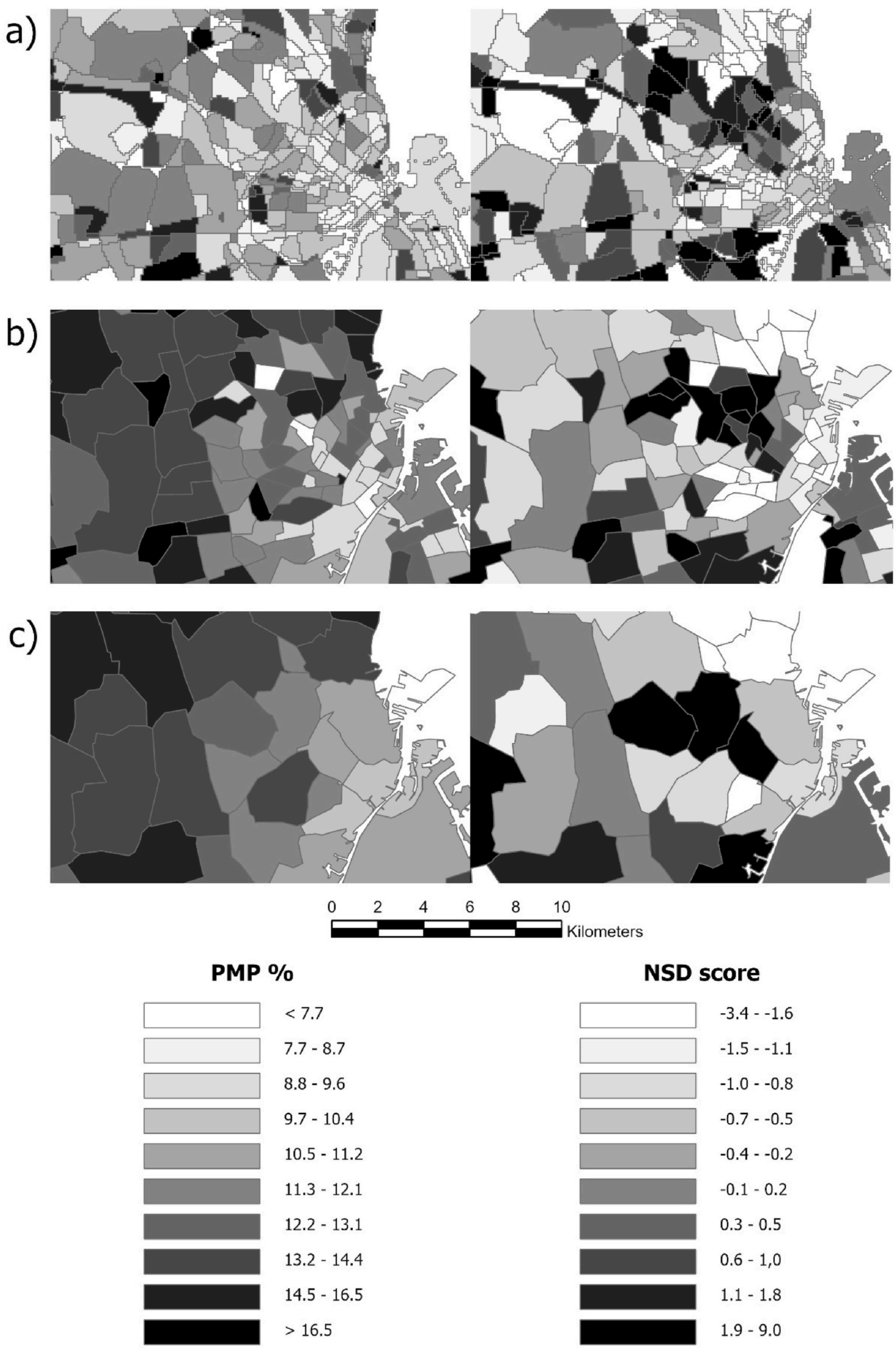

Fig. 1. Capital area of Denmark, mapped with % psychiatric medication purchases (left) and neighborhood socioeconomic deprivation score (right) divided into micro-areas (a), parishes (b) and postal codes (c). Note: Topography on square grids containing no households were excluded from map (a). Contains data from the Danish Agency for Data Supply and Efficiency, "DAGI", 2020.

Logistic multilevel random intercepts models take into account the nested structure of the data by considering that the individual probability that a phenomenon will occur (in this case, the purchase of psychiatric medication) is also statistically dependent on the subject's area of residence. This contextual dependence needs to be accounted for to obtain correct regression estimates and at the same time allows an examination of the significance of the context in which the individuals are embedded (Merlo et al., 2006).

'Empty' models, which include only a random intercept, were fitted first for each type of areal unit. From these models, intraclass correlations (ICC) were calculated separately for micro-areas, parishes and postal codes using the latent variable method supported by Snijders and Bosker (1999).

$$\mathrm{ICC} = \frac{var(u_{0j})}{var(u_{0j}) + (\pi^2/3)}$$

where var(u_{0j}) is the area-level variance and $(\pi^2/3) \approx 3.29$ refers to the variance of the standard logistic distribution, that is, the assumed level-1 variance component. The ICC indicates the percentage of the total variance that is attributable to the area-level variance (Snijders and Bosker, 1999). However, the individual-level variance is on the probability scale, and the area-level variance is on the logistic scale. Therefore, the ICC may not accurately represent the partitioning of variance, and it may have some interpretational drawbacks when used for binary responses. First, the ICC does not convey information regarding variation among clusters, and second, the ICC is not comparable to the fixed effects, which can be interpreted as odds ratios (Goldstein et al., 2002; Larsen and Merlo, 2005; Merlo et al., 2006). As an alternative, Larsen et al. (2000) and Larsen and Merlo (2005) suggest the use of the median odds ratio (MOR), which is calculated with the following formula:

$$\mathrm{MOR} = \exp\left(\sqrt{2 \times var(u_{0j})} \times \Phi^{-1}(0.75)\right)$$

where exp(·) is the exponential function, var(u_{0j}) is the area-level variance, Φ(·) is the cumulative distribution function of the normal distribution with a mean of 0 and a variance of 1, and $\Phi^{-1}(0.75)$ is the 75th percentile. The MOR quantifies the area-level variance as the median of the set of odds ratios obtained by comparing two individuals with identical covariates from two different randomly chosen areas. The MOR is the median odds ratio between the person with the higher propensity and the person with the lower propensity. The higher the MOR is, the higher the variation between areas, with an MOR of 1 indicating no variation between areas (Chaix et al., 2005; Larsen and Merlo, 2005). In general, there are no widely accepted thresholds that indicate a high vs a low value for the ICC or MOR; however, as both measures are a function of the area-level variance, they are closely related; for example an area-level variance = 0.04 corresponds to a MOR = 1.2 and an ICC = 0.01 (Merlo et al., 2006).

To determine the possible contextual effects of neighborhood deprivation, the NSD index was included as a level-2 predictor in the subsequent models to investigate the crude associations, and then all individual-level sociodemographic covariates were added in the final models to control for potential individual compositional effects. To compare the model fit for models with different areal units, the Akaike information criterion (AIC) (Akaike, 1973) and the Schwarz Bayesian criterion (BIC) (Schwarz, 1978) were calculated, with the lowest value indicating the best model fit. The individual AIC and BIC values are not interpretable on their own as they are affected by sample size and contain arbitrary constants. To assess the strength of evidence for each candidate model, one solution is to rescale the values to delta AIC and delta BIC (ΔAIC/BIC), calculated as AIC_m - AIC*, where AIC_m denotes the candidate model, and AIC* denotes the AIC with the minimum value. The same procedure can be used with the BIC values to calculate the delta BIC. This difference can then be used to determine the level of support for each candidate model. As a general rule of thumb, values greater than 10 indicate that there is essentially no support for the candidate model (Burnham and Anderson, 2002; Fabozzi et al., 2014).

3. Results

3.1. Descriptive statistics and spatial patterns

Table 1 describes the area size and population count for the three geographical units, showing that micro-areas in general are smallest and have less variability both in terms of inhabitants and size, while postal codes make up the largest of the three areal units and have higher variability than either micro-areas or parishes. Regarding psychiatric medication purchases, the micro-areas have the lowest mean proportion of people redeeming psychiatric medication prescriptions, at 11.76% compared to 13.45% and 14.34% for parishes and postal codes, respectively, and with a higher variability in terms of both standard deviation and interquartile range, indicating higher external heterogeneity between areas. For NSD, the different areas were very similar in terms of both average and median scores and variability between areas.

Fig. 1 shows the spatial patterns of psychiatric medication purchases and NSD mapped by micro-areas, parishes and postal codes on separate maps. At the ecological level, NSD and psychiatric medication purchases showed similar low to moderate correlations for all area delineations, with r = 0.46, 0.39 and 0.47 for micro-areas, parishes and postal codes, respectively. However, the maps clearly indicate a more differentiated pattern of both psychiatric medication purchases and NSD when micro-areas are considered, and the differences are blended out for postal codes in particular. Overall, the maps therefore reflect the tendency for the micro-areas, in addition to their smaller size, to have larger external variance, which results in spatial patterns that are not visible when looking at larger areas such as postal codes (for descriptive statistics for all study-variables, see supplementary material).

3.2. Multilevel models

Table 2 shows the empty logistic random intercept models. These models show that the proportion of the variance in psychiatric medication purchases between micro-areas was almost 3% (ICC = 0.027) followed by 1.5% (ICC = 0.015) and almost 1% (ICC = 0.009) for parishes and postal codes, respectively. Furthermore, the model using micro-areas showed a greater variation between areas in the odds of purchasing psychiatric medication (MOR = 1.33), indicating that if one person moved to another micro-area with a higher probability of psychiatric medication purchases, the median increase in their odds of

Table 1
Area characteristics.

	Micro-areas (7943 areas)	Parishes (2149 areas)	Postal codes (605 areas)
Area size[a]			
Median (IQR)	2.31 (7.26)	16.19 (16.50)	46.73 (69.76)
Mean (SD)	5.20 (9.53)	20.03 (15.50)	71.16 (70.47)
Population count			
Median (IQR)	253 (302)	252 (1188)	1315.5 (4960.6)
Mean (SD)	548.68 (1056.09)	2228.26 (6055.26)	8058.63 (20048.18)
Psychiatric medication purchase[b]			
Median (IQR)	11.21 (4.53)	13.27 (3.95)	14.28 (2.82)
Mean (SD)	11.76 (3.82)	13.45 (3.11)	14.34 (2.20)
Socioeconomic deprivation score			
Median (IQR)	−0.16 (1.69)	−0.07 (1.73)	0.07(2.04)
Mean[a] (SD)	0.01 (1.39)	0.01 (1.34)	0.11 (1.59)

IQR = interquartile range, defined as quartile 3 – quartile 1.
[a] Area size measured in square kilometers.
[b] In percentages.

Table 2
Empty logistic random intercept model estimates for psychiatric medication purchases with different neighborhood delineations ($N = 4,347,001$).

	M1 Micro-areas	M2 Parishes	M3 Postal codes
Area-level variance (SE)	0.090 (0.002)	0.049 (0.002)	0.029 (0.002)
MOR	1.33	1.23	1.18
ICC	0.027	0.015	0.009
AIC	3525598	3533126	3541503
BIC	3525624	3533152	3541530

SE = standard error. MOR = median odds ratio. ICC = intraclass correlation.

purchasing psychiatric medication would be 1.33. The heterogeneity between areas was lower when parishes (MOR = 1.23) and postal codes (MOR = 1.18) were used.

The lower AIC and BIC values indicated that the fit was better when micro-areas were used, and the ΔAIC/BIC >10 indicated stronger support for the model with micro-areas than for the two alternative models (Burnham and Anderson, 2002; Fabozzi et al., 2014).

Table 3 presents the odds ratios and 95% confidence intervals for the crude association between NSD and psychiatric medication purchases based on the logistic random intercept models. Higher NSD was associated with a higher probability of purchasing psychiatric medication for all three types of neighborhood delineations. For micro-areas and parishes, the results showed a general relational pattern of increasing probabilities of purchasing psychiatric medication as NSD increased, while postal codes showed some minor exceptions to this pattern. When comparing effect sizes, the model using micro-areas showed a stronger association for the highest deprivation decile (OR 1.77, 95% CI 1.71, 1.83) than parishes (OR 1.42, 95% CI 1.35, 1.49) and postal codes (OR 1.33 95% CI 1.26, 1.40). For these models, the ΔAIC/BIC >10 again indicates strong support for a better model fit with the model using micro-areas than those using parishes and postal codes.

After adjusting for individual-level covariates in Table 4, the effect sizes decreased in all the models, for micro-areas (OR 1.17, 95% CI 1.15, 1.20), parishes (OR 1.02, 95% CI 0.98, 1.06) and postal codes (OR 1.01 95% CI 0.96, 1.05). This indicates that a large part of the crude association between NSD and psychiatric medication purchases for micro-areas was explained by individual composition. For parishes and postal codes, the results showed that individual compositional effects completely explained the association, as these associations became statistically nonsignificant and indicated no contextual effect of NSD on psychiatric medication purchases when using these areas as neighborhood delineations. As one single exception to this, the 8th decile of NSD for postal codes was still significantly associated with psychiatric medication purchases after controlling for individual-level variables, but the association was weak (OR 1.08, 95% CI 1.03, 1.13). Similar to the previous models in Tables 2 and 3, the ΔAIC/BIC >10 again showed

Table 3
Logistic random intercept model estimates for the crude association between neighborhood socioeconomic deprivation (NSD) and psychiatric medication purchases with different neighborhood delineations ($N = 4,347,001$).

	M1 Micro-areas		M2 Parishes		M3 Postal codes	
	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)
NSD						
Least deprived	ref		ref		ref	
D2	1.07***	(1.04, 1.11)	1.01	(0.96, 1.05)	1.06*	(1.01, 1.12)
D3	1.10***	(1.06, 1.13)	1.03	(0.99, 1.08)	1.11***	(1.05, 1.18)
D4	1.12***	(1.09, 1.16)	1.07**	(1.02, 1.12)	1.13***	(1.07, 1.19)
D5	1.15***	(1.11, 1.18)	1.11***	(1.06, 1.16)	1.17***	(1.11, 1.23)
D6	1.21***	(1.17, 1.24)	1.16***	(1.11, 1.21)	1.21***	(1.14, 1.28)
D7	1.26***	(1.22, 1.30)	1.20***	(1.15, 1.26)	1.18***	(1.12, 1.25)
D8	1.37***	(1.33, 1.41)	1.24***	(1.19, 1.30)	1.31***	(1.24, 1.38)
D9	1.52***	(1.47, 1.57)	1.33***	(1.27, 1.39)	1.28***	(1.22, 1.34)
Most deprived	1.77***	(1.71, 1.83)	1.42***	(1.35, 1.49)	1.33***	(1.26, 1.40)
AIC	3523760		3532717		3541341	
BIC	3523906		3532863		3541487	

***p < 0.001, **p < 0.01, *p < 0.05.

Table 4
Logistic random intercept model estimates for the adjusted association between neighborhood socioeconomic deprivation (NSD) and psychiatric medication purchases with different neighborhood delineations ($N = 4,347,001$).

	M1 Micro-areas		M2 Parishes		M3 Postal codes	
	OR	(95% CI)	OR	(95% CI)	OR	(95% CI)
NSD						
Least deprived	ref		ref		ref	
D2	1.02	(0.99, 1.04)	0.98	(0.94, 1.01)	1.01	(0.96, 1.05)
D3	1.00	(0.98, 1.03)	0.97	(0.94, 1.01)	1.02	(0.97, 1.08)
D4	1.01	(0.99, 1.03)	0.98	(0.95, 1.02)	1.03	(0.98, 1.08)
D5	1.01	(0.99, 1.04)	0.99	(0.96, 1.03)	1.02	(0.97, 1.07)
D6	1.03**	(1.01, 1.06)	1.00	(0.97, 1.04)	1.03	(0.98, 1.09)
D7	1.04**	(1.01, 1.06)	1.01	(0.97, 1.05)	1.00	(0.95, 1.04)
D8	1.08***	(1.05, 1.11)	1.02	(0.98, 1.05)	1.08**	(1.03, 1.13)
D9	1.11***	(1.08, 1.13)	1.03	(0.99, 1.07)	1.03	(0.99, 1.08)
Most deprived	1.17***	(1.15, 1.20)	1.02	(0.98, 1.06)	1.01	(0.96, 1.05)
AIC	3163241		3163542		3164348	
BIC	3163547		3163848		3164654	

Adjusted for individual level: Gender, age, marital status, education, personal income and occupation status. ***p < 0.001, **p < 0.01, *p < 0.05.

that the best model fit was obtained when using micro-areas compared to parishes and postal codes (for full models showing estimates of the individual-level covariates, see supplementary material).

3.3. Sensitivity analyses

To analyze the robustness of the results, I performed various types of sensitivity analyses. First, to determine whether the results changed when the analysis focused on a specific group of medicine, the outcome variable psychiatric medication purchases was limited to ATC code N06A to focus solely on the purchase of antidepressants, which were the most widely sold type of psychiatric medication in Denmark in 2017 (The Danish Health Data Authority, 2019). With the adjusted models, the model using micro-areas still showed the strongest association for the highest degree of deprivation (OR 1.24, 95% CI 1.20, 1.27) and therefore a slightly larger effect than when focusing on psychiatric medication more broadly. For the two administrative delineations, the association remained statistically significant but with smaller effect sizes than for micro-areas, with an OR of 1.07 (95% CI 1.03, 1.13) for parishes and an OR of 1.06 (95% CI 1.01, 1.13) for postal codes.

Second, the NSD indices were modified. First, the indices were entered as continuous predictors in the models, and second, the indices were divided into quantiles instead of deciles. As continuous predictors, the NSD indices were statistically associated with psychiatric medication purchases for micro-areas and parishes, but the adjusted model using micro-areas still showed the strongest association, with an OR of 1.03 (95% CI 1.03, 1.04) for micro-areas and an OR of 1.01 (95% CI 1.00, 1.02) for parishes. With NSD divided into quantiles, the effect sizes for the highest degree of deprivation were slightly lower than in the model using deciles, with an OR of 1.13 (95% CI 1.11, 1.15) for micro-areas, an OR of 1.04 (95% CI 1.01, 1.07) for parishes and an OR of 1.02 (95% CI 0.98, 1.05) for postal codes.

To account for the potential contextual confounder of living in an urban vs. rural area, a categorical variable at the municipality level that divided the areas into four categories — 1) urban, 2) semi urban, 3) rural and 4) outer municipality (The Danish Ministry of Food, Agriculture and Fisheries and The Danish Ministry of the Interior and Health, 2011) — was included as a covariate in the adjusted models. However, this did not change the results substantially. Finally, the individual-level covariate of personal income was changed to household income, divided into quartiles, but this change did not change the results substantially either. For all models, the AIC and BIC were lowest for the models using micro-areas. Overall, the adjustments revealed the same pattern of results, indicating strong support for a better fit and stronger associations when using micro-areas as neighborhood delineations compared to parishes and postal codes.

4. Discussion

To compare the use of micro-areas divided by physical barriers to the use of other administrative delineations in terms of the relationship between NSD and psychiatric medication purchases, the first part of the analysis consisted of a visual and descriptive inspection of the patterns formed when using the different neighborhood delineations. Overall, the maps showed a tendency towards a more heterogeneous pattern for micro-areas that was gradually blended out when looking at parishes and postal codes. At the ecological level, all three types of neighborhood delineations showed low to moderate correlations between NSD and psychiatric medication purchases.

For the second part of the analysis, logistic multilevel random intercept models were used to investigate the possible contextual effects of NSD on individual psychiatric medication purchases and compare the use of different neighborhood delineations. Overall, this showed a higher heterogeneity among micro-areas than among parishes and postal codes for the odds of purchasing psychiatric medication. Furthermore, the contextual effect of NSD on psychiatric medication purchases was present only when micro-areas were used as neighborhood delineations and not when parishes and postal codes were used. In addition, for all models, the AIC and BIC were lowest for the models using micro-areas, showing a better model fit than the models using parishes and postal codes.

The findings from this study add to the existing literature demonstrating the effects of MAUP in relation to neighborhood effects on health outcomes (Chaix et al, 2005, 2006; Cockings and Martin, 2005; Flowerdew et al., 2008; Franzini and Spears, 2003; Messer et al., 2006; Parenteau and Sawada, 2011). Despite the fact that these studies compare different types of neighborhood delineations, vastly different approaches and areas are used, which makes it difficult to determine which type of neighborhood can best capture potentially true neighborhood effects. However, based on the findings from this study and the studies by Chaix et al. (2006, 2005), there is evidence suggesting that the smaller the area being used is, the stronger the association between contextual neighborhood deprivation and mental health treatment is. As these studies incorporated a different neighborhood delineation method with nonfixed spatially adaptive areas centered on residences of individuals, it is still difficult to directly relate the results to this study. Further studies should continue to theorize and test possible mechanisms for explaining the link between neighborhood deprivation and mental health conditions; furthermore, the mechanisms under study should correspond to the spatial scales being used (Visser et al., 2021).

In this study, the micro-areas used were divided by physical barriers. As previously mentioned, such barriers can potentially serve as barriers for social interaction (Feld, 1981; Grannis, 1998) and may reflect individuals' own perception of where known neighborhoods are separated from one another (Campbell et al., 2009; Grannis, 2009; Lynch, 1971). It is possible that several different types of mechanisms can be linked to the socioeconomic conditions of smaller areas divided by physical barriers, including mechanisms shaped by the cultural and social-interactive environment, as proposed by Galster (2013). Examples of such mechanisms are neighborhood disorder and low collective efficacy (low social cohesion, low trust and low informal social control) (Sampson et al., 1997), which can be viewed as social processes with a cultural component of shared expectations shaped by context, history and prior experiences (Sampson, 2012). Previous studies have found that such factors may lead to psychological distress among residents and act as a mediator or moderator for the association between NSD and mental health conditions (Fone et al., 2014; Kim, 2010; McElroy et al., 2019; Rios et al., 2012; Schmidt et al., 2020; Xue et al., 2005). However, further research is warranted to clarify these potential mechanisms.

If low collective efficacy and social disorder are main mechanisms linking neighborhood deprivation to mental health conditions and psychiatric medication purchases, it becomes clear why the use of arbitrary administrative boundaries can lead to misleading results, as it can be expected that the level of neighborhood deprivation in these areas reflects only a low degree the socially interactive environment that individuals experience and participate in on a daily basis. This is not to say that neighborhoods based on physical barriers perfectly capture all relevant contextual effects. As an example, people who live close to various attractive blue and green space barriers, such as lakes and forests, may have a higher socioeconomic position than people who live further away from these barriers (Schüle et al., 2019) and may thereby form homogeneous social enclaves that are disconnected from the surrounding area. Furthermore, social interaction and other activities may take place outside the barriers in surrounding neighborhoods (Graif et al., 2016), and other relevant mechanisms may exist (Galster, 2013).

In conclusion, it is relevant to focus not only on the MAUP but also on the UGCoP (Kwan, 2012). Particularly when neighborhood effects research is based on arbitrary administrative units that are not based on theoretical understandings of how neighborhoods can be divided, the results may suffer from both validity and reliability problems related to MAUP and UGCoP. As universal and true neighborhoods may be impossible to define and measure, the best way of measuring neighborhoods should instead depend on the mechanisms linking exposure to outcome. Therefore, studies should not view the MAUP and UGCoP as barriers to conducting useful research on neighborhood effects but instead see them as points of attention that can help expand and nuance the complex interplay between health outcomes and the context in which people are embedded.

The results of this study are also relevant from a policy perspective. First, administrative areas may be unsuitable for identifying relevant geographical differences in psychiatric medication use and possible contextual factors that explain such differences, and second, administrative areas may be unsuitable for the delimitation of targeted interventions in local areas. This indicates that better operationalizations of neighborhoods are needed for policy and practice. However, despite the fact that smaller areas may be better at predicting health-related outcomes, such as psychiatric medication purchases, such areas may also be more difficult to use as boundaries for the implementation of complex social interventions. The advantages of the micro-areas used in this study are that the algorithm can be adapted to form larger areas with a higher number of occupants that are still based on physical barriers as separators (Lund, 2018).

One limitation of the study was the cross-sectional design, which increases the risk of reverse causation, also known as the selection problem, in studies investigating neighborhood effects (Sampson et al., 2002). However, evidence of a causal link between neighborhood deprivation and mental health conditions has been found in both experimental and cohort studies (Crump et al., 2011; Galea et al., 2007; Leventhal and Brooks-Gunn, 2003; Ludwig et al., 2013; White et al., 2017). Furthermore, a recent study linking neighborhood, genetic and health data found evidence against selection as an explanation for neighborhood gradients in mental health. (Belsky et al., 2019). In addition, a recent review of longitudinal studies found significant associations only in studies with follow-up periods of less than 5 five years, which could indicate that studies assessing the effect of neighborhoods on mental health conditions at close to the same time point might be most appropriate (Richardson et al., 2015).

Another limitation was my inability to fully test the MAUP by isolating both the scaling and aggregation problems (Openshaw, 1983). As previously mentioned, this was tested by Lund (2018), who found higher socioeconomic homogeneity for the micro-areas than for parishes and for different modifications of the parishes, such as reducing them to quarter size, as well as for areas based completely on random clustering where the physical barriers were removed and the only considerations were areas with at least 100 inhabitants. Instead of this systematic approach, the goal of this study was to compare micro-areas separated by physical barriers, which were based on a theoretical understanding of neighborhoods, to different, larger arbitrary administrative delineations often used as practical alternatives. As a result, different types of scaling and aggregation were compared, but the effects were not isolated. More studies on this issue are warranted to examine the effects of using physical barriers to create neighborhood delineations when size is held constant, as it is possible that the stronger associations found with the use of micro-areas are due only to their smaller size and not to the use of physical barriers as separators.

In addition, the focus on psychiatric medication purchases overlooks important aspects of mental health, including emotional well-being, psychological well-being, and social well-being (Keyes, 2009). Furthermore, the use of psychiatric medication purchases fails to identify mental health conditions that are untreated or treated without prescription medications. In addition, some types of psychiatric medication are used to treat nonpsychiatric conditions such as neuropathic pain, narcolepsy, spasticity, seizures, epilepsy, motion sickness and/or allergies (The Danish Health Data Authority, 2021) and thereby affect the validity of psychiatric medication purchases as an indicator of mental health treatment.

Despite these limitations, this study adds to the existing literature by comparing automatically generated micro-areas divided by physical barriers with two administrative area delineations as neighborhood measures to determine the association between NSD and psychiatric medication purchases. Based on high-quality register data for the Danish population, the findings indicate evidence that smaller areas divided by physical barriers can reveal contextual neighborhood effects after adjusting for individual-level covariates that are not present when administrative areas are used as neighborhoods. Continued use of administrative areas as measures of neighborhoods presents the risk of overlooking or underestimating important geographical differences in mental health conditions as well as contextual factors that may explain these differences. Based on the findings of this study, the use of the smallest areas possible divided by larger physical barriers may provide a useful alternative to administrative delineations. In general, the findings point to the continued importance of thorough conceptualizations and operationalizations of neighborhoods and of the comparison and validation of different neighborhood measures for future studies analyzing neighborhoods and the potential importance of the surrounding physical and social environment for health and behavioral outcomes.

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Declaration of competing interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2021.102675.

References

Akaike, H., 1973. Information theory and an extension of the maximum likelihood principle. In: Proceedings of the 2nd International Symposium on Information Theory. Second Int. Symp. Inf. Theory.

Allik, M., Leyland, A., Travassos Ichihara, M.Y., Dundas, R., 2020. Creating small-area deprivation indices: a guide for stages and options. J. Epidemiol. Community Health 74, 20–25. https://doi.org/10.1136/jech-2019-213255.

Almeida, O.P., Pirkis, J., Kerse, N., Sim, M., Flicker, L., Snowdon, J., Draper, B., Byrne, G., Lautenschlager, N.T., Stocks, N., Alfonso, H., Pfaff, J.J., 2012. Socioeconomic disadvantage increases risk of prevalent and persistent depression in later life. J. Affect. Disord. 138, 322–331. https://doi.org/10.1016/j.jad.2012.01.021.

Annequin, M., Weill, A., Thomas, F., Chaix, B., 2015. Environmental and individual characteristics associated with depressive disorders and mental health care use. Ann. Epidemiol. 25 https://doi.org/10.1016/j.annepidem.2015.02.002.

Arcaya, M.C., Tucker-Seeley, R.D., Kim, R., Schnake-Mahl, A., So, M., Subramanian, S.V., 2016. Research on neighborhood effects on health in the United States: a systematic review of study characteristics. Soc. Sci. Med. 168, 16–29. https://doi.org/10.1016/j.socscimed.2016.08.047.

Baadsgaard, M., Quitzau, J., 2011. Danish registers on personal income and transfer payments. Scand. J. Publ. Health 39, 103–105. https://doi.org/10.1177/1403494811405098.

Belsky, D.W., Caspi, A., Arseneault, L., Corcoran, D.L., Domingue, B.W., Harris, K.M., Houts, R.M., Mill, J.S., Moffitt, T.E., Prinz, J., Sugden, K., Wertz, J., Williams, B., Odgers, C.L., 2019. Genetics and the geography of health, behaviour and attainment. Nat. Hum. Behav. 3, 576–586. https://doi.org/10.1038/s41562-019-0562-1.

Bender, A.M., Kawachi, I., Jørgensen, T., Pisinger, C., 2015. Neighborhood deprivation is strongly associated with participation in a population-based health check. PloS One 10, e0129819.

Bloomfield, K., Berg-Beckhoff, G., Seid, A.K., Stock, C., 2018. Area-level relative deprivation and alcohol use in Denmark: is there a relationship? Scand. J. Publ. Health 47, 428–438. https://doi.org/10.1177/1403494818787101.

Bocquier, A., Cortaredona, S., Verdoux, H., Sciortino, V., Nauleau, S., Verger, P., 2013. Social inequalities in new antidepressant treatment: a study at the individual and

neighborhood levels. Ann. Epidemiol. 23 https://doi.org/10.1016/j.annepidem.2012.12.008.
Burnham, K.P., Anderson, D.R., 2002. Model selection and multimodel inference. In: A Practical Information-Theoretic Approach, 2nd. Springer-verlag new york inc., New york, ny.
Cabrera-Barona, P., Blaschke, T., Gaona, G., 2018. Deprivation, healthcare accessibility and satisfaction: geographical context and scale implications. Appl. Spat. Anal. Policy 11, 313–332. https://doi.org/10.1007/s12061-017-9221-y.
Campbell, E., Henly, J.R., Elliott, D.S., Irwin, K., 2009. Subjective constructions of neighborhood boundaries: lessons from a qualitative study of four neighborhoods. J. Urban Aff. 31, 461–490. https://doi.org/10.1111/j.1467-9906.2009.00450.x.
Carstairs, V., Morris, R., 1989. Deprivation: explaining differences in mortality between scotland and england and wales. Br. Med. J. 299 https://doi.org/10.1136/bmj.299.6704.886.
Chaix, B., Leyland, A.H., Sabel, C.E., Chauvin, P., Råstam, L., Kristersson, H., Merlo, J., 2006. Spatial clustering of mental disorders and associated characteristics of the neighbourhood context in Malmö, Sweden, in 2001. J. Epidemiol. Community Health 60. https://doi.org/10.1136/jech.2005.040360.
Chaix, B., Merlo, J., Subramanian, S.V., Lynch, J., Chauvin, P., 2005. Comparison of a spatial perspective with the multilevel analytical approach in neighborhood studies: the case of mental and behavioral disorders due to psychoactive substance use in Malmö, Sweden, 2001. Am. J. Epidemiol. 162 https://doi.org/10.1093/aje/kwi175.
Chaskin, R.J., 1997. Perspectives on neighborhood and community: a review of the literature. Soc. Serv. Rev. 71, 521–547.
Cockings, S., Martin, D., 2005. Zone design for environment and health studies using pre-aggregated data. Soc. Sci. Med. 60, 2729–2742. https://doi.org/10.1016/j.socscimed.2004.11.005.
Coulton, C.J., Korbin, J., Chan, T., Su, M., 2001. Mapping residents' perceptions of neighborhood boundaries: a methodological note. Am. J. Community Psychol. 29, 371–383. https://doi.org/10.1023/A:1010303419034.
Crump, C., Sundquist, K., Sundquist, J., Winkleby, M.A., 2011. Neighborhood deprivation and psychiatric medication prescription: a Swedish national multilevel study. Ann. Epidemiol. 21, 231–237. https://doi.org/10.1016/j.annepidem.2011.01.005.
Deng, Y., 2016. Challenges and complications in neighborhood mapping: from neighborhood concept to operationalization. J. Geogr. Syst. 18, 229–248. https://doi.org/10.1007/s10109-016-0232-z.
Diez Roux, A.V., 2001. Investigating neighborhood and area effects on health. Am. J. Publ. Health 91, 1783–1789. https://doi.org/10.2105/ajph.91.11.1783.
Ellen, I.G., Mijanovich, T., Dillman, K.N., 2001. Neighborhood effects on health: exploring the links and assessing the evidence. J. Urban Aff. 23, 391–408. https://doi.org/10.1111/0735-2166.00096.
Fabozzi, F.J., Focardi, S.M., Rachev, S.T., Arshanapalli, B.G., 2014. Appendix E: model selection criterion: AIC and BIC. In: The Basics of Financial Econometrics, pp. 399–403. https://doi.org/10.1002/9781118856406.app5.
Feld, S.L., 1981. The focused organization of social ties. Am. J. Sociol. 86, 1015–1035. https://doi.org/10.1086/227352.
Flowerdew, R., Manley, D.J., Sabel, C.E., 2008. Neighbourhood effects on health: does it matter where you draw the boundaries? Soc. Sci. Med. 66, 1241–1255. https://doi.org/10.1016/j.socscimed.2007.11.042.
Fone, D., White, J., Farewell, D., Kelly, M., John, G., Lloyd, K., Williams, G., Dunstan, F., 2014. Effect of neighbourhood deprivation and social cohesion on mental health inequality: a multilevel population-based longitudinal study. Psychol. Med. 44 https://doi.org/10.1017/S0033291713003255.
Foster, K.A., Aaron Hipp, J., 2011. Defining neighborhood boundaries for social measurement: advancing social work research. Soc. Work. Res. 35, 25–35. https://doi.org/10.1093/swr/35.1.25.
Franzini, L., Spears, W., 2003. Contributions of social context to inequalities in years of life lost to heart disease in Texas, USA. Soc. Sci. Med. 57, 1847–1861. https://doi.org/10.1016/S0277-9536(03)00018-2.
Galea, S., Ahern, J., Nandi, A., Tracy, M., Beard, J., Vlahov, D., 2007. Urban neighborhood poverty and the incidence of depression in a population-based cohort study. Ann. Epidemiol. 17, 171–179. https://doi.org/10.1016/j.annepidem.2006.07.008.
Galster, G., 2001. On the nature of neighbourhood. Urban Stud. 38, 2111–2124. https://doi.org/10.1080/00420980120087072.
Galster, G.C., 2013. The Mechanism(s) of Neighbourhood Effects: Theory, Evidence, and Policy Implications. Springer Netherlands. https://doi.org/10.1007/978-94-007-2309-2-2.
Goldstein, H., Browne, W., Rasbash, J., 2002. Partitioning variation in multilevel models. Understand. Stat. 1, 223–231. https://doi.org/10.1207/s15328031us0104_02.
Graif, C., Arcaya, M.C., Diez Roux, A.V., 2016. Moving to opportunity and mental health: exploring the spatial context of neighborhood effects. Soc. Sci. Med. 162 https://doi.org/10.1016/j.socscimed.2016.05.036.
Grannis, R., 2009. From the Ground up: Translating Geography into Community through Neighbor Networks. Princeton University Press. https://doi.org/10.1177/0094306110367909x.
Grannis, R., 1998. The importance of trivial streets: residential streets and residential segregation. Am. J. Sociol. 103, 1530–1564. https://doi.org/10.1086/231400.
Haynes, R., Daras, K., Reading, R., Jones, A., 2007. Modifiable neighbourhood units, zone design and residents' perceptions. Health Place 13, 812–825. https://doi.org/10.1016/j.healthplace.2007.01.002.
Ivert, A.K., Torstensson Levander, M., Merlo, J., 2013. Adolescents' utilisation of psychiatric care, neighbourhoods and neighbourhood socioeconomic deprivation: a multilevel analysis. PloS One 8. https://doi.org/10.1371/journal.pone.0081127.
Jablonska, B., Kosidou, K., Ponce de Leon, A., Wettermark, B., Magnusson, C., Dal, H., Dalman, C., 2020. Neighborhood socioeconomic characteristics and utilization of ADHD medication in schoolchildren: a population multilevel study in stockholm county. J. Atten. Disord. 24 https://doi.org/10.1177/1087054716643257.
Jensen, V.M., Rasmussen, A.W., 2011. Danish education registers. Scand. J. Publ. Health 39, 91–94. https://doi.org/10.1177/1403494810394715.
Jivraj, S., Murray, E.T., Norman, P., Nicholas, O., 2019. The impact of life course exposures to neighbourhood deprivation on health and well-being: a review of the long-term neighbourhood effects literature. Eur. J. Publ. Health. https://doi.org/10.1093/eurpub/ckz153.
Juhász, A., Nagy, C., Páldy, A., Beale, L., 2010. Development of a Deprivation Index and its relation to premature mortality due to diseases of the circulatory system in Hungary, 1998–2004. Soc. Sci. Med. 70, 1342–1349. https://doi.org/10.1016/j.socscimed.2010.01.024.
Julien, D., Richard, L., Gauvin, L., Kestens, Y., 2012. Neighborhood characteristics and depressive mood among older adults: an integrative review. Int. psychogeriatrics 24, 1207–1225. https://doi.org/10.1017/S1041610211002894.
Keyes, C.L.M., 2009. Toward a science of mental health. In: The Oxford Handbook of Positive Psychology. Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195187243.013.0009.
Kim, J., 2010. Neighborhood disadvantage and mental health: the role of neighborhood disorder and social relationships. Soc. Sci. Res. 39, 260–271. https://doi.org/10.1016/j.ssresearch.2009.08.007.
Kjærulff, T.M., Bihrmann, K., Andersen, I., Gislason, G.H., Larsen, M.L., Ersbøll, A.K., 2019. Geographical inequalities in acute myocardial infarction beyond neighbourhood-level and individual-level sociodemographic characteristics: a Danish 10-year nationwide population-based cohort study. BMJ Open 9, e024207. https://doi.org/10.1136/bmjopen-2018-024207.
Kwan, M.P., 2012. The uncertain geographic context problem. Ann. Assoc. Am. Geogr. 102 https://doi.org/10.1080/00045608.2012.687349.
Larsen, K., Merlo, J., 2005. Appropriate assessment of neighborhood effects on individual health: integrating random and fixed effects in multilevel logistic regression. Am. J. Epidemiol. 161 https://doi.org/10.1093/aje/kwi017.
Larsen, K., Petersen, J.H., Budtz-Jørgensen, E., Endahl, L., 2000. Interpreting parameters in the logistic regression model with random effects. Biometrics. https://doi.org/10.1111/j.0006-341x.2000.00909.x.
Leventhal, T., Brooks-Gunn, J., 2003. Moving to opportunity: an experimental study of neighborhood effects on mental health. Am. J. Publ. Health 93, 1576–1582. https://doi.org/10.2105/ajph.93.9.1576.
Lofors, J., Sundquist, K., 2007. Low-linking social capital as a predictor of mental disorders: a cohort study of 4.5 million Swedes. Soc. Sci. Med. 64, 21–34. https://doi.org/10.1016/j.socscimed.2006.08.024.
Lovasi, G.S., Moudon, A.V., Smith, N.L., Lumley, T., Larson, E.B., Sohn, D.W., Siscovick, D.S., Psaty, B.M., 2008. Evaluating options for measurement of neighborhood socioeconomic context: evidence from a myocardial infarction case–control study. Health Place 14, 453–467. https://doi.org/10.1016/j.healthplace.2007.09.004.
Ludwig, J., Duncan, G.J., Gennetian, L.A., Katz, L.F., Kessler, R.C., Kling, J.R., Sanbonmatsu, L., 2013. Long-Term neighborhood effects on low-income families: evidence from moving to opportunity. Am. Econ. Rev. 103, 226–231.
Lund, R.L., 2020. Moving to prosperity? The effect of prolonged exposure to neighborhood deprivation. Scand. J. Educ. Res. 64, 471–487. https://doi.org/10.1080/00313831.2019.1577753.
Lund, R.L., 2019. Dissecting the Local. Aalborg Univ. Det Samf. Fak. Ph.D.-Serien.
Lund, R.L., 2018. From the dark end of the street to the bright side of the road: automated redistricting of areas using physical barriers as dividers of social space. Methodol. Innov. 11 https://doi.org/10.1177/2059799118814386.
Lynch, K., 1971. The Image of the City. MIT Press, Cambridge.
Maguire, A., French, D., O'Reilly, D., 2016. Residential segregation, dividing walls and mental health: a population-based record linkage study. J. Epidemiol. Community Health 70. https://doi.org/10.1136/jech-2015-206888.
Mair, C., Roux, A.V.D., Galea, S., 2008. Are neighbourhood characteristics associated with depressive symptoms? A review of evidence. J. Epidemiol. Community Health 62, 940–946. https://doi.org/10.1136/jech.2007.066605.
March, D., Hatch, S.L., Morgan, C., Kirkbride, J.B., Bresnahan, M., Fearon, P., Susser, E., 2008. Psychosis and place. Epidemiol. Rev. 30, 84–100. https://doi.org/10.1093/epirev/mxn006.
Matthews, S.A., 2008. The salience of neighborhood: some lessons from sociology. Am. J. Prev. Med. 34, 257–259. https://doi.org/10.1016/j.amepre.2007.12.001.
McElroy, E., McIntyre, J.C., Bentall, R.P., Wilson, T., Holt, K., Kullu, C., Nathan, R., Kerr, A., Panagaki, K., McKeown, M., Saini, P., Gabbay, M., Corcoran, R., 2019. Mental health, deprivation, and the neighborhood social environment: a network analysis. Clin. Psychol. Sci. 7 https://doi.org/10.1177/2167702619830640.
Meijer, M., Bloomfield, K., Engholm, G., 2013a. Neighbourhoods matter too: the association between neighbourhood socioeconomic position, population density and breast, prostate and lung cancer incidence in Denmark between 2004 and 2008. J. Epidemiol. Community Health. https://doi.org/10.1136/jech-2011-200192.
Meijer, M., Engholm, G., Grittner, U., Bloomfield, K., 2013b. A socioeconomic deprivation index for small areas in Denmark. Scand. J. Publ. Health 41, 560–569. https://doi.org/10.1177/1403494813483937.
Meijer, M., Mette Kejs, A., Stock, C., Bloomfield, K., Ejstrud, B., Schlattmann, P., 2012. Population density, socioeconomic environment and all-cause mortality: a multilevel survival analysis of 2.7 million individuals in Denmark. Health Place 18, 391–399. https://doi.org/10.1016/j.healthplace.2011.12.001.
Merlo, J., Chaix, B., Ohlsson, H., Beckman, A., Johnell, K., Hjerpe, P., Råstam, L., Larsen, K., 2006. A brief conceptual tutorial of multilevel analysis in social

epidemiology: using measures of clustering in multilevel logistic regression to investigate contextual phenomena. J. Epidemiol. Community Health. https://doi.org/10.1136/jech.2004.029454.

Messer, L.C., Laraia, B.A., Kaufman, J.S., Eyster, J., Holzman, C., Culhane, J., Elo, I., Burke, J.G., O'Campo, P., 2006. The development of a standardized neighborhood deprivation index. J. Urban Health 83, 1041–1062. https://doi.org/10.1007/s11524-006-9094-x.

Messer, L.C., Vinikoor-Imler, L.C., Laraia, B.A., 2012. Conceptualizing neighborhood space: consistency and variation of associations for neighborhood factors and pregnancy health across multiple neighborhood units. Health Place 18, 805–813. https://doi.org/10.1016/j.healthplace.2012.03.012.

Noble, S., McLennan, D., Noble, M., Plunkett, E., Gutacker, N., Silk, M., Wright, G., 2019. The English Indices of Deprivation 2019 (London).

Openshaw, S., 1983. In: The Modifiable Areal Unit Problem, CATMOG, 38. Geo Books, Norwich.

Osler, M., Christensen, U., Lund, R., Gamborg, M., Godtfredsen, N., Prescott, E., 2003. High local unemployment and increased mortality in Danish adults; results from a prospective multilevel study. Occup. Environ. Med. 60, e16. https://doi.org/10.1136/oem.60.11.e16. –e16.

Parenteau, M.-P., Sawada, M.C., 2011. The modifiable areal unit problem (MAUP) in the relationship between exposure to NO2 and respiratory health. Int. J. Health Geogr. 10, 58. https://doi.org/10.1186/1476-072X-10-58.

Pedersen, C.B., 2011. The Danish civil registration system. Scand. J. Publ. Health 39, 22–25. https://doi.org/10.1177/1403494810387965.

Pickett, K.E., Pearl, M., 2001. Multilevel analyses of neighbourhood socioeconomic context and health outcomes: a critical review. J. Epidemiol. Community Health 55, 111–122. https://doi.org/10.1136/jech.55.2.111. LP –.

Richardson, R., Westley, T., Gariépy, G., Austin, N., Nandi, A., 2015. Neighborhood socioeconomic conditions and depression: a systematic review and meta-analysis. Soc. Psychiatr. Psychiatr. Epidemiol. 50, 1641–1656. https://doi.org/10.1007/s00127-015-1092-4.

Rios, R., Aiken, L.S., Zautra, A.J., 2012. Neighborhood contexts and the mediating role of neighborhood social cohesion on health and psychological distress among hispanic and non-hispanic residents. Ann. Behav. Med. 43, 50–61. https://doi.org/10.1007/s12160-011-9306-9.

Riva, M., Apparicio, P., Gauvin, L., Brodeur, J.-M., 2008. Establishing the soundness of administrative spatial units for operationalising the active living potential of residential environments: an exemplar for designing optimal zones. Int. J. Health Geogr. 7, 43. https://doi.org/10.1186/1476-072X-7-43.

Root, E., 2012. Moving neighborhoods and health research forward: using geographic methods to examine the role of spatial scale in neighborhood effects on health. In: Annals of the Association of American Geographers. Taylor & Francis Ltd.

Ross, C.E., 2000. Neighborhood disadvantage and adult depression. J. Health Soc. Behav. 41, 177–187. https://doi.org/10.2307/2676304.

Sampson, R.J., 2012. Great American City - Chicago and the Enduring Neighborhood Effect. University of Chicago Press, Chicago.

Sampson, R.J., Morenoff, J.D., Gannon-Rowley, T., 2002. Assessing "neighborhood effects": social processes and new directions in research. Annu. Rev. Sociol. 28, 443–478. https://doi.org/10.1146/annurev.soc.28.110601.141114.

Sampson, R.J., Raudenbush, S.W., Earls, F., 1997. Neighborhoods and violent crime: a multilevel study of collective efficacy. Science 80, 277. https://doi.org/10.1126/science.277.5328.918.

Sariaslan, A., Larsson, H., D'Onofrio, B., Långström, N., Fazel, S., Lichtenstein, P., 2015. Does population density and neighborhood deprivation predict schizophrenia? A nationwide Swedish family-based study of 2.4 million individuals. Schizophr. Bull. 41, 494–502. https://doi.org/10.1093/schbul/sbu105.

Schmidt, N.M., Nguyen, Q.C., Kehm, R., Osypuk, T.L., 2020. Do changes in neighborhood social context mediate the effects of the moving to opportunity experiment on adolescent mental health? Heal. Placebo 63. https://doi.org/10.1016/j.healthplace.2020.102331.

Schüle, S.A., Hilz, L.K., Dreger, S., Bolte, G., 2019. Social inequalities in environmental resources of green and blue spaces: a review of evidence in the WHO European region. Int. J. Environ. Res. Publ. Health 16, 1216. https://doi.org/10.3390/ijerph16071216.

Schwarz, G., 1978. Estimating the dimension of a model. Ann. Stat. 6 https://doi.org/10.1214/aos/1176344136.

Silva, M., Loureiro, A., Cardoso, G., 2016. Social determinants of mental health: a review of the evidence. Eur. J. Psychiatr. 30, 259–292.

Snijders, T., Bosker, R., 1999. Multilevel Analysis: an Introduction to Basic and Advanced Multilevel Analysis. Sage, Thousand Oaks CA.

StataCorp, 2019. Stata Statistical Software: Release, 16.

Stockdale, S.E., Wells, K.B., Tang, L., Belin, T.R., Zhang, L., Sherbourne, C.D., 2007. The importance of social context: neighborhood stressors, stress-buffering mechanisms, and alcohol, drug, and mental health disorders. Soc. Sci. Med. 65, 1867–1881. https://doi.org/10.1016/j.socscimed.2007.05.045.

Tarkiainen, L., Martikainen, P., Laaksonen, M., Leyland, A.H., 2010. Comparing the effects of neighbourhood characteristics on all-cause mortality using two hierarchical areal units in the capital region of Helsinki. Health Place 16, 409–412. https://doi.org/10.1016/j.healthplace.2009.10.008.

Tarkiainen, L., Moustgaard, H., Korhonen, K., Noordzij, J.M., Beenackers, M.A., Van Lenthe, F.J., Burstrom, B., Martikainen, P., 2021. Association between neighbourhood characteristics and antidepressant use at older ages: a register-based study of urban areas in three European countries. J. Epidemiol. Community Health 75, 426–432. https://doi.org/10.1136/jech-2020-214276.

The Danish Health Data Authority, 2021. Medstat. The Danish Health Data Authority. URL. https://medstat.dk/en. (Accessed 15 September 2021).

The Danish Health Data Authority, 2019. Nye Tal for Medicinsalg I 2018: Færre Bruger Psykofarmaka. The Danish Health Data Authority. URL. https://sundhedsdatastyrelsen.dk/da/nyheder/2019/medstat_psykofarmaka_101219. (Accessed 15 September 2021).

The Danish Ministry of Environment, 2010. Databeskrivelse: DAGI Postnummer v1.0. The Danish Ministry of Environment.

The Danish Ministry of Food, 2011. Agriculture and Fisheries, the Danish Ministry of the Interior and Health. Landdistriktsredegørelse. Regeringens redegørelse til folketinget.

Truong, K.D., Ma, S., 2006. A systematic review of relations between neighborhoods and mental health. J. Ment. Health Pol. Econ. 9, 137–154.

UNESCO Institute for Statistics, 2012. International Standard Classification of Education: ISCED 2011. UNESCO Institute for Statistics Montreal.

Verdoux, H., Pambrun, E., Cortaredona, S., Tournier, M., Verger, P., 2015. Antipsychotic prescribing in youths: a French community-based study from 2006 to 2013. Eur. Child Adolesc. Psychiatr. 24 https://doi.org/10.1007/s00787-014-0668-y.

Visser, K., Bolt, G., Finkenauer, C., Jonker, M., Weinberg, D., Stevens, G.W.J.M., 2021. Neighbourhood deprivation effects on young people's mental health and well-being: a systematic review of the literature. Soc. Sci. Med. https://doi.org/10.1016/j.socscimed.2020.113542.

Wallach Kildemoes, H., Toft Sørensen, H., Hallas, J., 2011. The Danish national prescription registry. Scand. J. Publ. Health 39, 38–41. https://doi.org/10.1177/1403494810394717.

White, J., Greene, G., Farewell, D., Dunstan, F., Rodgers, S., Lyons, R.A., Humphreys, I., John, A., Webster, C., Phillips, C.J., Fone, D., 2017. Improving mental health through the regeneration of deprived neighborhoods: a natural experiment. Am. J. Epidemiol. 186, 473–480. https://doi.org/10.1093/aje/kwx086.

Wilson, K.C.M., Taylor, S., Copeland, J.R.M., Chen, R., McCracken, C.F.M., 1999. Socio-economic deprivation and the prevalence and prediction of depression in older community residents: the MRC–ALPHA study. Br. J. Psychiatry 175, 549–553. https://doi.org/10.1192/bjp.175.6.549.

Xue, Y., Leventhal, T., Brooks-Gunn, J., Earls, F.J., 2005. Neighborhood residence and mental health problems of 5- to 11-year-olds. Arch. Gen. Psychiatr. 62 https://doi.org/10.1001/archpsyc.62.5.554.