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# Neighborhood social context and suicide mortality: A multilevel register-based 5-year follow-up study of 2.7 million individuals

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ABSTRACT

Previous studies have linked neighborhood social characteristics to suicide mortality. However, the effects of the operational definition of neighborhoods and the general importance of neighborhood context on suicide mortality have received little attention, with most studies using various administrative areas as neighborhood delineations. In this study, neighborhoods were delineated by micro-areas generated with an automated redistricting algorithm and divided by physical barriers, such as large roads. The geographic data were linked to register data on the Danish adult population in the age range of 20–59 years in December 2013 (N = 2,672,799 individuals nested into 7943 neighborhoods). This cohort was followed for five years to evaluate the association between suicide mortality and neighborhood socioeconomic deprivation, social fragmentation, and population density. We used the median hazard ratio (MHR) to quantify the general contextual effect (GCE) of neighborhoods on suicide mortality and hazard ratios to quantify the specific contextual effects (SCEs) using multilevel survival models stratified by age group. The results showed a larger GCE and larger SCEs of neighborhoods on suicide mortality for individuals aged 20–39 years compared with those aged 40–59 years. After controlling for individual characteristics, higher suicide mortality was observed for individuals living in the least densely populated neighborhoods and the most socially fragmented neighborhoods for both age groups. We found cross-level interactions between neighborhood population density and gender and ethnicity for those aged 40–59 years, as well as between neighborhood social fragmentation and ethnicity for those aged 20–39 years. The results indicate that beyond individual characteristics, the neighborhood social context may affect the risk of suicide, especially for people aged 20–39 years.

## 1. Introduction

According to the World Health Organization, close to 800,000 people die by suicide every year (WHO, 2021); among adults aged 30–49 years, suicide is the fifth leading cause of death (WHO, 2014). Even though 79% of suicides worldwide occur in low- and middle-income countries, the European region has the second highest age-standardized suicide rate, at 12.85 deaths per 100,000 people. The severity of the problem has been highlighted by both the European Commission (European Commission, 2020) and the United Nations, and the reduction in suicide mortality is one of the indicators of the sustainable development goals for 2030 (United Nations, 2020).

Several risk factors have been established, with previous suicide attempts and mental disorders being two of the strongest predictors (Cavanagh et al., 2003; Yoshimasu et al., 2008). Of the social risk factors, both single marital status and low socioeconomic status have been associated with a higher risk of suicide but with weaker effect sizes (Huang et al., 2017; Yoshimasu et al., 2008). However, when considering the prevalence of exposures associated with suicide, the population attributable risks (PARs) for low educational achievement and employment status have been found to be of a similar magnitude to affective and substance use disorders. From a public health and policy perspective, this indicates that focusing on social factors can have similar population-level effects as strategies that target more proximal psychiatric risk factors in the prevention of suicide (Li et al., 2011).

In addition to social risk factors operating at the level of the individual, other studies have focused on contextual factors of the social environment surrounding individuals. This perspective can be traced back to the classic study by Durkheim, in which he argued that too low or too high levels of social integration and moral regulation can increase the risk of suicide (Durkheim, 1970). Since then, various contextual factors have been studied, including the three major factors of urbanicity

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vs. rurality, socioeconomic deprivation, and social fragmentation. The findings highlighted in multiple review studies tend toward a higher risk of suicide in more rural and socioeconomically deprived areas (Casant and Helbich, 2022; Hirsch, 2006; Hirsch and Cukrowicz, 2014; Rehkopf and Buka, 2006; Solmi et al., 2017). Furthermore, studies have found a higher suicide mortality in the most socially fragmented areas (e.g., Hagedoorn et al., 2020; Hagedoorn and Helbich, 2022). There are several potential theoretical explanations for the link between these contextual factors and suicide mortality. For example, living in a deprived neighborhood may lead to increased feelings of hopelessness (Rehkopf and Buka, 2006), and less densely populated and socially fragmented neighborhoods may affect suicide mortality through a lack of social integration, increased social isolation and certain community attitudes toward mental illness and help-seeking (Solmi et al., 2017).

In addition, previous studies have found heterogeneity in the results related to sociodemographic characteristics such as age, gender and ethnicity (Agerbo et al., 2007; Hagedoorn et al., 2020; Hagedoorn and Helbich, 2022; Kanamori et al., 2020; O'Farrell et al., 2016), which highlights the importance of taking interactions between area-level and individual characteristics into account.

However, most previous studies were ecological studies and thereby hindered inference to individual risk and the ability to separate compositional effects from possible contextual effects. This means that it is unclear whether the associations are a result of differences in the characteristics of which the areas are comprised (composition) or attributable to real effects of area level properties (context) (Agerbo et al., 2007; Diez Roux, 2002). To avoid this issue and the associated problem of potential 'ecological fallacies', more recent studies have sought to separate compositional effects on suicide mortality from contextual effects. The results of these studies are mixed, some with null findings and others finding that associations between area levels of deprivation, rurality or social fragmentation were explained by compositional effects (Agerbo et al., 2007; Allen and Goldman-Mellor, 2018; Borrell et al., 2002; O'Reilly et al., 2008; Zammit et al., 2014). Additionally, other studies found significant associations between these contextual factors and suicide mortality even after controlling for composition (Collings et al., 2009; Cubbin et al., 2000; Dupéré et al., 2009; Dykxhoorn et al., 2021; Hagedoorn et al., 2020; Hagedoorn and Helbich, 2022; Jasilionis et al., 2020; Kanamori et al., 2020; Martikainen et al., 2004). In these studies, the geographically fixed areas varied from census-based boundaries, with populations ranging from 400 to 700 residents (Dupéré et al., 2009), to regions, with an average population size of 58,806 (Martikainen et al., 2004). The influence of different area delineations was highlighted by Kanamori et al. (2020), who found that individual sociodemographic characteristics explained the excess suicide risk in rural municipalities but not the excess risk in rural neighborhoods. Other studies found a similar pattern (Rehkopf and Buka, 2006; Rezaeian et al., 2006) and concluded that ecological studies that used smaller areas, instead of larger areas, such as counties, were more likely to find a significant association between area socioeconomic characteristics and suicide rates. Therefore, the possible mechanisms linking contextual area characteristics to suicide mortality may operate only in smaller areas, such as neighborhoods.

To our knowledge, almost all recent studies explicitly focusing on neighborhoods have used census or administratively defined areas (Allen and Goldman-Mellor, 2018; Collings et al., 2009; Cubbin et al., 2000; Dupéré et al., 2009; Dykxhoorn et al., 2021; Hagedoorn and Helbich, 2022; Johnson et al., 2017; Yoon et al., 2015). However, there is little reason to believe that such areas are valid measures of meaningful neighborhoods (Flowerdew et al., 2008), especially when the neighborhood characteristics of interest are related to the individuals' social environment, as these areas are not necessarily related to the different social processes and interactions taking place in neighborhoods and potentially affecting the residents (Diez Roux, 2001; Sampson et al., 2002). Thus, as an alternative to delineating neighborhoods as geographically fixed administrative areas, Hagedoorn et al. (2020) used 300-, 600- and 1000-m circular buffers around each subject's residential address to assess individual Dutch neighborhoods. Using this method, suicide mortality remained associated with neighborhood deprivation and levels of urbanicity in the total population and with social fragmentation in women after adjusting for composition.

However, as emphasized by Chaix et al. (2009), it is important to distinguish between territorial neighborhoods and ego-centered neighborhoods. Territorial neighborhoods have fixed boundaries such as administrative areas, independent of a specific individual. In contrast, ego-centered neighborhoods have sliding boundaries that follow specific individuals so that individuals are allocated to their own unique neighborhood (Chaix et al., 2009). While ego-centered neighborhoods, such as the one used by Hagedoorn et al. (2020), are a promising method of accurately capturing the local environmental conditions to which an individual is exposed, alternative measures of meaningful territorial neighborhoods are still needed to investigate between-area variability and to separate contextual effects from compositional effects when using multilevel modeling.

The neighborhood context should also influence individual health to be considered relevant for informing public health measures. Therefore, the general contextual effect (GCE), often measured with the intraclass correlation, the median odds ratio (MOR), median rate ratio (MRR) or median hazard ratio (MHR) based on the between-area variance, needs to be investigated before estimating specific contextual effects (SCEs), such as specific contextual variables, e.g., neighborhood socioeconomic deprivation, to determine the overall importance of the specific context. In general, the higher the GCE is the more important the context is for understanding individual differences in the outcome. This is important to consider because even though a contextual variable may have a substantial SCE and explain a large part of the between-area variance, the between-area variance may be very low in the first place, suggesting a rather unimportant impact of the context on the outcome (Merlo et al., 2018). However, to our knowledge, only the study by Kanamori et al. (2020), of all studies focusing on neighborhoods and suicide mortality, used geographically fixed nonadminstrative areas and reported not only SCEs but also the GCE. The results provided evidence for a relevant GCE from neighborhoods on suicide mortality when using the Swedish Demographic Statistical Area (DeSO) developed by Statistics Sweden as neighborhoods, as well as SCEs in the form of urban-rural inequalities in suicide (Kanamori et al., 2020).

The fact that different types of areas can potentially lead to different results is also known as the modifiable areal unit problem (MAUP) (Openshaw, 1983). In addition, different types of neighborhood delineations may lead to different results based on the extent to which these areas deviate from the true, causally relevant geographic context of the outcomes under study, also known as the uncertain geographic context problem (UGCoP) (Kwan, 2012).

In our study, neighborhoods were based on the definition of neighborhoods as ecological contexts with social and psychological meanings (Chaskin, 1997) and measured on a microlevel scale using factors such as the physical boundaries and social interactions within neighborhoods (Sampson et al., 2002). The use of physical boundaries and barriers, such as larger roads and railroad tracks, as dividers was based on findings that such barriers can also function as social dividers and thereby promote or hinder social interaction (Feld, 1981; Grannis, 1998) and further result in high within-group sociodemographic homogeneity (Foster and Aaron Hipp, 2011; Lund, 2018). Furthermore, residents may use such major physical barriers to identify their own neighborhood from that of other areas (Campbell et al., 2009; Grannis and Rick, 2009). These neighborhoods, which we call "micro-areas", were created using an automated redistricting algorithm (Lund, 2018). Micro-areas have been shown to produce higher within-group sociodemographic homogeneity (Lund, 2018) and higher GCEs and SCEs when focusing on socioeconomic deprivation and individual purchases of psychiatric medication compared with other administrative units (Jakobsen, 2021). However, as only one previous study focusing on neighborhood rurality and suicide mortality has used geographically fixed alternatives to census or administratively defined areas (Kanamori et al., 2020), the use of these alternative nonadministrative neighborhood delineations and the influence of neighborhood context on suicide mortality require further investigation, as it remains unknown whether neighborhoods truly affect suicide mortality.

To address the above shortcomings, we conducted a multilevel register-based 5-year follow-up study on 2.7 million adult individuals nested in 7943 micro-areas to examine how socioeconomic deprivation, population density and social fragmentation might affect individual suicide risk.

We conducted multilevel survival analyses to investigate the GCE and SCEs for micro-areas on suicide mortality stratified by age group. Furthermore, we tested for cross-level interactions related to gender, age and ethnicity to test the possible heterogeneity of the associations between neighborhood contextual factors and suicide mortality in relation to individual sociodemographic characteristics.

## 2. Methods

### *2.1. Design and data sources*

Data for this study were obtained from two different sources: (1) register data on suicide mortality as well as area-level and individual-level sociodemographic characteristics from Statistics Denmark and (2) geographic grid data from The Danish Geodata Agency. Data on suicide were obtained from the Danish Cause of Death Register, with suicide defined according to the ICD10 (World Health Organization, 1993) codes X60-X84 and Y870. The georeferenced data consisted of the national square grid, which divides Denmark into vectors of 100 × 100 m cells, and of topographic maps that contained information on buildings, roads, rivers, railroads, etc. The georeferenced data were linked to the registers, but since Statistics Denmark has very strict discretionary criteria to maintain data anonymity, the data had to be clustered into groups containing at least 100 inhabitants and 50 households per measurable geographic unit before they could be linked to individual-level data.

The study population consisted of the entire Danish population in the age range of 20–59 years in December 2013 (N = 2,937,040). The sample was restricted to respondents who provided information on all variables used in the analyses, resulting in a final sample of N = 2,672,799 (see Fig. 1). Information on micro-areas was missing if an individual did not fall within the specific criteria for the micro-areas (as described below). An example could be a small island or small isolated village that has no immediate neighboring areas and falls below the discretion criteria set by Statistics Denmark. Missing data were omitted from the analysis rather than being imputed because of the large register-based sample and the absence of major differences in suicide rate, age and gender between the sample and the full population. The cohort was followed for five years until December 31st, 2018, resulting in 13,059,255 person-years. Individuals who emigrated or died from nonsuicide causes were censored. Those who returned during the study period were not subsequently reincluded.

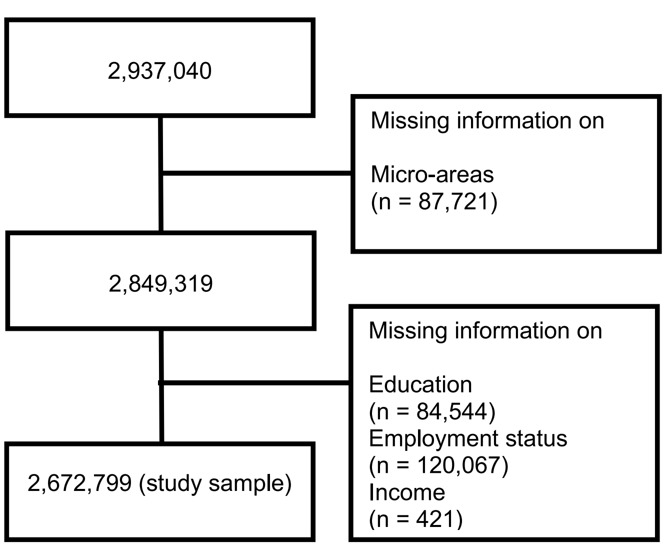


**Fig. 1.** Flow chart.

### *2.2. Spatial modeling*

To capture the effect of the local neighborhood, this study employed automated redistricting based on an inductive, recursive algorithm to isolate smaller socioeconomic clusters (Lund, 2018). The establishment of cities, communities and housing follow the principles of closeness, except in cases where these entities are separated by physical barriers, including roads, railways, rivers, lakes, forests or other objects that may not have been intended as separators but often act as such (Feld, 1981; Grannis, 1998; Lund, 2018). According to this logic, the micro-areas in this study were established by examining how individuals cluster in preexisting geographic areas. The methodology involved two distinct steps implemented in Python. First, the rules for overall geographic subdivision and measures that ensured that a minimum number of inhabitants were located in each geographic entity were established. Second, clustering occurred based on strict discretionary criteria. As previously mentioned, Statistics Denmark has strict discretionary criteria in regard to geographic clustering. Thus, to meet the discretionary criteria, further steps were implemented: (1) ensuring at least 100 inhabitants per area, (2) combining areas to minimize the number of merges needed, (3) combining areas to minimize the geographic size, and (4) creating merges as close to the 100-inhabitant rule as possible. These criteria were designed to determine areas that were small in geographic size and number of inhabitants. While these criteria can be regarded as procedural algorithmic steps calculated in a sequence, this would create computational problems in regard to reproducibility, especially as the geographic starting location for the clustering would have a potentially problematic effect on area creation. Thus, the problem was not only be a computational problem but also an optimization problem, determining the number of permutations needed to ensure the optimal solution (where all criteria are solved) and that closest to the critical value set. As the initial volume of spatial units after step one was 21,384 and an average area shared 5.4 borders with adjacent areas, the total number of calculations needed to identify the optimal solution would require years of computation. Thus, instead of solving the total set of data as a single unit, a set of gradient descent cost functions were implemented to seek faster computations and facilitate solving the data without creating a matrix of all possible merges. The advantage of this optimization is that merged solutions can be objectively evaluated to select the best solution. In this study, this resulted in 7943 areas with a median population of 322 (IQR = 388) and a median size of 2.37 square kilometers (IQR = 6.98). For a more in-depth explanation of the distinct computational approach, see (Kristiansen and Lund, 2022; Lund, 2018).

### *2.3. Neighborhood characteristics*

Based on previous contextual socioeconomic deprivation scores, we created a composite index of socioeconomic deprivation measured at baseline, with the following three indicators: the 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, recipients of cash benefits and persons on leave (Bender et al., 2015; Jakobsen, 2021; Juhász et al., 2010; Meijer et al., 2013); the proportion of the population between 30 and 64 years of age in the area with a total annual personal income in the lowest income quartile (Bender et al., 2015; Jakobsen, 2021; Meijer et al., 2013); and the proportion of the population between 30 and 64 years of age in the area with basic education (levels 0–2) as the highest attained educational level based on the UNESCO International Standard Classification of Education (ISCED) (UNESCO Institute for Statistics, 2012) (Bender et al., 2015; Jakobsen, 2021; Juhász et al., 2010; Lund, 2020). The age restriction of individuals between 30 and 64 years old was designed to capture individuals who were likely to have graduated and were of working age.

Social fragmentation in each neighborhood was measured using three indicators: residential mobility in the area (the proportion of individuals who moved in the previous year), the proportion of people living alone in the area and the proportion of unmarried individuals in the area (Congdon, 1996, 2013; Dykxhoorn et al., 2021; Hagedoorn et al., 2020). To determine the relative weight of each indicator, all indicators were standardized to z scores and used to construct a composite index for neighborhood socioeconomic deprivation and a composite index for neighborhood social fragmentation via principal component analysis (PCA). Population density was measured as the total number of individuals of all ages per square kilometer, which has previously been established as a valid indicator of urban/rural differences in suicide mortality (Helbich et al., 2017). All three neighborhood characteristics were divided into quintiles to investigate potential nonlinear effects.

### 2.4. Individual-level variables

Individual-level variables were measured at baseline as potential confounders and included gender, age, marital status, education, personal income, employment status and ethnicity. Age was grand mean-centered by subtracting the sample mean from the respondent's age. Marital status was collapsed into three categories: married, cohabiting or single. Education was measured as the highest attained education according to the ISCED and collapsed into three categories: levels 0–2 ('basic education'), levels 3–5 ('medium education') and levels 6–8 ('high education') (UNESCO Institute for Statistics, 2012). Income was measured as the total annual personal income (excluding rental income from one's own accommodation and before deducting labor-market and pension contributions) and categorized into quartiles. Employment status was collapsed into three basic categories: employed, unemployed, and nonworking, which included students and pensioners/early retirees. Ethnicity was dichotomized to Danish or other.

### 2.5. Statistical analysis

For a descriptive overview, we calculated the incidence rate for suicides per 100,000 person-years for all level-1 and level-2 predictors. To determine the association between neighborhood socioeconomic deprivation, population density, social fragmentation, and suicide risk, we estimated hazard ratios (HR) using two-level Weibull mixed-effects parametric survival models, with random intercepts at the micro-area level and individuals nested within micro-areas. The models can be viewed as shared frailty models with lognormal frailty. The models were conducted using the *Mestreg* command in Stata version 17 (StataCorp, 2021). As previous research indicates that the associations between area-level factors and suicide mortality may vary with age, we examined the models per age group (20–39 years and 40–59 years) based on previous studies using similar age groups (Agerbo et al., 2007; Hagedoorn et al., 2020; O'Farrell et al., 2016). To quantify the area-level variance for suicide mortality, we used the MHR calculated with the following formula when the frailty is log-normally distributed:

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

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 MHR indicates the median hazard ratio when comparing the hazard of a randomly chosen individual from an area with higher suicide mortality to that of a randomly chosen individual from an area with lower suicide mortality (Austin et al., 2017; Bengtsson and Dribe, 2010). One advantage of the MHR is that it allows the direct comparison of the GCE with the fixed effect odds ratios of the covariates in the model, which makes it possible to compare the importance of the contextual effect with that of other individual-level variables (Austin et al., 2017; Merlo et al., 2006).

## 3. Results

### 3.1. Descriptive statistics

Table 1 shows the suicide incidence rates per 100,000 person-years for neighborhood and individual characteristics stratified by age group. Suicide rates were highest in the most deprived and socially fragmented neighborhoods for both age groups (20–39-year-olds and 40–59-year-olds). For population density, the highest suicide rates were found in the least dense neighborhoods for those aged 20–39 years, while the highest suicide rates were found in the densest neighborhoods for those aged 40–59 years. For individual characteristics, suicide rates were highest among the unemployed and nonworking people, people in the second lowest income quartile, people with only basic education, single individuals, men, and people with Danish ethnicity for both age groups.

### 3.2. Multilevel models

Table 2 shows the multilevel regression models. For individuals 20–39 years old, the null model showed that the HRs for suicide risk varied between neighborhoods, with an MHR of 1.60. Furthermore, a likelihood-ratio test showed evidence in favor of the random-effects model over the fixed-effects model ($p = 0.0258$). For the older age group (between 40 and 59 years old), less variance was observed between neighborhoods, with an MHR of 1.18; the evidence did not favor the random-effects model over the fixed-effects model ($p = 0.3254$).

The models including all neighborhood characteristics but not adjusted for individual characteristics showed that all neighborhood characteristics were significantly associated with suicide mortality for both age groups. People living in the most socioeconomically deprived neighborhoods had an almost 50% excess suicide risk than those living in the least deprived areas for both 20–39-year-old individuals (HR: 1.49, 95% CI: 1.02, 2.20) and 40–59-year-old individuals (HR: 1.41, 95% CI: 1.10, 1.80). An excess risk was also observed for people living in the most socially fragmented areas for both 20–39-year-old individuals (HR: 2.39, 95% CI: 1.54, 3.72) and 40-59-year-old individuals (HR: 2.20, 95% CI: 1.67, 2.90). Furthermore, an excess suicide risk was found for people in the least densely populated areas, with an almost threefold increased risk for individuals aged 20–39 (HR: 2.86, 95% CI: 1.97, 4.15) and a 58% higher risk for the older age group (HR: 1.58, 95% CI: 1.23, 2.20). In these models, the MHR was reduced to 1.35 for the younger age group and 1.00 for the older age group, which indicates no excess risk at the area level for people aged 40–59 after neighborhood socioeconomic deprivation, social fragmentation and population density were taken into account.

After adjusting for individual-level characteristics, all associations between neighborhood characteristics and suicide were attenuated. Socioeconomic deprivation became nonsignificant for both age groups, indicating that these associations were explained by compositional effects. However, people aged 20–39 in the most socially fragmented neighborhoods still showed an almost twofold increased risk of suicide compared to those in the least socially fragmented neighborhoods (HR: 1.89, 95% CI: 1.21, 2.79) and a more than twofold excess risk if living in the least densely populated neighborhoods (HR: 2.19, 95% CI: 1.51, 3.18). For the older age group, these specific contextual effects were

**Table 1**
Descriptive statistics of the study variables.

| | 20–39 years | | 40–59 years | |
|---|---|---|---|---|
| | No. (%) or mean (SD) | Suicide rate[a] | No. (%) or mean (SD) | Suicide rate[a] |
| **Neighborhood characteristics** | | | | |
| **Socioeconomic deprivation** | | | | |
| Q1 (least deprived) | 185,089 (14.98) | 5.422 | 314,71 (21.90) | 10.305 |
| Q2 | 237,18 (19.19) | 7.373 | 296,24 (20.62) | 13.084 |
| Q3 | 241,445 (19.54) | 7.159 | 295,36 (20.55) | 14.645 |
| Q4 | 274,698 (22.23) | 7.135 | 276,816 (19.26) | 17.664 |
| Q5 (most deprived) | 297,388 (24.06) | 10.810 | 253,873 (17.67) | 20.428 |
| **Social fragmentation** | | | | |
| Q1 (least fragmented) | 178,399 (14.44) | 5.584 | 329,995 (22.96) | 11.405 |
| Q2 | 183,16 (14.82) | 6.895 | 315,704 (21.97) | 12.847 |
| Q3 | 199,305 (16.13) | 8.105 | 300,536 (20.91) | 13.997 |
| Q4 | 256,799 (20.78) | 8.532 | 272,928 (18.99) | 15.717 |
| Q5 (most fragmented) | 418,137 (33.84) | 8.594 | 217,836 (15.16) | 23.935 |
| **Population density** | | | | |
| Q1 (most dense) | 411,781 (33.32) | 6.754 | 223,73 (15.57) | 18.142 |
| Q2 | 245,113 (19.83) | 8.993 | 284,039 (19.77) | 14.704 |
| Q3 | 202,63 (16.40) | 7.082 | 294,94 (20.52) | 13.985 |
| Q4 | 187,173 (15.15) | 7.081 | 307,941 (21.43) | 12.787 |
| Q5 (least dense) | 189,103 (15.30) | 10.002 | 326,349 (22.71) | 15.967 |
| **Individual characteristics** | | | | |
| **Employment status** | | | | |
| Employed | 831,941 (67.32) | 5.379 | 1,197,123 (83.31) | 10.670 |
| Unemployed | 126,265 (10.22) | 18.739 | 111,479 (7.76) | 29.923 |
| Nonworking | 277,594 (22.46) | 10.261 | 128,397 (8.94) | 43.275 |
| **Income** | | | | |
| Q1 (lowest) | 474,762 (38.42) | 10.039 | 193,439 (13.46) | 28.181 |
| Q2 | 308,624 (24.97) | 9.118 | 359,579 (25.02) | 20.315 |
| Q3 | 262,595 (21.25) | 4.720 | 405,603 (28.83) | 11.261 |
| Q4 (highest) | 189,819 (15.36) | 4.524 | 478,378 (33.29) | 8.893 |
| **Education (ISCED)** | | | | |
| Basic education (levels 0–2) | 240,324 (19.45) | 16.064 | 306.725 (21.34) | 21.732 |
| Medium education (levels 3–5) | 643,246 (52.05) | 7.306 | 736.419 (51.25) | 14.746 |
| High education (levels 6–8) | 352,23 (28.50) | 3.064 | 393.855 (27.41) | 10.154 |
| **Marital status** | | | | |
| Married | 409,935 (33.17) | 4.768 | 879.733 (61.22) | 8.862 |
| Cohabiting | 349,567 (28.29) | 3.925 | 186.528 (12.98) | 11.859 |
| Single | 476,298 (38.54) | 13.408 | 370.738 (25.80) | 31.269 |
| **Gender** | | | | |
| Women | 613,47 (49.64) | 3.784 | 716,711 (50.08) | 8.060 |
| Men | 622,33 (50.36) | 11.799 | 720,288 (50.12) | 21.882 |
| **Ethnicity** | | | | |
| Danish | 1,062,759 (86.00) | 8.266 | 1,310,648 (91.21) | 15.601 |
| Non-Danish | 173.041 (14.00) | 4.841 | 126,351 (8.79) | 8.285 |
| **Age** | 29.65 (5.91) | – | 49.25 (5.66) | – |

SD = standard deviation.
[a] Suicide incidence rate per 100,000 person-years.

reduced to HR: 1.43, 95% CI: 1.08, 1.90 for social fragmentation and HR: 1.42, 95% CI: 1.10, 1.83 for population density. For both age groups individual characteristics were associated with suicide mortality, with individuals who were unemployed, nonworking, single people and men showing especially higher risks. When adjusting for individual characteristics, the MHR was reduced to 1.26 for the younger age group and 1.00 for the older age group.

We found cross-level interactions between population density and both gender and ethnicity for individuals aged 40–59, showing that the excess risk of suicide in the least densely populated areas was only present for men (HR: 1.59, 95% CI: 1.21, 2.10) and not women (HR: 1.01, 95% CI: 0.68, 1.52). Furthermore, the results showed a higher risk associated with living in the least vs. the most densely populated areas for individuals with a non-Danish ethnicity (HR: 4.57, 95% CI: 1.99, 10.43) compared to ethnic Danes (HR: 1.34, 95% CI: 1.03, 1.73). In addition, we found a cross-level interaction between social fragmentation and ethnicity for individuals aged 20–39, showing that the excess risk of suicide in the most socially fragmented areas was only present for ethnic Danes (HR: 2.12, 95% CI: 1.33, 3.37) and not for people with a non-Danish ethnicity (HR: 0.52, 95% CI: 0.17, 1.63).

### 3.3. Sensitivity analyses

To test the robustness of our results, we performed various sensitivity analyses. First, we considered that different types of areas could reflect different contextual features and mechanisms; for example political and economic contexts might exert a greater effect in larger areas such as municipalities, while social interaction mechanisms might be more important in smaller areas such as neighborhoods (Kanamori et al., 2020; Rehkopf and Buka, 2006). In other words, the micro spatial context cannot be fully understood in isolation from the macro framework representing the “context of context” (Petrović et al., 2021). To adjust for this possible effect, we included the municipality levels of socioeconomic deprivation, social fragmentation, and population density in the full models along with the neighborhood-level variables. However, this did not change the results, and the variables at the municipality-level had no significant impact on suicide mortality. In addition, we tested the use of Danish parishes, the smallest administrative area in Denmark, as an alternative neighborhood unit. When using parishes, the general contextual effect (GCE) was smaller with MORs of 1.21 and 1.10 for the different age groups compared to the MORs of 1.60 and 1.18, when using the micro-areas. These findings

**Table 2**
Suicide mortality hazard ratios (HRs) stratified by age group.

| | 20–39 years | | | | | 40–59 years | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Null | Model 1 | | Model 2 | | Null | Model 1 | | Model 2 | |
| | HR | HR | (95% CI) | HR | (95% CI) | HR | HR | (95% CI) | HR | (95% CI) |
| ***Fixed effects*** | | | | | | | | | | |
| **Neighborhood characteristics** | | | | | | | | | | |
| **Socioeconomic deprivation** | | | | | | | | | | |
| Q1 (least deprived) | | Ref | | Ref | | | Ref | | Ref | |
| Q2 | | 1.17 | (0.81, 1.70) | 1.05 | (0.72, 1.52) | | 1.13 | (0.91, 1.41) | 1.01 | (0.81, 1.26) |
| Q3 | | 1.01 | (0.69, 1.49) | 0.83 | (0.56, 1.22) | | 1.19 | (0.95, 1.50) | 0.98 | (0.78, 1.24) |
| Q4 | | 0.97 | (0.65, 1.43) | 0.74 | (0.50, 1.09) | | 1.32 | (1.04, 1.67) | 0.99 | (0.78, 1.26) |
| Q5 (most deprived) | | 1.49 | (1.02, 2.20) | 0.99 | (0.67, 1.47) | | 1.41 | (1.10, 1.80) | 0.93 | (0.72, 1.21) |
| **Social fragmentation** | | | | | | | | | | |
| Q1 (least fragmented) | | Ref | | Ref | | | Ref | | Ref | |
| Q2 | | 1.19 | (0.81, 1.75) | 1.11 | (0.76, 1.63) | | 1.05 | (0.85, 1.28) | 0.98 | (0.79, 1.20) |
| Q3 | | 1.53 | (1.04, 2.24) | 1.32 | (0.90, 1.94) | | 1.14 | (0.92, 1.41) | 1.00 | (0.80, 1.24) |
| Q4 | | 1.87 | (1.24, 2.82) | 1.54 | (1.02, 2.33) | | 1.35 | (1.06, 1.73) | 1.06 | (0.83, 1.36) |
| Q5 (most fragmented) | | 2.39 | (1.54, 3.72) | 1.89 | (1.21, 2.97) | | 2.20 | (1.67, 2.90) | 1.43 | (1.08, 1.90) |
| **Population density** | | | | | | | | | | |
| Q1 (most dense) | | Ref | | Ref | | | Ref | | Ref | |
| Q2 | | 1.69 | (1.28, 2.24) | 1.40 | (1.06, 1.85) | | 1.14 | (0.93, 1.41) | 1.11 | (0.90, 1.37) |
| Q3 | | 1.55 | (1.12, 2.16) | 1.24 | (0.90, 1.73) | | 1.29 | (1.03, 1.61) | 1.23 | (0.98, 1.55) |
| Q4 | | 1.92 | (1.33, 2.76) | 1.50 | (1.04, 2.16) | | 1.30 | (1.02, 1.66) | 1.22 | (0.95, 1.56) |
| Q5 (least dense) | | 2.86 | (1.97, 4.15) | 2.20 | (1.51, 3.19) | | 1.58 | (1.23, 2.20) | 1.42 | (1.10, 1.83) |
| **Individual characteristics** | | | | | | | | | | |
| **Employment status** | | | | | | | | | | |
| Employed | | | | Ref | | | | | Ref | |
| Unemployed | | | | 2.28 | (1.69, 3.07) | | | | 1.72 | (1.38, 2.15) |
| Nonworking | | | | 1.80 | (1.37, 2.36) | | | | 2.58 | (2.14, 3.09) |
| **Income** | | | | | | | | | | |
| Q1 (lowest) | | | | Ref | | | | | Ref | |
| Q2 | | | | 1.04 | (0.81, 1.34) | | | | 0.89 | (0.74, 1.06) |
| Q3 | | | | 0.70 | (0.48, 1.01) | | | | 0.69 | (0.55, 0.86) |
| Q4 (highest) | | | | 0.65 | (0.43, 0.99) | | | | 0.50 | (0.40, 0.64) |
| **Education (ISCED)** | | | | | | | | | | |
| Basic education (levels 0–2) | | | | Ref | | | | | Ref | |
| Medium education (levels 3–5) | | | | 0.66 | (0.53, 0.81) | | | | 1.09 | (0.94, 1.26) |
| High education (levels 6–8) | | | | 0.36 | (0.25, 0.50) | | | | 1.13 | (0.93, 1.38) |
| **Marital status** | | | | | | | | | | |
| Married | | | | Ref | | | | | Ref | |
| Cohabiting | | | | 0.75 | (0.55, 1.04) | | | | 1.13 | (0.91, 1.40) |
| Single | | | | 2.05 | (1.58, 2.65) | | | | 2.38 | (2.06, 2.75) |
| **Gender** | | | | | | | | | | |
| Women | | | | Ref | | | | | Ref | |
| Men | | | | 2.93 | (2.35, 3.64) | | | | 2.92 | (2.54, 3.36) |
| **Ethnicity** | | | | | | | | | | |
| Danish | | | | Ref | | | | | Ref | |
| Non-Danish | | | | 0.52 | (0.37, 0.72) | | | | 0.42 | (0.31, 0.56) |
| **Age (grand mean centered)** | | | | 1.07 | (1.05, 1.09) | | | | 1.00 | (0.99, 1.01) |
| ***Random effects*** | | | | | | | | | | |
| **Area level variance** | 0.24 | 0.10 | | 0.06 | | 0.03 | 0.00 | | 0.00 | |
| **MHR** | 1.60 | 1.35 | | 1.26 | | 1.18 | 1.00 | | 1.00 | |
| **AIC** | 9789.956 | 9758.418 | | 9328.313 | | 20731.52 | 20653.09 | | 19848.6 | |

demonstrate the relevance of the MAUP and UGCoP and indicate that the micro-areas are more relevant than parishes or municipalities when studying geographical inequalities in suicide mortality.

Second, we tested different modifications of the neighborhood characteristics, using quartiles instead of quintiles and modeling the neighborhood-level predictors as continuous variables. These modifications did not substantially alter the results, indicating that our findings were robust.

## 4. Discussion

In this study, we investigated how neighborhood socioeconomic deprivation, population density and social fragmentation might affect suicide mortality. We found a larger GCE from neighborhoods on suicide mortality for individuals aged 20–39 years compared with those aged 40–59 years. Furthermore, an excess suicide risk was observed for individuals living in the most socioeconomically deprived, socially fragmented, and least densely populated neighborhoods for both age groups. After adjusting for individual characteristics, these associations were largely attenuated, indicating that a large part of the association between neighborhood social characteristics and suicide mortality was due to compositional effects. In the adjusted models, the suicide risk remained significantly higher for both age groups in the least densely populated and most socially fragmented neighborhoods. We found cross-level interactions between population density and both gender and ethnicity for those aged 40–59 years, showing a higher suicide risk associated with population density for men than for women as well as for individuals with a non-Danish ethnicity compared to ethnic Danes. In addition, we found a higher risk associated with living in highly socially fragmented neighborhoods for ethnic Danes compared with individuals with a non-Danish ethnicity for those aged 20–39 years.

In general, our findings showing an excess suicide risk associated with living in socially fragmented and low population density neighborhoods are consistent with two of the most recent studies investigating neighborhood effects on suicide mortality (Hagedoorn and Helbich, 2022; Kanamori et al., 2020). As stated in the introduction, these findings may be explained by the potential mechanisms of increased social isolation and lack of integration in less densely populated and socially fragmented neighborhoods as well as community attitudes toward mental illness and help seeking (Solmi et al., 2017).

In line with other studies (Kanamori et al., 2020; Rehkopf and Buka, 2006; Rezaeian et al., 2006), our findings that neighborhood factors were significantly associated with suicide risk, while the same characteristics at the municipality level were not, indicate that contextual factors are more relevant to suicide mortality when measured at smaller geographic scales, which may reflect mechanisms in individuals' daily immediate environment rather than the broader political and economic context. This illustrates the importance and relevance of both the MAUP and UGCoP for understanding geographical inequalities in suicide mortality. Associations between urbanization and suicide mortality are therefore possibly less due to overall differences between urban vs. rural environments but rather a result of variations in contextual differences that exist in both urban and more rural settings. Contextual characteristics measured at aggregate levels in large administrative areas may often encompass very heterogeneous areas (Rezaeian et al., 2006). A municipality may include large variation in neighborhoods, including less or more socially fragmented, socioeconomically deprived or affluent, densely populated or less populated areas (Kanamori et al., 2020); therefore, studies investigating only large areas may underestimate or overlook important contextual effects from smaller areas, which may serve as a more important and causally relevant context for understanding suicide mortality.

The cross-level interactions showing an excess suicide risk living in less densely populated neighborhoods, especially for older men and individuals with a nonnative ethnicity, were also found in other studies (Cheung et al., 2012; Kanamori et al., 2020). Men living in remote and rural areas may be prone to certain masculinity ideals, such as stoicism, which may result in less help-seeking behavior during hardship and despair (Alston, 2012; Kanamori et al., 2020). In addition, nonnative individuals might be prone to fewer social interactions and lower social integration than ethnic Danes in less densely populated areas. While we do not have a clear explanation for the interaction between ethnicity and social fragmentation, we hypothesize that people with foreign backgrounds may more frequently encounter socially fragmented environments and therefore be less affected by them. However, additional research on this topic is needed.

Similar to the study by Kanamori et al. (2020), which showed an MRR of 1.33 for men and 1.43 for women between neighborhoods using multilevel Poisson null models with individuals 20 years or older, we also found evidence for a relevant GCE. This indicates that the use of small nonadministrative areas divided by physical barriers may be a promising method of capturing neighborhood effects on mental health outcomes that are related to the social environment. This corroborates earlier research that found that micro-areas, compared with Danish administrative areas, showed a higher MOR as well as specific fixed-effects odds ratios associated with living in socioeconomically deprived neighborhoods for psychiatric medication purchases (Jakobsen, 2021). However, while Kanamori et al. (2020) found a substantial GCE when the results were stratified by sex, our results indicate that neighborhood characteristics may not be equally important for all age groups. Other studies have reported age differences as well, but the results are inconsistent (Hagedoorn et al., 2020; Jasilionis et al., 2020), and more research on this topic is warranted.

When focusing on the magnitude of the SCEs in our study, the effect sizes showed that for people aged 20–39, the excess risk associated with living in the least densely populated areas was comparable to the excess risk of being unemployed and being single. Furthermore, for this age group, the GCE from neighborhoods was comparable to the fixed-effects estimates for income. This indicates that both the GCE and SCEs on suicide mortality associated with living in certain neighborhoods may be equally important as some individual characteristics for people aged 20–39 years.

One key strength of this study was our ability to assess micro-areas instead of relying on administrative delineations. In Denmark, as in most countries, statistical analyses often rely on existing geographic units, and there are no widely available alternatives to municipalities or parishes, which are demonstrably worse at capturing socioeconomic homogeneity than almost all other geographic units (Lund, 2019). The use of micro-areas increases within-neighborhood homogeneity and thus increases the chance of actually detecting neighborhood effects as opposed to arbitrary aggregated effects that lack practical significance for the individuals living in a given area (Lund, 2020). While studies in other countries have used smaller units, such as studies that rely on K nearest neighbors (Östh, 2018; Östh et al., 2015) and Bayesian spatial models (Borgoni and Billari, 2003), they all suffer from the same problem: they focus solely on the individual and neglect the effect of the surrounding geography. One of the few other geographic units that incorporates the physical environment as well as the number of inhabitants is the new Swedish Demographic Statistical Areas (DeSO) unit used by Kanamori et al. (2020), which replaced the former well-known SAMS (Small Areas for Market Statistics) in 2020. While these units are based on the same concepts as the micro-areas of this study, they still rely on relatively large geographic units in regard to the number of inhabitants. The scalability of area size is a factor when considering larger cities. Nevertheless, a core strength of the present study was a large increase in measurement precision for neighborhood-level effects compared to other known methods of assessing area-level statistics. In relation to the MAUP and UGCoP, future studies should continue developing and testing new alternatives to administrative delineations when studying area effects on suicide mortality to more accurately measure the most relevant geographic context.

Furthermore, the use of high-quality Danish register data that encompassed almost the entire population between 20 and 59 years of age is a strength of our study. In addition, we included not only neighborhood characteristics but also social characteristics at the municipality level as control variables in our sensitivity analyses, which strengthens the robustness of the associations detected between neighborhood characteristics and suicide mortality, as it is possible that factors measured at the neighborhood level may be confounded by other relevant contexts, such as the municipality context (Kanamori et al., 2020; Kwan, 2012).

Our study also had several limitations. Despite its longitudinal design, selection bias might still have occurred, meaning that the association between neighborhood characteristics and suicide mortality rates was caused by differential selection of people into certain neighborhoods (Sampson et al., 2002). However, previous experimental studies have found evidence for a causal link between neighborhood factors and mental health conditions (Foverskov et al., 2022; Leventhal and Brooks-Gunn, 2003; Ludwig et al., 2013; White et al., 2017). Furthermore, the recent study by Hagedoorn and Helbich (2022) found significant associations between neighborhood characteristics and suicide mortality when studying residential mobility and neighborhood change, and a recent study by Belsky et al. (2019) linking neighborhood, genetic and health data found evidence against selection bias for neighborhood gradients in mental health. In addition, we were limited by the use of register data, and thus we were unable to assess residents' own perceptions of their neighborhood, such as their perceptions of collective efficacy (Sampson et al., 1997). Future studies should identify the mechanisms that explain the relationship between neighborhood factors and suicide mortality.

Despite these limitations, this study adds to the existing literature by using a new method of automatically generating neighborhoods divided by physical barriers to study the GCE and SCEs on suicide mortality. We found evidence that the neighborhood context influences suicide mortality, as neighborhoods with especially low population density were a contextual risk factor. The findings of this study may inform public health interventions focusing on neighborhood-level factors, which may be important to consider in addition to the already well-known individual risk factors.

## Credit author statement

**Andreas Lindegaard Jakobsen**: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Visualization, Project administration, **Rolf Lyneborg Lund**: Conceptualization, Methodology, Software, Formal analysis, Resources, Data curation, Writing – review & editing, Funding acquisition.

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## Declaration of competing interest

None.

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