Childhood neighborhoods and cause-specific adult mortality in Sweden 1939–2015

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Abstract
The socioeconomic health gradient has widened since the mid-21st century, but the role of childhood neighborhoods remains underexplored. Most neighborhood studies on health are cross-sectional, and longitudinal research is lacking.

We analyze how socioeconomic neighborhood conditions in childhood influence cause-specific deaths in adulthood. We use uniquely detailed geocoded longitudinal microdata for the Swedish town of Landskrona, 1939-1967, linked to Swedish national registers, 1968-2015. We measure neighborhood SES by social class and use dynamic sizes of individual neighborhoods. Cox proportional hazards models are employed to estimate the impact of neighbor's social class in childhood (ages 1-17) on mortality in ages 40-69. We control for class origin, class in adulthood, schools, and physical neighborhood characteristics.

The class of the nearby, same-age, childhood neighbors had a lasting effect on male all-cause and preventable, but not non-preventable, mortality. Men who grew up with having 10% more children from white-collar families as close-proximity neighbors had an 8% lower mortality risk due to preventable causes of death in adulthood. The mortality for women was not affected by their childhood neighbors, although both a lower adult class and class origin increased their mortality.

Because preventable causes of death are linked to lifestyle factors, this study highlights the potential lasting influence of childhood neighborhood peers on the health behavior of men growing up before the health gradient was fully established. Hence, our applied life-course perspective on childhood neighborhoods is crucial to better understand the mortality differentials by SES.

Introduction

All developed countries have a marked socioeconomic status (SES) gradient in health and mortality, and the disparities in health by SES have grown in recent decades [1, 2]. Whereas the causes of the gradient are debated, it is widely recognized that the health gap by social status depends on conditions over the entire life course. Childhood SES affects lifestyles, habits, and opportunities later in life, with a direct impact on health [3, 4]. Childhood neighborhoods may affect adulthood health through several mechanisms related to the social and physical properties of places people grew up in [5-8]. Possible pathways include peer influence on lifestyle [9, 10], educational attainment [11], and persistent effects of exposure to pollution and green space in childhood [12]. These pathways may be related to family of origin SES as well as childhood neighborhood SES. Moreover, social segregation can have lasting negative social effects, as demonstrated by the isolation of low-SES groups in poverty-stricken areas of the large urban centers in the U.S. [13]. Within such areas, individuals are exposed to concentrated poverty, social control and cohesion, social and ethnic segregation, and violence [14, 15], with detrimental effects on health. Poor physical properties, related to negative health outcomes in the long term, include environmental pollution and the absence of green spaces [12, 16].

We contribute to the limited literature about long-term effects of childhood neighborhoods on health and mortality, using a longitudinal design and by identifying individual childhood neighborhoods. Most studies about neighborhood effects on health take a cross-sectional approach, and longitudinal research is lacking [5]. We know that there are immediate effects of neighborhoods on health of both adults and children (see, e.g., [17, 18]), but the long-term health consequences are understudied. Much neighborhood research is based on heavily segregated, large urban areas in the U.S., in which race, SES and health interact. The question is to what extent health is affected by neighborhoods in smaller, less segregated cities, in which much of the world's population lives. Further, we use detailed spatial and longitudinal observations. Most longitudinal studies have only estimated neighborhood conditions using broad administrative units [19], which are relatively imprecise [20]. Studies using more detailed spatial estimates often lack a longitudinal component. Finally, surprisingly little attention has been given in previous research to sex differences in neighborhood effects, despite empirical evidence for such differences for several outcomes including education and SES attainment (e.g., [11, 21]). Health of men and women are most likely not affected in the same way by childhood neighborhood conditions as, for example, peer influences could differ by sex.

We analyze how neighborhood conditions in childhood influence cause-specific deaths in adulthood (age 40-69 years). We measure neighborhoods in detail, using uniquely geocoded longitudinal microdata for the city of Landskrona, 1939-1967, linked to Swedish national registers, 1968-2015. Mechanisms linking childhood SES to deaths in this age group could be related to unhealthy lifestyles including drug, alcohol, and tobacco use, risk-taking behavior, and suicide. Hence, we group causes of death by whether they are largely preventable or non-preventable, and expect larger effects for preventable causes of death. Our main research question is: what are the long-term implications of the childhood neighborhood SES for adult preventable and non-preventable mortality, net of SES origin and SES attainment in adulthood? We hypothesize that growing up in a high-SES neighborhood promotes health in adulthood, whereas growing up in a low-SES neighborhood is associated with poor health outcomes. Furthermore, we expect sex differences in the neighborhood influence because patterns of adolescent engagement with unhealthy and risky behavior differs between boys and girls [22]. Lastly, we capture aspects of the socioeconomic and physical environment at the neighborhood level and school districts. As information is not grouped by administrative units, we are able to dynamically vary the size of the neighborhood as well as identify at what scales and for what neighbors the effect occurs.

Materials and Methods

We include two childhood SES variables and one variable for adult SES: geographically weighted share of high social-class children in the neighborhood (white-collar share); parental social class (class origin); and social class in adulthood (adult class). We estimate Cox proportional hazards models to analyze the impact of childhood neighbors on all-cause and cause-specific mortality in the age group 40-69. In addition to the class variables, we adjust for individual characteristics and the physical environment. However, as for any study using observational data, despite our detailed neighborhood measures and longitudinal analysis, we are not able to statistically estimate causal effects.

Data and study area

The study setting is the port town of Landskrona in southern Sweden. The town experienced rapid industrialization in the first half of the 20th century, connected to shipbuilding, textiles, food processing, and manufacturing. The population grew from 20 000 in 1940 to 30 000 in 1970. Landskrona's social and economic development during the period was similar to other comparable cities in Sweden [23].

Data on childhood conditions come from the Scanian Economic-Demographic Database (SEDD) and cover the period 1939-1967 [24]. These data are drawn from historical continuous population registers linked to income and taxation registers and contain information on births, marriages, deaths, occupation, income, and migration [25]. Previously, the population have been geocoded at the address level, providing full residential histories of the individuals living in the town from 1939 to 1967 [11]. Address points are linked to buildings in the city, and we use information on building and demolition years of structures and roads, and major industries and schools. Hence, these geographic data correctly represent the town in each year of the study period.

For the follow-up period, 1968-2015, individuals in SEDD are linked to longitudinal register data from Statistics Sweden (SCB) and the National Board of Health and Welfare, using unique personal numbers introduced in 1947. The follow-up is nationwide and include all individuals residing in Sweden. From these registers, we have information on cause-specific mortality (ICD-coded) and occupation (see details in Supplementary Information, section 1).

Analytical strategy

In the first step, we follow children and their neighbors longitudinally within Landskrona. For the period 1939-1967, we estimate neighborhood variables at the address-level for all children aged 1-17 (birth cohorts 1928-1966). Here, 97.3% of these children's survival time have been geocoded (see details in Supplementary Information, section 1). Moreover, we measure class origin and other family and environmental characteristics throughout childhood. We measure the social class of all same-age neighbors to analyze children's socioeconomic neighborhood conditions. As we accurately observe each move across the city, we can measure neighborhood properties continuously. We also measure some physical differences between neighborhoods, including possible exposure to environmental pollution, and account for the changing geography.

In the follow-up, we analyze all-cause and cause-specific mortality in ages 40-69. We exclude observations for children who died or left Sweden before 1968. Right censoring occurs at emigration and, for the 1957-1966 birth cohorts, when the observation period ends in 2015. The Cox model accounts for this type of censoring. In total, 17 380 ([48.9%] women) individuals could be followed-up on at least one occasion from age 40 (totaling 384 371 person-years in 1968-2015) (Supplementary Information, section 1.3).

Mortality variables

We categorize deaths as preventable or non-preventable following Ericsson et al. [26] and Debiasi and Dribe [27], of which the latter uses the same data sources as this work. This categorization is a slightly modified version of the Avoidable Mortality in the European Union (AMIEHS) [28], in which deaths caused by injuries are defined as preventable mortality. In our follow-up, we observe 1 893 deaths (women: 751 [39.7%] deaths). Deaths due to preventable causes are 772 (men) and 489 (women). Of these preventable deaths, circulatory system diseases (41.6%), external causes such as accidents and injuries (13.9%), respiratory diseases and lung cancers (12.4%), and other cancers (16.6%), are most common for men, whereas respiratory diseases and lung cancer (28.2%), other cancers (32.7%), and circulatory system diseases (20.0%) are the most common for women. In addition, alcohol-related deaths are more common for men (19.0%) than for women (8.2%) (Supplementary Information, section 1.5).

Social class variables

Class origin is measured by father's occupation, and adult class by own occupation. Occupations are classified by skill level and degree of supervision according to HISCLASS (see [1, 27, 29]). Data on occupation 1939-1967 is obtained from several sources: birth registers, marriage registers, population registers, and income registers. For most of the period, occupation data are registered on an annual basis. Occupational data 1968-2015 is taken from the quinquennial censuses 1970-1990, and the annual occupational register from 2001 onwards. We define four social classes (Supplementary Information, section 1.4):

- White-collar high (higher managers and professionals)
- White-collar low (lower managers and professionals, clerical and sales personnel)
- Blue-collar high (foremen, medium-skilled workers, farmers)
- Blue-collar low (low/unskilled workers)

For class origin, we use the highest social class attained by the family head (usually the father) in childhood (ages 1-17). Adult class is included as a time-varying covariate. The occupation recorded in the previous year is used for individuals aged 60 or older, as well as for those who died before their occupation was registered. In the historical period, a missing occupation represents a small and highly diverse group, whereas in the modern period, missing occupations are more commonly associated with unemployment.

Childhood neighborhood variable (geographically weighted white-collar share)
We use two approaches to measure and define individual neighborhoods in childhood: (1) k-nearest neighbors [11, 19, 30]; and (2) Euclidean distances. For both approaches, each individual is the center of their own neighborhood, and same-aged children outside the household are defined as neighbors. The first type uses an adaptive neighborhood bandwidth in which the k-nearest individuals are defined as neighbors. The second type uses a fixed Euclidean distance bandwidth; that is, individuals within a given radius from an individual are defined as neighbors. Hence, for the adaptive bandwidth, the geometric size of the neighborhood varies by population density, but the specified k neighbors remain constant; for the fixed bandwidth, the number of neighbors vary by population density but not the specified radius. Therefore, by combining these two approaches to define neighborhoods, we can better analyze at what scale any effects from neighbors operate.

At two time-points every year (May 31 and November 30), 1939-1967, we construct matrices with information on the Euclidean distances between each child and all other children of the same (± 1 year) age. Information on social class is also included for all children. From these bi-annual matrices, we first create individual neighborhoods using the two approaches (k-nearest neighbors and Euclidean distances). Thereafter, we measure the geographically weighted (GW) share of each social class within the neighborhood. That is, we assume that nearby neighbors had a greater influence than neighbors residing farther away and use a Gaussian distance-decay function to model the decline (see Supplementary Information, section 2.2, and [11] for full details and equation). Moreover, we vary the size of the neighborhoods using a range of: (1) nearest neighbors ($k = 10$-100); and (2) Euclidean distances (100 (10) 400 m), to study how the impact from neighbors changes when increasing the bandwidths. As a supplementary sensitivity analysis, we also create surrounding neighborhoods, which are defined using the k-nearest neighbors approach at $k = 50$-100 where $k < 50$ are excluded (Supplementary Information, section 2.5).

We use a continuous variable to analyze children's neighborhood SES: the average GW share, throughout the observation period, of neighbors being either from high or low white-collar families (white-collar share). For example, a white-collar share of 30% at $k = 25$ represents the average GW percentage of white-collar neighbors, of the 25 nearest same-aged children, that an individual had throughout childhood. Hence, this variable captures the exposure to high-class children in the childhood neighborhood. Moreover, to visualize the effect more clearly, the white-collar share variable ranges from 0 to 10, meaning that one unit increase represents a 10% increase of the GW white-collar share in the neighborhood.

Other individual and neighborhood variables
We adjust the statistical models for several individual and environmental variables (Supplementary Information, section 2.1). Childhood variables are birth year, presence of parents, place of birth, household size, elementary school districts, population density, proximity to major road, and building type. These childhood variables are based on survival-time averages or highest values during the ages 1-17. The variable proximity to major road accounts for changes in the road network 1939-1967 to measure possible exposure to environmental pollution more accurately. Other physical neighborhood variables used in the sensitivity tests are described in Supplementary Information, section 2.9. Lastly, we adjust for marital status in adulthood.

Statistical models
We estimate four main models for all-cause adult mortality, using Cox proportional hazards models. Separate models are run by sex and sizes of neighborhoods (10-100 nearest neighbors, and neighbors within 100 (10) 400 meters from each individual). We also estimate separate models for mortality due to preventable and non-preventable diseases. The basic model adjusts only for the white-collar share and birth year (model 1). We extend this model by adding class origin (model 2), childhood physical environmental and other individual variables (model 3), and adult class and marital status (model 4a). In the cause-specific analysis, we employ a competing risk model (model 4b) [31] adjusting for the same variables as in model 4a and using the k-nearest neighbor approach with $k = 30$ (Supplementary Information, section 2.3).

We do the following sensitivity analyses. We estimate models without a distance decay weight, and models including the white-collar share of only surrounding neighborhoods ($k = 100$, $k < 50$ excluded) (Supplementary Information, section 2.4, 2.5). We also estimate models using the white-collar share of adult neighbors without children under 18 in the household (Supplementary Information, section 2.6). Because of the higher population density of such adults compared to same-aged children, these models use a larger range of k ($k = 25$ (25) 500) (Supplementary Information, Fig. S4, S12). To include more controls for the built environment, we extend models 4a with the variables building density and distance to city center (Supplementary Information, section 2.9). Moreover, as the effects from childhood neighbors may differ across sex and social class, we include an interaction between white-collar share and class origin/sex (Supplementary Information, section 2.7). Lastly, as there are much fever deaths among the women (deaths = 741; N = 8 492) compared to men (deaths = 1 142; N = 8 888), differences in neighborhood effects on mortality for the sexes could be related to the share of deaths. Therefore, we estimate models for men in which we randomly reduce the number of deaths to 800, while keeping all survivors (Supplementary Information, section 2.8). The overall conclusions are not changed in these sensitivity checks.

Data sharing

The individual-level data from the SEDD and the Statistics Sweden are protected by Swedish personal integrity laws, and other regulations. The analyses are performed on Statistics Sweden's restricted platform Microdata Online Access, and it is not allowed to openly share these data. See https://www.ed.lu.se/databases/sedd and https://www.scb.se/en/services/guidance-for-researchers-and-universities for more information on how to access these data. The code and scripts used in the analyses will be available at a dataverse.

Results

Descriptive results

Supplementary Information, section 3.1, displays descriptive statistics of the main variables. Most children grew up in blue-collar dominated neighborhoods, and the average white-collar share was approximately 33% regardless of the neighborhood size. The share of blue-collar neighbors and neighbors with missing occupation information was about 65% and 2%, respectively (Supplementary Information, Fig. S2, S3). For the four class-origin groups, the average white-collar share was: white-collar high 38.5%; white-collar low 30.8%; blue-collar high 28.0%; and blue-collar low 26.6%, measured at k = 30 (Supplementary Information, Tables S4-S6). See also Supplementary Information, Fig. S6, for further details regarding the distribution of the white-collar shares among the class-origin groups (which follows a slightly right-skewed normal distribution). Moreover, about 55% of the children came from a blue-collar origin, and approximately 33% belonged to the blue-collar working class as adults. Note that the class origin represented the highest social class measured between the ages 1 to 17, whereas the class of the neighbors was measured at every age, 1-17, and year. With regards to the two neighborhood approaches, the average Euclidean distance increases approximately from 100 m at k = 15, to 250 m at k = 50, and to 350 m at k = 100 (Supplementary Information, Fig. S4).

Fig. 1 shows an example of two individual neighborhoods using the k-nearest neighbor approach, at two specific points in time (the k-25 nearest same-age neighbors are marked). Fig. 1a and b show how the k-25 neighborhood of a child aged eight changed over time. In 1950, there was a high share of blue-collar, and especially low blue-collar, neighbors; in 1960, there was a high share of white-collar and high blue-collar neighbors. Meanwhile, Fig. 1d and e show how a relatively densely populated area in 1950 of mainly blue-collar children (aged 7-9) decreased in density to 1960. As a result, the geometric size of the k-25 neighborhood increased. This change resulted mainly from an aging of the population in the area.

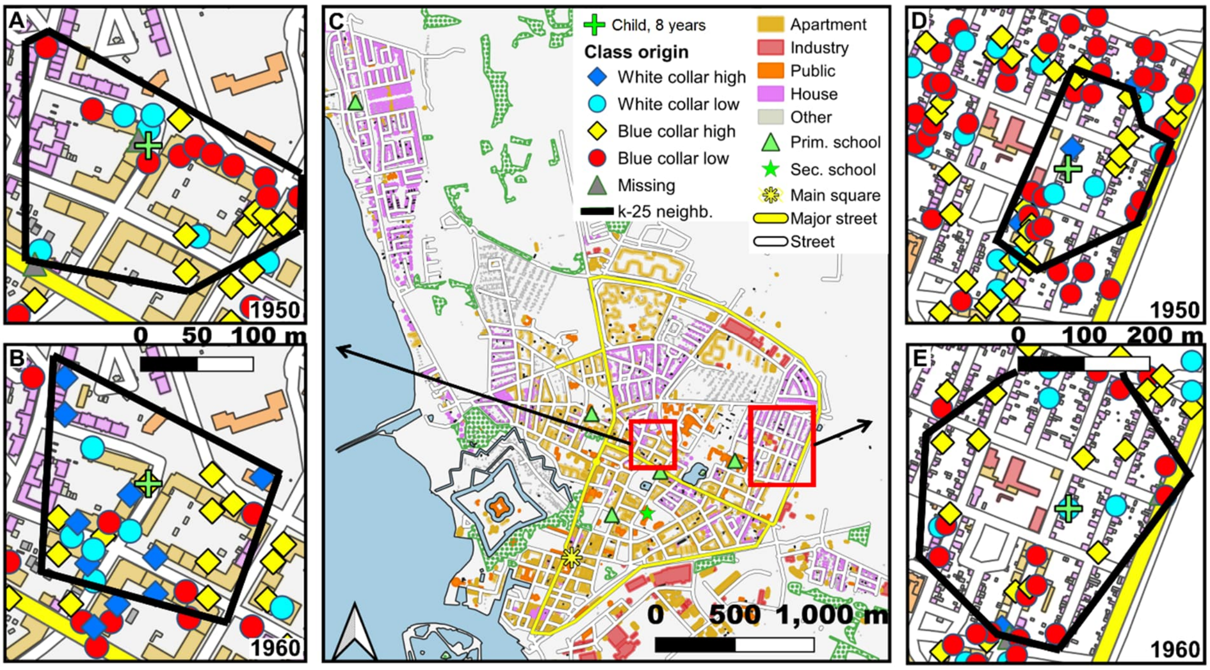

Fig. 1 Example of individual neighborhoods for four children, all aged eight, containing the 25 nearest neighbors of ages seven to nine, in Landskrona. The green cross represents the address point of a child, whereas the black line represents the k-25 neighborhood. (A) address point of a child in the inner city in 1950-05-15; (B) same address point as in A but for a child in 1960-05-15; (C) overview map of Landskrona in 1960; (D) address point for a child in a residential area in 1950-05-15; (E) same address point as in D but for a child in 1960-05-15. The background map shows buildings, streets (white and yellow lines), schools, and class origin of the children aged seven to nine in the area.

Fig. 2 shows the development of the child population and their white-collar share for three periods in Landskrona. Both continuity and changing patterns can be observed. There are indications that many of the middle and higher classes are gradually moving out to the periphery of the city as new areas are being built (Fig. 2b and c, areas 1-2). This can also be seen in the area around Landskrona's secondary school and cultural center, in which the white-collar share reduces whereas the population remain constant (Fig. 2a-c, area 4). Some blue-collar areas, on the other hand, such as in Fig. 2a-c, area 3, remain static throughout the period according to both population and class. In summary, the maps in Fig. 1 and 2, as well as the white-collar share distribution in Fig S6 (Supplementary Information), illustrate a pronounced spatial and temporal variation of the exposure to neighbors also in a relatively homogeneous city like Landskrona.

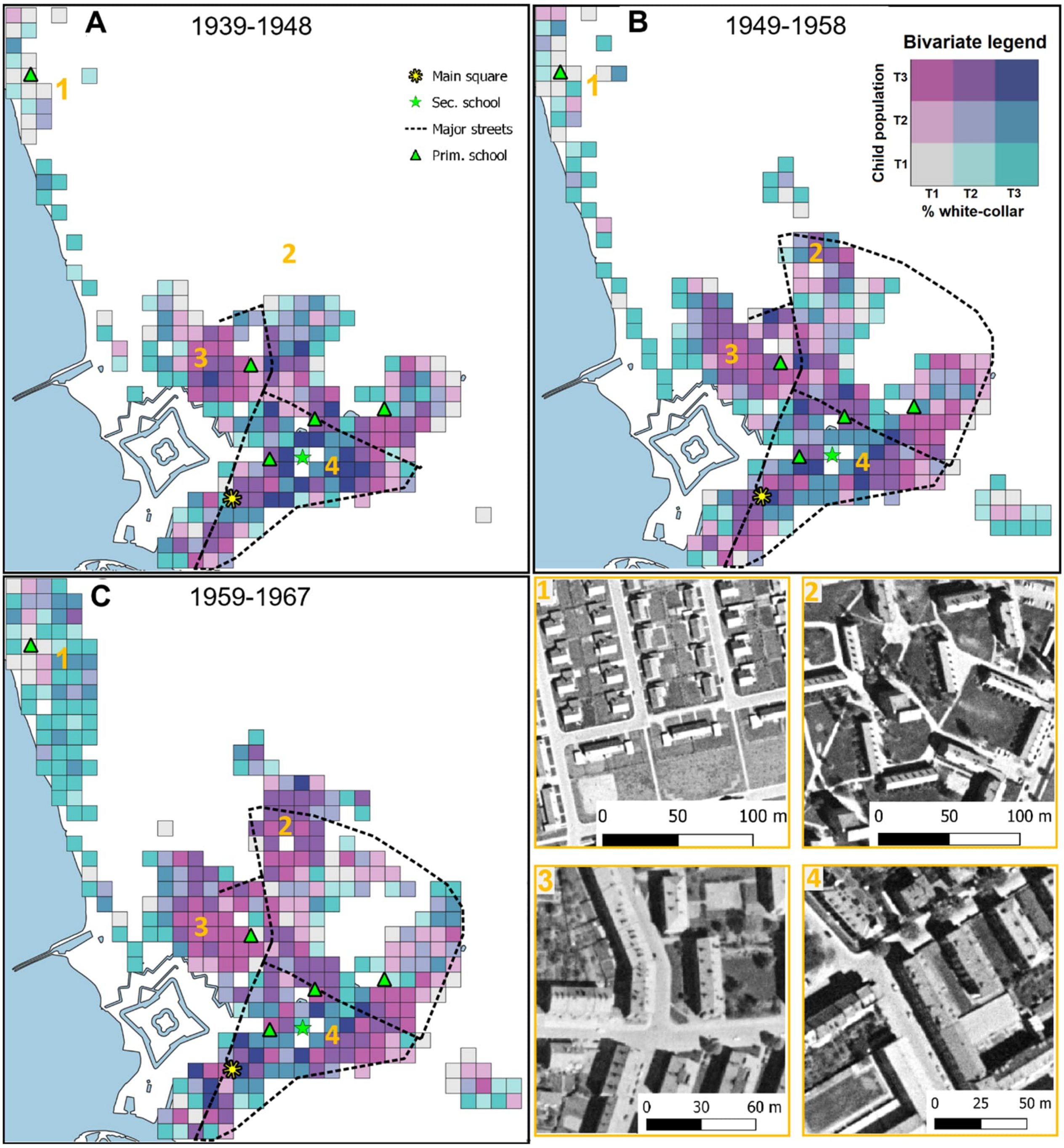

Fig. 2 Bivariate maps showing tertiles of child population and percentage of children from white-collar background (all geocoded children ever resided in Landskrona, aged 0-18) by $100m^2$ grids. (A) 1939-1948; (B) 1949-1958; (C) 1959-1967. For every period, each child is assigned to the address point they spent most of their time within and counted once. The address points, including information on child population and percentage of white-collars, are in turn spatially joined to the grid they intersect with in order to increase the readability of the map. The percentage of white-collars is based on the highest social class attained by the family head in childhood. The numbers (1-4) show aerial photographs in 1966 of four distinct areas in the town: 1) villa area in Borstahus emerging in the early 1960s; 2) apartment blocks in Sandvången emerging in the early 1950s; 3) blue-collar apartments blocks in the periphery of the inner-city; and 4) inner-city housing near the cultural center of Landskrona.

Fig. 3 shows the cumulative hazards of all-cause and cause-specific mortality by quartiles of the white-collar share, for men and women separately. Large neighborhood differences are observed for all-cause and preventable mortality for men, with a mortality gradient for the white-collar share quartiles (Fig. 3a and c). For women, the mortality gradient is less clear, although consistent differences in mortality levels are observed between the lowest and highest quartiles of white-collar share (Fig. 3b and d). Lastly, for non-preventable mortality, small or no mortality differences are observed, with no mortality gradient (Fig. 3e and f).

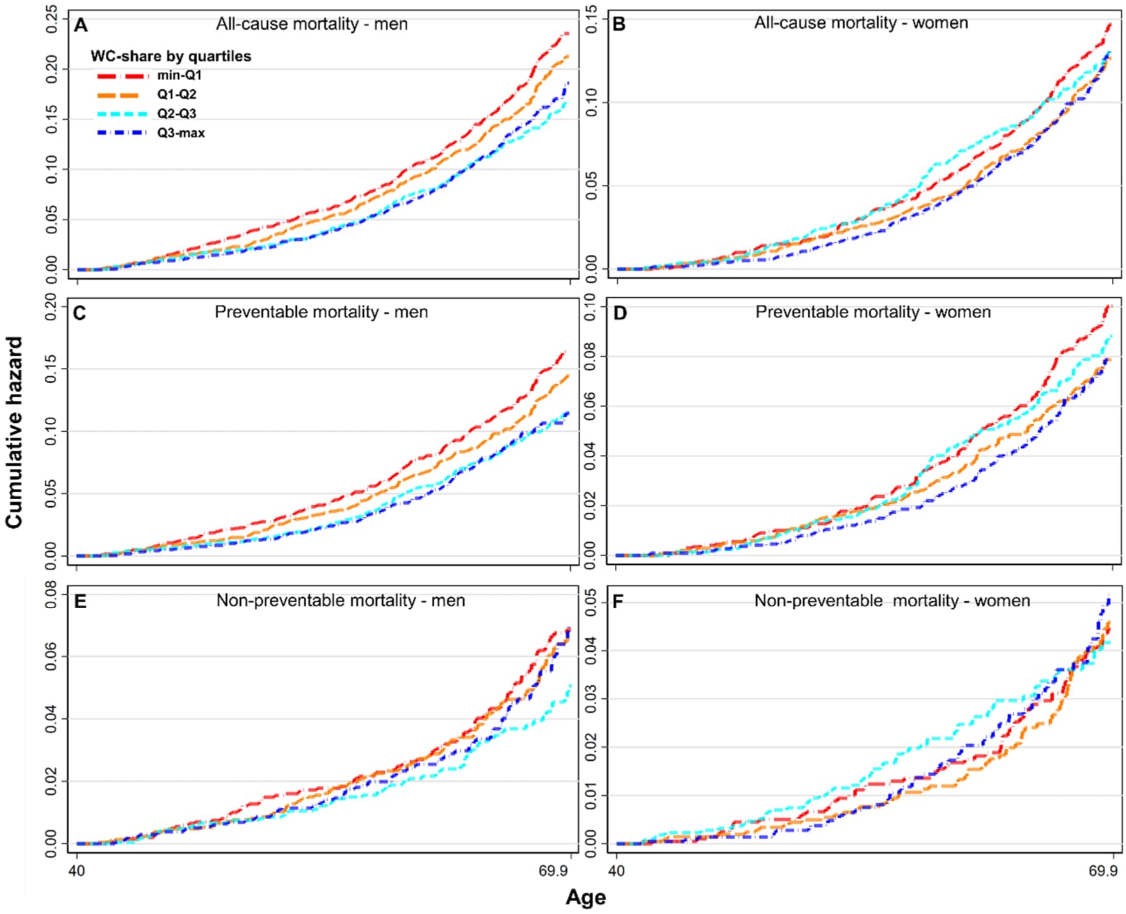

Fig. 3 Nelson–Aalen cumulative hazards by quartiles of white-collar share in childhood neighborhoods. Ages 40-69, 1939 to 2015. (A) all-cause mortality, men; (B) all-cause mortality, women; (C) preventable mortality, men; (D) preventable mortality, women; (E) non-preventable mortality, men; (F) non-preventable mortality, women.

Empirical results

Fig. 4 shows the results for all-cause mortality, for men and women separately, for model 1 and 4a, and for the two neighborhood approaches: ranging from 10 to 100 using the k-nearest neighbors; and from 100 to 400 m using the Euclidean distance (one model at every 10 meters). The figure shows only the variable white-collar share (Supplementary Information, Table S7 shows the full regression outputs at k = 30). Men who grew up with a relatively high share of white-collar neighbors had a consistently lower mortality in adulthood than men growing up with lower shares of white-collar neighbors (Fig. 4 a and b). This effect of white-collar share is robust across the models (model 1 – model 4a), but the effects attenuate with the inclusion of the adult class variable (model 4a) (Supplementary Information, Fig. S7 includes results from models 2 and 3). The effects change also with the neighborhood size: the strongest effects for men are found between 25 and 35 k (Fig. 4a) and around 150 m (Fig. 4b). For example, at k = 30, growing up with a 10% higher share of white-collar neighbors decreases the mortality risk by 6% (HR 0.94, 95% CI 0.88-1.00). For women, in contrast, we find no evidence for an effect of white-collar share on all-cause mortality.

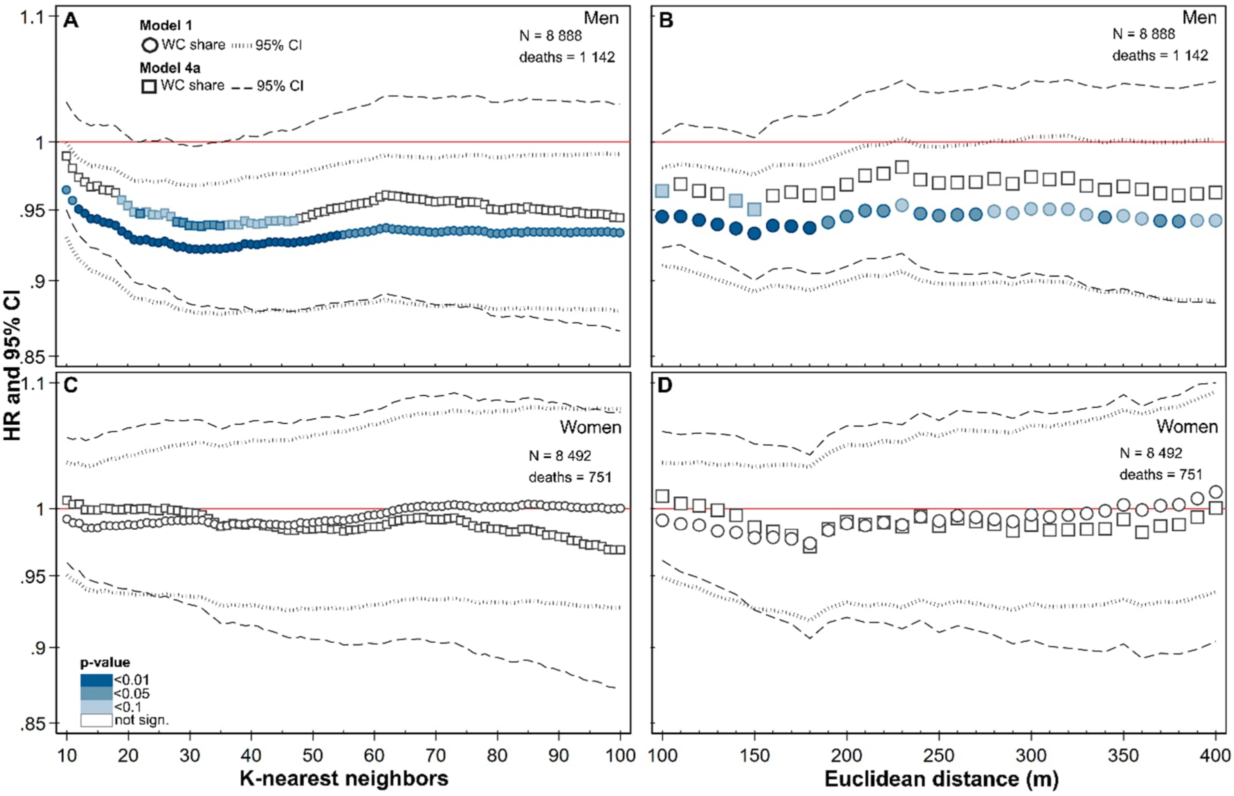

Fig. 4 Impact of childhood neighborhoods and control variables on all-cause mortality, ages 40-69, 1939 to 2015. Only the variable white-collar share and the results of models 1 and 4a are shown here. (A) k-nearest neighbors approach, men; (B) Euclidean distance approach, men; (C) k-nearest neighbors approach, women; (D) Euclidean distance approach, women.

Fig. 5 and 6 show the effect of white-collar share (k = 30), class origin, and adult class, on all-cause (Fig. 5a and 6a), preventable (Fig. 5a and 6b), and non-preventable (Fig. 5c and 6c) mortality (model 4a and b; Supplementary Information, Table S7 includes the full set of estimates). The figures reveal that the white-collar share in childhood neighborhoods was important for men's mortality in preventable causes but not for mortality attributed to non-preventable causes. Men who grew up with having an additional 10% more children from white-collar families as neighbors experienced an 8% lower preventable mortality in adulthood (HR 0.92, 95% CI 0.86-0.99). For women, no effects are observed from the white-collar share on mortality in preventable or non-preventable causes.

Adult class was important for both sexes, as blue-collar workers had higher mortality than white-collar workers. In addition, adults with missing occupations had much higher mortality than all other classes, for both men and women. For men, there was also a mortality gradient for adult class, at least when judging from the point estimates (Fig. 5a). Here, the class gradient was clearer for preventable causes than for non-preventable causes (Fig. 5b and c). The impact of class origin on preventable causes was somewhat stronger for women than for men (Fig. 5b and 6b).

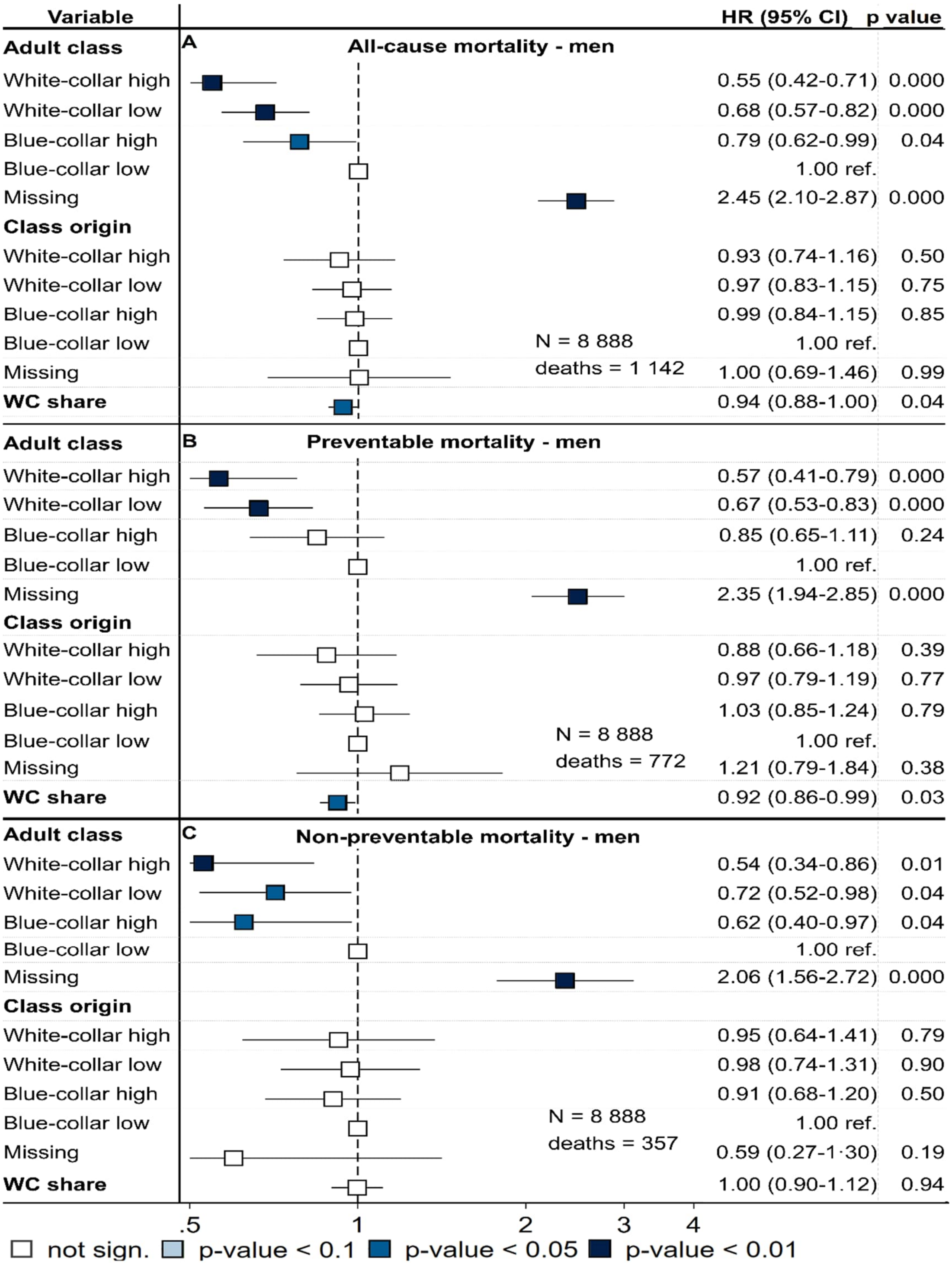

Fig. 5 Impact of childhood neighborhoods and control variables on all-cause and cause-specific mortality, ages 40-69, 1939 to 2015, men (models 4a and 4b), at k = 30. Only the variable groups adult class and class origin, and white-collar share, are shown. (A) all-cause mortality; (B) preventable mortality; (C) non-preventable mortality.

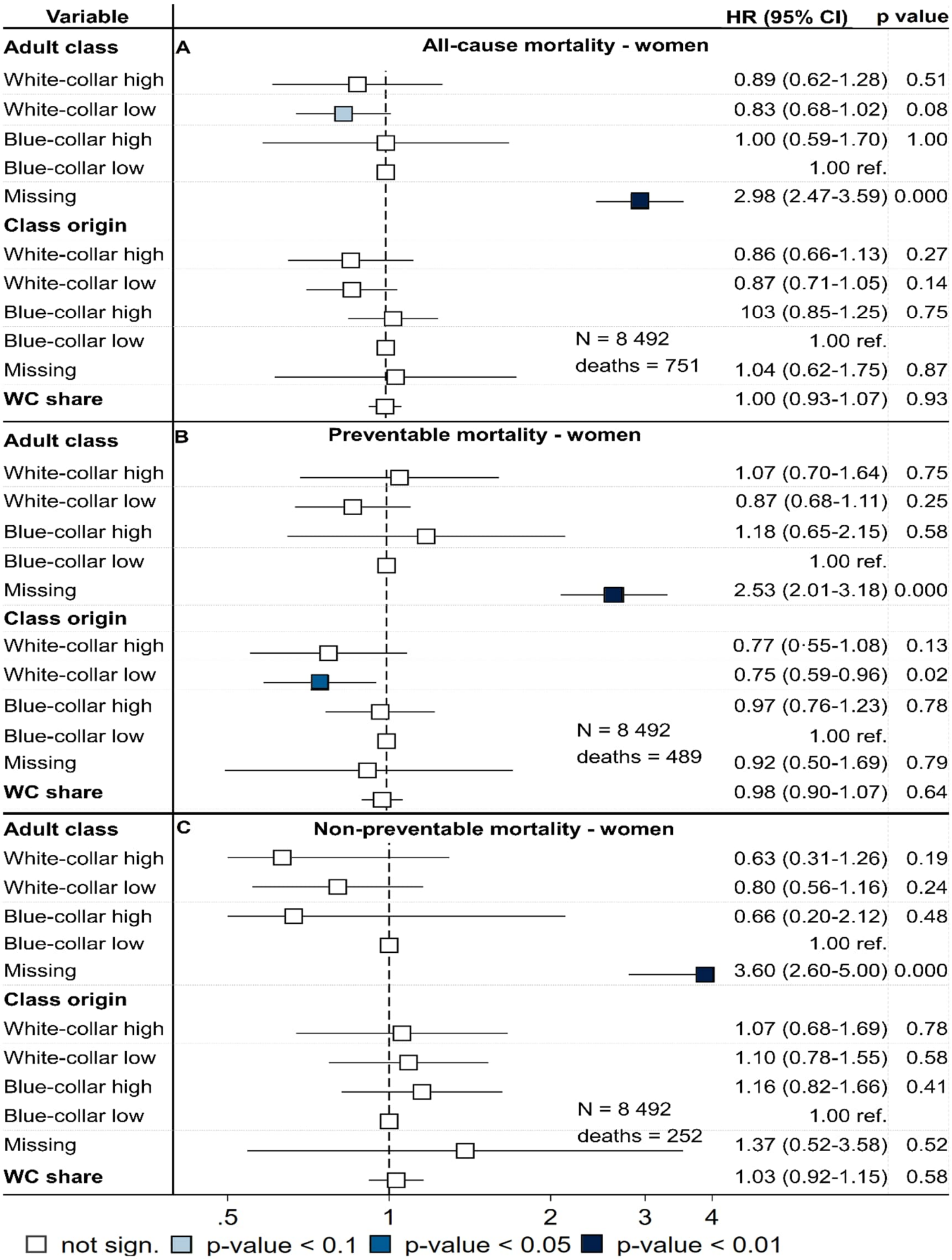

Fig. 6 Impact of childhood neighborhoods and control variables on all-cause and cause-specific mortality, ages 40-69, 1939 to 2015, women (models 4a and 4b), at k = 30. Only the variable groups adult class and class origin, and white-collar share, are shown. (A) all-cause mortality; (B) preventable mortality; (C) non-preventable mortality

Results from the sensitivity analyses are presented in Supplementary Information, section 4. The models using no distance decay show similar effects as the models with Gaussian distance decay (Supplementary Information, section 4.1). The results from the interaction models show that the effect of white-collar share differs significantly between men and women. We do not find evidence, however, that the effect of white-collar share in childhood differs by class origin (Supplementary Information, section 4.4). Moreover, neither men's nor women's mortality was affected by the social class of their adult neighbors without children in the household (Supplementary Information, section 4.3). In addition, the models including the white-collar share in only the surrounding neighborhoods (k = 100, k < 50 excluded) show no significant effects on mortality (Supplementary

Information, section 4.2). Hence, the effects of the white-collar share on men's mortality likely operated in smaller neighborhoods of same-aged children (i.e., more nearby resident children). When including more controls for the built environment, the effects of the white-collar share and the statistical significance slightly increase for men (Supplementary Information, section 4.6). Lastly, the results from the models with reduced number of deaths for men does not indicate that the differences in neighborhood effects between men and women are related to the number or share of deaths (Supplementary Information, section 4.5).

Discussion

Socioeconomic conditions in childhood neighborhoods had lasting effects on male but not female all-cause and preventable mortality in adulthood. Adult mortality due to preventable causes was lower for men who grew up with a relatively high share of children from white-collar families as close-proximity neighbors, even when adjusting for class origin, own class position in adulthood, and physical neighborhood properties. We found no effects from childhood neighbors on mortality due to non-preventable causes. Overall, these findings are line with a previous study of Finland, using areal neighborhoods (250m^2 grids), which shows that children who grew up in socially disadvantaged neighborhoods had higher risk of a range of diseases later in life [6]. However, we show that women were not affected by their childhood neighbors, although both a lower adult class and class origin increased their mortality. Taken together, our results suggest that the class position of the nearby, same-age, neighbors in childhood have long-term consequences for men's risk of premature death, regardless of their own social class.

Both social and physical properties of childhood neighborhoods may have long-term effects on health and longevity. Neighborhood peers may directly influence attitudes, norms, and behavior, resulting in differences in lifestyle in adolescence and adulthood [10]. Poor physical properties, such as areas with high environmental pollution, are usually concentrated in poor neighborhoods [32, 33]. High-class neighborhoods, on the other hand, may be healthier places to grow up in, providing children with better access to green spaces, less traffic and fewer roads, and better-quality housing. In addition, such areas often provide lower degrees of stress factors (e.g., related to safety and violence). Although, we controlled for several of the physical neighborhood properties, the focus of this paper is on the social aspects of the neighborhoods. Our study indicates that the childhood neighbor's class has a significant effect on mortality in adulthood among men, primarily due to preventable causes of death. As our findings also suggest that the impact of nearby children of the same age, rather than adult neighbors, were important for men's mortality, they highlight the potential influence of peer-effects and lifestyle factors on health outcomes.

Our results suggest large sex rather than class differences in the neighborhood effects. Peer influences, as well as the function and sizes of social networks, differ by sex in some contexts [34-37]. In addition, boys and girls have different patterns of health behaviors [22]. Nevertheless, network ties are usually stronger also within the same SES groups [38], and as Chetty at al. [39] show, children are less likely to connect with each other across SES groups even when they live in the same neighborhoods. Therefore, especially clusters of high-class children may have been able to influence each other's lifestyles, resulting in improved health behavior in adolescence and adulthood.

It may appear contradictory that men's mortality was significantly influenced by their childhood neighbor's class but not by their class origin. However, as particularly negative behavior is expected to be contagious in neighborhoods [10], men growing up in more deprived neighborhoods may have, regardless of their own class, been more likely to adopt negative health behavior, such as smoking, excessive alcohol consumption, low level of physical activity, and bad diet. Future studies are nevertheless needed to better understand these underlying mechanisms between class origin, sex, and SES of peers in childhood.
The socioeconomic mortality gradient emerged in Sweden during the 1960s, and has since then widened [1, 27]. The health gradient is determined by a complex interaction between several factors related to lifestyle, working life, environment, health care, and conditions and events across in the life course (see [1, 27]). We found strong and lasting effects of childhood neighbors for men growing up before the health gradient was fully established. This points to the crucial importance of a life-course perspective to fully understand the mortality differentials by SES and the rise of the social gradient in health. Only few studies have applied a life-course perspective to the health gradient and included social class origin when studying the relationship between SES and health (e.g., [26]). Besides, as we use geocoded longitudinal microdata at the address-level, as well as repeated measures of neighborhoods throughout childhood, we can better capture the effects of sustained neighborhood exposure [40].

This study has some limitations. We studied mortality at ages 40-69, which is a relatively young age, and therefore likely to have been related to differences in lifestyle, risk-taking behavior, and chronic or genetic diseases. Moreover, we were unable to model changes in neighborhood conditions (see e.g. Kivimäki et al. [41])

because of our relatively small sample size. On the other hand, we analyzed neighborhood effects for the entire town of Landskrona. We thus avoided bias caused by individuals' health-related self-selection into certain neighborhoods. The low proportion of immigrants in our population, however, precluded separate analyses of the foreign-born. Therefore, the generalizability of our findings to other and more ethnically diverse urban settings remains unknown. In addition, as the segregation has increased in cities world-wide, the real impact of childhood neighborhoods on mortality may be stronger in such urban areas in Sweden and abroad.

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Statements and Declarations

Competing Interest
The authors have no relevant financial or non-financial interests to disclose.

Ethics approval
The data come from the Scanian Economic-Demographic Database (1939-1967), which includes personal data as well as sensitive personal data (related to country of birth and health). The historical data have been linked to contemporary registers (1968-2015) from Statistics Sweden (SCB) and the National Board of Health and Welfare. These registers also contain personal data as well as sensitive personal data as defined in General Data Protection Regulation (GDPR).

This study is within the framework of the larger research project “Economic Demography from a Micro-level Perspective” which has been approved for research by the Swedish Ethical Review Authority, Lund, (dnr 161/2006, dnr 627/2010), and with instructions from the Swedish Authority for Privacy Protection, Stockholm (dnr 1999-2005). The analyses of the neighborhood conditions and their effects on the Landskrona population fall within the granted approval. All data used are in a pseudonymized form, and the identifying keys are kept secure by SCB. Moreover, all data used for analysis are stored at SCB’s restricted platform MONA (Microdata Online Access).

Supplementary Information for: Childhood neighborhoods and cause-specific adult mortality in Sweden 1939-2015

This SI document includes:

Supporting text
Figures S1 to S14
Tables S1 to S9
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1. Data and sample

1.1 Description of study population and area

We study individuals growing up in the city of Landskrona 1939-1967, and follow them to adulthood for the period 1968-2015, regardless of where in Sweden they live.

Landskrona is not representative of Sweden in a statistical sense, but its social and economic developments in this period were similar to other cities in Sweden [1]. The city experienced rapid industrialization in the first half of the 20th century, connected to shipbuilding, industries related to sugar and textile. The population grew from 13,000 in 1900 to 30,000 in 1970. From the 1960s, and especially from the mid-1970s, the industrial crisis hit Landskrona hard with population decline and a contracting labor market. Hence, the period for which we measure neighborhood conditions (1939-1967) encapsulates housing shortages, a vast urban development, and the beginning of an industrial decline.

The historical data (1939-1967) come from the Scanian Economic-Demographic Database (SEDD) [2]. See also [3] for a detailed description of the SEDD. The sources are continuous population registers linked to income and taxation registers. The SEDD contains information on birth, marriages, deaths, occupation and income, and in- and out-migration. For the period 1968-2015, those individuals in SEDD surviving to at least 1947 (when unique personal numbers were introduced in Sweden) and their descendants have been linked to national registers from Statistics Sweden (SCB), the National Board of Health and Welfare (Socialstyrelsen) and the Military Archives (Krigsarkivet, Pliktverket). This work was carried out within a research program at the Centre for Economic Demography at Lund University. The national registers contain information on health outcomes (cause-specific mortality, cognitive and physical status at military conscription, early retirement and sickness benefits, women's health status at childbirth, and patient data), income, occupation and education. Hence, we can conduct a nation-wide and long-term follow-up from 1968 to 2015, analyzing causes of death from 1968. As we can make a follow-up in the entire country for the whole period, we avoid potential bias due to selective out-migration from Landskrona.

1.2 Geocoding process

The process of geocoding the population of Landskrona, as well as the recreation of the historical geography, for the period 1939-1967, is described in the SI Appendix of [4]. As seen in Fig. S1, 97.3% of the individual's survival time (ST) in our sample was geocoded.

1.3 Sample selection

The selection criteria of the individuals was as follows (Fig. S1). Individuals that were of age 1-17 in Landskrona between 1939 and 1967, and born between 1928-1966 (n = 21 352), had to have an address that could be geocoded (20 995). In addition, these individuals had to be observed on the dates May 31 or November 30, or both, between 1939 and 1967. This was required in order to create bi-annual matrices with Euclidean distances between every individual at these dates. Of these children (n = 20 527), 17 380 ([48.9%] women) could be followed-up on at least one occasion from age 40 (totaling 384 371.2 person-years overall, 1968-2015) in the national register data for the period 1968-2015.

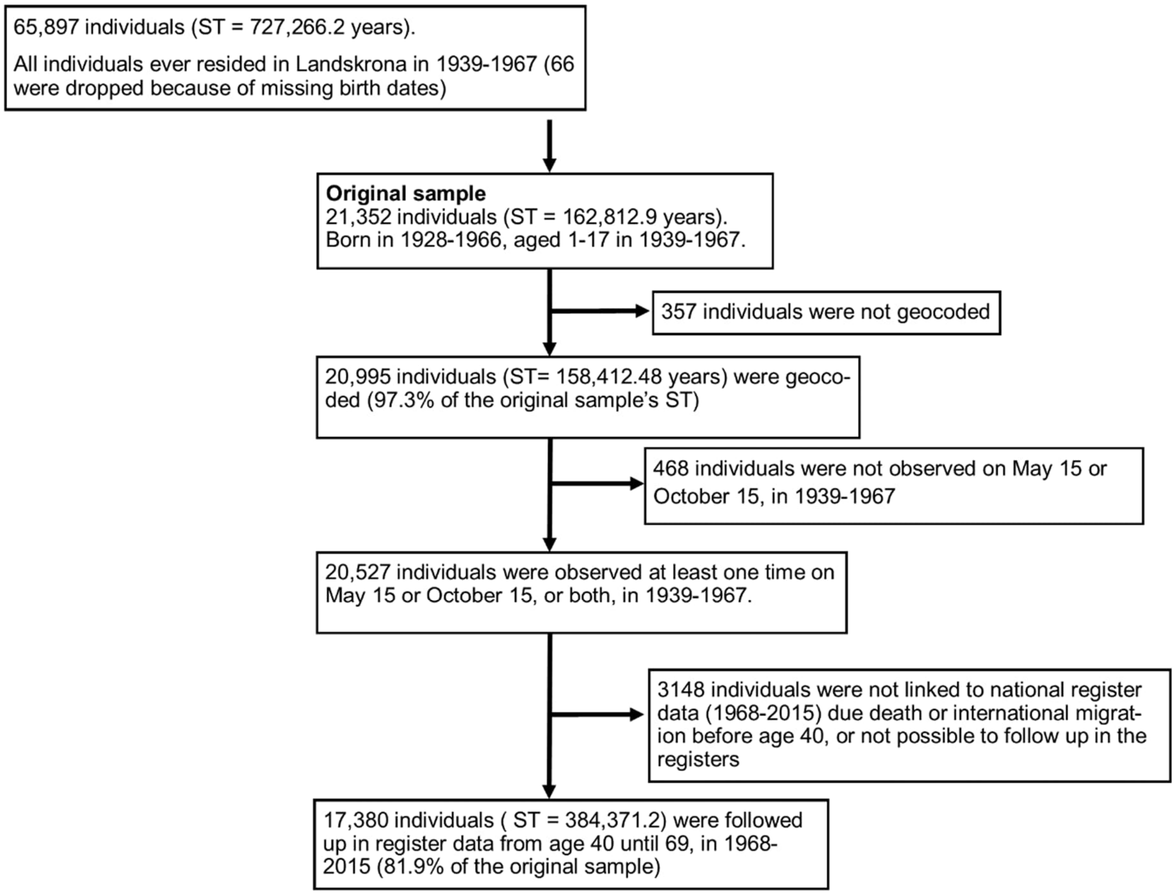

Fig. S1 Flow chart of sample selection.

1.4 HISCLASS

Class origin and adult class are based on the HISCLASS, a 12-category class scheme based on skill level, sector and degree of supervision [5]: 1) higher managers; 2) higher professionals; 3) lower managers; 4) lower professionals; clerical and sales personnel; 5) lower clerical and sales personnel; 6) foremen; 7) medium-skilled workers; 8) farmers and fishermen; 9) lower-skilled workers; 10) lower-skilled farm workers; 11) unskilled workers; and 12) unskilled farm workers (1). We aggregated these classes into four groups: white-collar high (HISCLASS 1-2; white-collar low (HISCLASS 3-5); Blue-collar high (HISCLASS 6-8); Blue-collar low (HISCLASS 9-12).

1.5 Mortality data

From the Swedish National Board of Health and Welfare, we obtain the Cause of Death register for the period 1968-2015. The causes of deaths are coded by the International Classification of Diseases (ICD) and provided at the three-character category level. Throughout the follow-up period, three versions of ICD are used in the registers: ICD-8 for the period 1969-1986; ICD-9 for the period 1987-1996; and ICD-10 for the period 1997-2015.

We follow the categorization of Ericsson et al. [6] when grouping the ICD codes according to the preventable and non-preventable causes of deaths. This grouping is based on the Avoidable Mortality in the European Union (AMIEHS) classification [7]. However, in addition to the AMIEHS' 45 indicators of possibly preventable deaths, Ericsson et al. [6] classify injuries as preventable deaths as well. Except for the missing causes of deaths, all other deaths not classified as preventable are classified as non-preventable.

The classification by preventability is available in the supplementary material by [6] at: https://academic.oup.com/ije/article/48/5/1701/5423850?login=true#supplementary-data.

Moreover, to provide more details on the common causes of deaths in the study population, we follow Debiasi and Dribe [8] to group the diseases according to the specific population and sample size (Tables S1, S2). Based on the ICD-chapters, these are: (1) infectious and parasitic diseases (including pneumonia and influenzas); (2) circulatory diseases; (3) respiratory diseases (including lung, larynx, trachea, bronchus, lip, oral cavity, and pharynx cancers); (4) other cancers; (5) external causes; (6) other and ill-defined causes of death (other/unknown/undefined); and (7) missing causes of death. For group one, Debiasi and Dribe [8] included influenza and pneumonia (respiratory diseases according to ICD) as these are mostly communicable diseases associated with issues such as housing conditions and crowding. Moreover, to better capture diseases related to smoking, respiratory diseases and smoking-related cancers are grouped together (group 3). Group 6 (Other/unknown/undefined) mostly consists of causes of deaths that do not belong to any chapters related to groups 1-5. Lastly, we add information on number of alcohol-related causes for each disease group.

Table S1. Disease groups, men, 1968-2015.

	Preventable deaths		**Non-preventable deaths (N)**
Disease groups	**N**	**Alcohol-related (n = 147)**	
Infectious and parasitic diseases	23	5 (21.7%)	5
Circulatory system diseases	321	40 (12.5%)	34
Respiratory & lung cancers	96	2 (2.1%)	23
Other cancers	128	2 (1.6%)	167
External causes (including injuries, accidents)	107	41 (38.3%)	48
Other/unknown/undefined	97	57 (58.8%)	80
Missing cause of death		13	
Total	772		357

Table S2. Disease groups, women, 1968-2015.

	Preventable deaths		**Non-preventable deaths (N)**
Disease groups	**N**	**Alcohol-related (n=40)**	
Infectious and parasitic diseases	7	1 (14.3%)	6
Circulatory system diseases	98	1 (1.0%)	15
Respiratory & lung cancers	138	2 (1.4%)	13
Other cancers	160	0 (0.0%)	138
External causes (including injuries, accidents)	41	15 (36.6%)	12
Other/unknown/undefined	45	21 (46.7%)	68
Missing cause of death		10	
Total	489		252

2. Methods and analyses

2.1 Main analyses: Explanation of individual and neighborhood control variables
This section explains the individual and neighborhood control variables not described in detail in the Main Manuscript.

Childhood variables

Household size: A categorical variable of the number of members in the household in childhood: up to 4 members, 5 or more members, or missing information. Family and household size affected the health of children during the early 1900s in Sweden [9] and may also be used as a proxy for crowding. This variable is based on the survival-time average household size throughout childhood.

Parent ever missing: A categorical variable indicating whether a parent has ever been missing in the household throughout the childhood.

- Both parents always present
- Mother missing: The mother has been missing at least one time during the childhood.
- Father missing: The father has been missing at least one time during the childhood.
- Both missing: Both parents has been missing at least one time during the childhood.
- NA: Missing information about parent presents in the household.

Research has shown that especially mothers have an influence on their children's health, and death of a parent may have long-term effects [10]. Therefore, indications of having lost a parent may negatively affect the morality in later life.

Birth year: Year of birth of the individual.

Elementary school district: Five schools provided elementary education in the city during the period 1939-1967: *Borstahusskolan* (north periphery), *Värnaskolan* (center), *Albanoskolan* (north west), *Gustav Adolf-skolan* (east) and *Tuppaskolan* (south) (Landskrona city archives, see Hedefalk and Dribe [4] for more information). Although we do not know the exact school that each child attended, children were usually assigned to the nearest school. Hence, we estimated school districts by assigning each child to the school nearest to their home (an exception of this rule was made when we assumed that some children were assigned *Värnaskolan* instead of the closer *Albanoskolan* because a major road naturally separated them from the latter school). Moreover, each child is assigned the school that he/she spent the most survival time in. Using this categorical variable, we can control for some peer effects in school and thereby avoid conflating neighborhood and school effects.

Birthplace: A binary variable indicating whether the child was born in Landskrona municipality.

We control for the physical environment within the neighborhood, which affects both physical and mental health [11-17] (see also references in Main Manuscript). One factor we try to account for in the models is air pollution, specifically lead exposure (lead in petrol was forbidden in 1985) from traffic, which affects health of children [11-15]. Another factor is the overall built environment, which affect the wellbeing of individuals [16, 17]. The variables that use information from roads and buildings are time-dependent because they account for the construction of new roads and buildings throughout the study period. The physical environmental variables are as follows:

Proximity to major road: Whether the child spent most of his/her survival time within 100 m of the nearest major road segment. The rationale of the 100 m threshold is based on previous research [13].

Building type: The type of building that the child spent the majority of his/her survival time in. This builds on information on the type of building in which the address point is located. Apartment block or single house/town house.

(Log) Population density: Total population within a 100-meter buffer from the address point. This variable is computed from the bi-annual neighborhood matrices and the population density is the average value of all measures for each child. The nearby population density is correlated with lower well-being and higher air pollution [15, 17] and is also used as a proxy for more concentrated built environments.

Adulthood variables

Marital status: A time-varying categorical variable indicating whether the individual is married/in a partnership or not.

2.2 Main analyses: White-collar share

As described in the Main Manuscript, the geographically weighted (GW) white-collar share variable is based on the class-origin share of the childhood neighbors at two points in time for each specific year. We use two approaches to measure and define individual neighborhoods in childhood:

1. k-nearest neighbors: the k-nearest individuals are defined as neighbors, using k = 10-100.
2. Euclidean distances: all individuals within a given radius from an individual are defined as neighbors, using m = 100-400 (one measure at every 10 m).

For both approaches, each individual is the center of their own neighborhood and same-age children outside the household are defined as neighbors. We assume that nearby neighbors had a greater influence than neighbors residing farther away and use a Gaussian distance-decay function to model the decline and thus measure the GW share of the neighbors class-origin.

For the specified neighbors of individual *i*, we define the geographically weighted share of each class origin *c* as follows (source: [4])

$$GW\ neighborhood\ class_c = \sum_{j=1}^{j=n}\left(\frac{W_{ij_c}}{\sum_{j=1}^{j=n} W_{ij}}\right) \qquad (1)$$

$$W_{ij} = e^{-0.5\cdot\left(\frac{d_{ij}}{b}\right)^2}$$

where W_{ij} is the spatial weight implemented as a Gaussian distance function between individual *i* and any neighbor *j* and j_c is the neighbor of the specific class *c*. In the Gaussian distance function, the bandwidth *b* limits the search of the neighbors, and d_{ij} is the Euclidean distance between the address points of individual *i* and neighbor *j*. When using the k-nearest neighbors approach, *b* becomes adaptive and dependent on the k; hence, it represents the maximum distance between individual *i* and its k-nearest neighbors. When using the Euclidean distance approach, *b* represents a specified Euclidean distance in meters. Moreover, to account for the variation in population density and uneven distribution of address points in the data, we use the relative spatial weight between individual *i* and neighbor *j* (relative to the spatial weights of all other neighbors). The Gaussian distance function is chosen as it is commonly used when modelling spatial relationships [18, 19].

2.3 Main analyses: Cox and competing risks regressions

The Cox proportional hazards model used to analyze the impact on mortality from childhood neighborhoods (models 1 – 4a) is defined as:

$$h_i(t) = h_0(t)e^{\beta_1 x_{i1}+\cdots+\beta_k x_{ik}} \qquad (2)$$

where the hazard rate (h_i (t)) is the conditional probability that death occurs at the time (t), h_0 (t) is the baseline hazard function, x_i represents the independent variables that affect the hazard, and β represents the parameters that describe the influences of the variables [20].

The independent variables in the vector x_i are included in the four Cox regression models (model 1 - model 4a) in the following order:

$$x_{M1} = \beta 1 birthyear + \beta 2 whitecollarshare$$

$$x_{M2} = x_{M1} + \beta 3 classorigin$$

$$x_{M3} = x_{M2} + \beta 4 householdsize + \beta 5 parentmissing + \beta 6 birthplace + \beta 7 schooldistrict + \beta 8 proximitymainroad + \beta 9 populationdensity + \beta 10 buildingtype$$

$$x_{M4a} = x_{M3} + \beta 11 adultclass + \beta 12 maritaltatus$$

The competing risks model 4b adjusts for the same variables as in model 4a but separating for deaths from preventable and non-preventable causes of deaths. This method is further described in Fine and Gray [21].

The stcox and stcrreg packages in STATA were used to perform the Cox and competing risks models (STATA v 17.0).

For all models, we perform standard tests based on Schoenfeld residuals to test the proportionality of the hazards. We found no violations in this assumption in the main explanatory variables.

2.4 Sensitivity analyses 1: Models with no distance decay function

As a sensitivity test, we estimate the full models (model 4aa) in which the share of the neighbors' class origin within each neighborhood is unweighted. That is, we use a white-collar without spatial weights/distance decay, and therefore W_{ij} equals to 1 in SI Eq. 1. In this sensitivity test, we use the k-nearest neighbors approach.

2.5 Sensitivity analyses 2: Models with surrounding neighborhoods

In this sensitivity test, we measure the effect from the nearest 50-100 neighbors, in which the nearest 1-49 neighbors are excluded. Hence, we try to capture the effect from surrounding neighborhoods. First, we adjust model 4a by replacing the white-collar share of the individual (local) neighborhood with the white-collar share of the surrounding neighborhood (model 4c). Thereafter, we extend model 4c by adding the white-collar share of the individual neighborhood (model 4d) to study how the white-collar share of the two types of neighborhood influence each other. In this sensitivity test, we use the k-nearest neighbors approach.

2.6 Sensitivity analyses 3: Models using adults without children in the household as neighbors

Here we define neighborhoods using adults without children under 18 years in the household. That is, we use model 4a in which the variable white-collar share is based on adult neighbors instead of same-aged neighbors. This is done to analyse possible effects from adults within the neighborhoods, as well as to separate such effects from the effects of same-aged children (peer-effects). Because of the higher population density of such adults compared to same-aged children, these models use a larger range of k (k = 25-500, one model at every 25 k). In this sensitivity test, we use the k-nearest neighbors approach.

2.7 Sensitivity analyses 4: Models including interactions between white-collar share and class origin/sex

In this sensitivity test, we include interactions between white-collar share and class origin, and white-collar share and sex, using model 4a. We do this to analyze whether the effect of white-collar share on mortality differ significantly for men and women and for each class origin group.

2.8 Sensitivity analyses 5: Models with reduced number of deaths for men

As shown in the Main Manuscript, we only observe significant effects from the white-collar share on men's mortality but not on women's mortality. One explanation to these findings could be that we observe more deaths for men (n = 1142) compared to women (n = 741), whereas the number of individuals are similar for men (N = 8 888) and women (N = 8 492). Hence, if the number of deaths increased for women we may observe similar mortality effects as for men. Therefore, in this sensitvity test, we randomly remove 342 men who dies, resulting in a sample of N = 8 546 with 800 deaths, and estimate models 1 and 4a for the men. If we observe no effects from the white-collar share on men's mortality using this sample, it may be an indication that the insignificant results for women are driven by few deaths.

2.9 Sensitivity analyses 6: Models including more controls for the physical environment

To control for the built environment in a more comprehensive way, we estimate model 4a extended with the following two variables.

Proximity to city center: The average distance in childhood to the main city square in Landskrona (averaged by the survival time).

Building density: The average square meters of buildings (of all types) within a 100-meter buffer from the address points that an individual has resided at in childhood (averaged by the survival time). This variable is used as a proxy for more concentrated built environment and less green areas.

3. Main results

3.1 Descriptive statistics

Tables S3-S6 show the distribution of the time at risk on the independent variables used in models 4a and b, for men and women, as well as for men and women of white-collar (white-collar high and low) and blue-collar (blue-collar high and low) class origin separately.

Table S3. Distribution of the and time at risk in person-years on the categorical variables (throughout childhood and adulthood).

	All class origin groups		White-collar class origin		Blue-collar class origin	
	Men (%)	**Women (%)**	**Men (%)**	**Women (%)**	**Men (%)**	**Women (%)**
Class origin						
White-collar high	13.88	14.43	-	-	-	-
White-collar low	29.65	31.70	-	-	-	-
Blue-collar high	32.20	29.29	-	-	-	-
Blue-collar low	21.27	23.64	-	-	-	-
NA	2.99	1.94	-	-	-	-
Adult class						
White-collar high	14.02	7.19	19.33	10.33	9.89	4.40
White-collar low	35.27	43.97	39.58	49.87	32.04	38.77
Blue-collar high	12.35	2.56	8.97	1.85	14.83	3.09
Blue-collar low	22.01	29.80	16.78	23.55	26.09	35.31
NA	16.35	16.48	15.34	14.40	17.14	18.43
Marital status						
Single	35.98	34.02	33.91	33.99	37.52	33.97
Married/in partnership	63.05	63.48	65.14	63.68	61.49	63.36
NA	0.97	2.50	0.95	2.32	0.99	2.67
Household size						
Under 5	62.24	61.13	62.05	63.44	61.12	58.64
5-	37.76	38.87	37.95	36.56	38.88	41.36
Parent ever missing						
Parents present always	69.29	69.23	73.66	70.52	68.78	69.85
Only father	15.96	16.87	16.84	17.38	14.76	16.11
Only mother	2.81	2.55	2.55	2.37	3.16	2.77
Both missing	6.21	7.15	5.96	6.92	6.28	6.81
NA	5.73	4.21	0.99	2.82	7.10	4.46
Proximity to main road						
<100m	37.43	36.14	37.21	35.98	36.55	36.17
>=100m	62.57	63.86	62.79	64.02	63.45	63.83
Birthplace						
Not Landskrona	33.88	33.49	36.92	38.54	29.46	28.28
Landskrona	62.47	63.12	61.07	59.66	65.49	66.86
NA	3.65	3.39	2.00	1.79	5.05	4.87
Elementary school district						
Albanoskolan (north)	38.76	39.32	35.58	36.69	41.77	41.96
Borstahusskolan (far north)	4.51	4.37	6.01	5.83	3.40	3.03
Gustav Adolf-skolan (east)	18.14	18.90	14.79	15.45	21.13	21.91
Tuppaskolan (south)	22.65	21.56	23.82	23.83	20.63	19.38
Varnaskolan (center)	15.94	15.85	19.80	18.20	13.08	13.73
Building type						
Apartment	79.39	79.12	80.53	78.68	78.52	79.70
Single/chain house	20.61	20.88	19.47	21.32	21.48	20.30
Individuals	8888	8492	3883	3893	4746	4429
Person-years	192 545.9	189 371.2	83 811.5	87 559.1	102 969.1	98 576.1

Table S4. Distribution of the and time at risk in person-years on the continuous variables. White-collar share measured at k = 30.

	Men			**Women**		
	Mean	Min	Max	Mean	Min	Max
White-collar share	30.4%	0.0%	93.5%	30.0%	0.0%	91.2%
Log pop. density (pop. within 100m R)	1.50	0	4.42	1.50	0	4.02
Birth year	1946.66	1928	1966	1946.22	1928	1966
Individuals		8888			8492	
Person-years		192 545.9			189 371.2	

Table S5. Distribution of the and time at risk in person-years on the continuous variables. White-collar class origin. White-collar share measured at k = 30.

	Men			**Women**		
	Mean	Min	Max	Mean	Min	Max
White-collar share	33.7%	0.8%	93.5%	32.9%	0.0%	91.2%
Log pop. density (pop. within 100m R)	1.42	0	4.16	1.41	0	4.02
Birth year	1947.40	1928	1966	1946.74	1928	1966
Individuals		3883				3893
Person-years		83 811.5			87 559.1	

Table S6. Distribution of the and time at risk in person-years on the continuous variables. Blue-collar class origin. White-collar share measured at k = 30.

	Men			**Women**		
	Mean	Min	Max	Mean	Min	Max
White-collar share	27.5%	0.0%	83.6%	27.3%	0.0%	88.6%
Log pop. density (pop. within 100m R)	1.57	0	4.42	1.58	0	3.98
Birth year	1946.00	1928	1966	1945.78	1928	1966
Individuals		4746			4429	
Person-years		102 969.1			98 576.1	

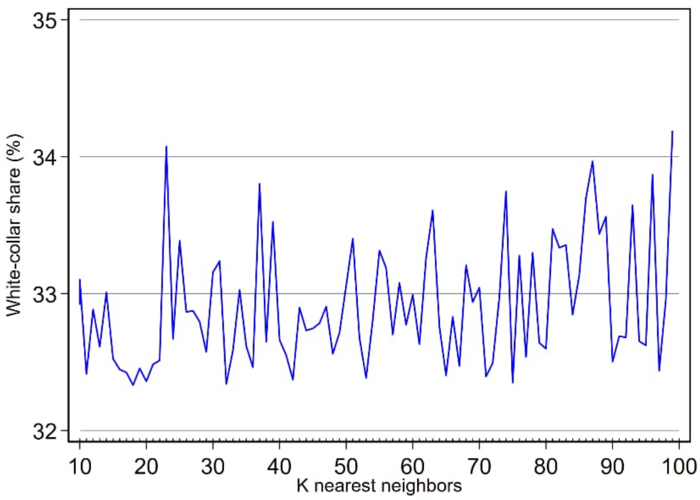

Fig. S2. Average white-collar share at each k-neighborhood (based on survival-time average), k 10 to 100, both women and men, 1939-1967. K-nearest neighbors approach.

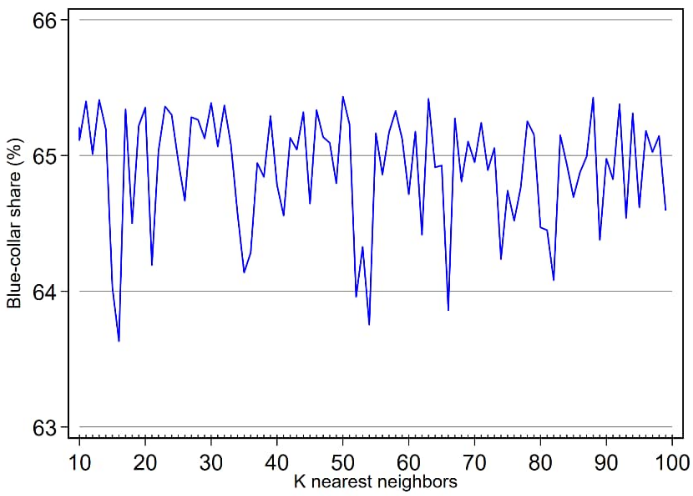

Fig. S3. Average blue-collar share at each k-neighborhood (based on survival-time average), k 10 to 100, both women and men, 1939-1967. K-nearest neighbors approach.

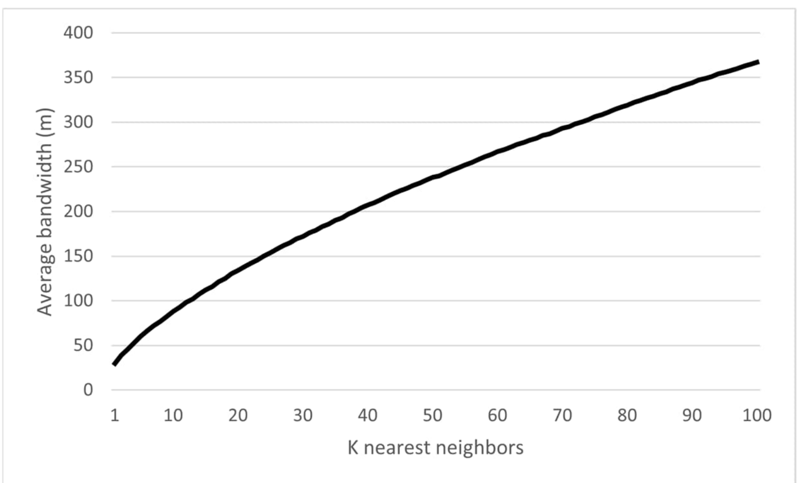

Fig. S4. Average geometric size in meters of the individual childhood neighborhoods, k 1 to 100, both women and men, 1939-1967. The size for each individual neighborhood represents the distance to the neighbor residing farthest away. K-nearest neighbors approach.

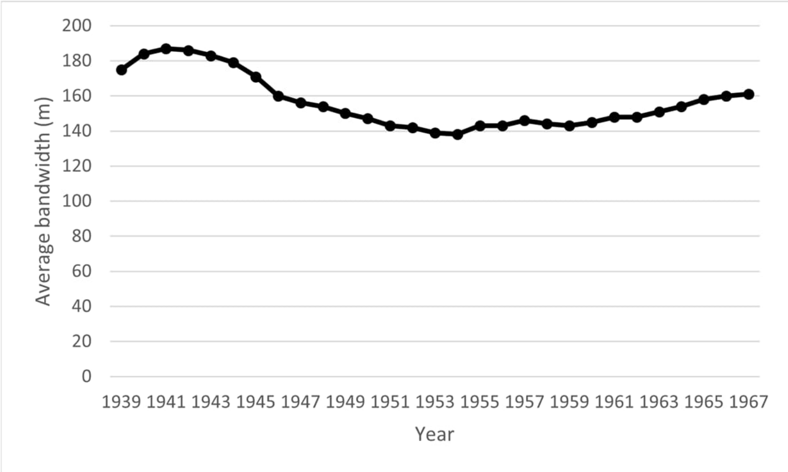

Fig. S5. Annual average bandwidth in meters of the individual childhood neighborhoods, k-25, both women and men, 1939-1967. The bandwidth for each individual neighborhood represents the distance to the neighbor residing farthest away when using the k-nearest neighbors approach.

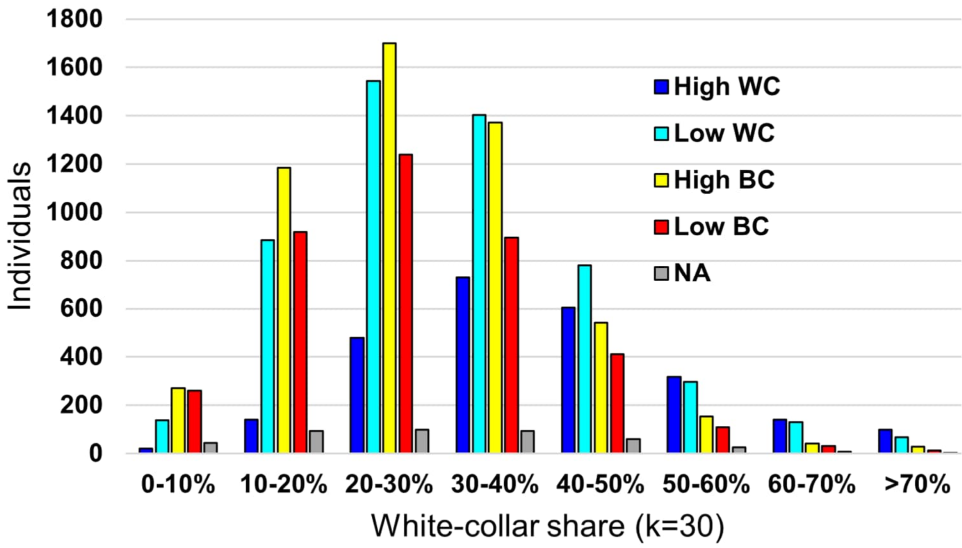

Fig. S6. Distribution of individuals on class origin and categories of white-collar shares, measured at k = 30. Both women and men, 1939-1967.

3.2 Full regression outputs models 4a and 4b

Table S7. Impact of childhood neighborhoods on all-cause and cause-specific mortality, ages 40-69, Landskrona and Sweden, 1939 to 2015 (models 4a and b). Complete model results. K-nearest neighbors approach.

	All-cause mortality (M4)				**Preventable mortality (M4b)**				**Non-preventable mortality (M4b)**			
	Men		**Women**		**Men**		**Women**		**Men**		**Women**	
	HR	**P>z**	**HR**	**P>z**	**HR**	**P>z**	**HR**	**P>z**	**HR**	**P>z**	**HR**	**P>z**
Adult class												
White collar high	0.548	0.000	0.886	0.514	0.570	0.001	1.071	0.751	0.543	0.009	0.627	0.192
White collar low	0.682	0.000	0.834	0.080	0.667	0.000	0.868	0.254	0.715	0.036	0.802	0.241
Blue collar high	0.785	0.042	1.000	0.999	0.848	0.235	1.184	0.579	0.624	0.037	0.657	0.482
Blue collar low	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC
NA	2.454	0.000	2.976	0.000	2.354	0.000	2.531	0.000	2.058	0.000	3.601	0.000
Class origin												
White collar high	0.925	0.504	0.861	0.274	0.879	0.385	0.771	0.128	0.946	0.785	1.067	0.781
White collar low	0.974	0.749	0.865	0.144	0.970	0.768	0.752	0.022	0.982	0.899	1.103	0.576
Blue collar high	0.985	0.846	1.032	0.749	1.026	0.786	0.968	0.784	0.907	0.500	1.162	0.405
Blue collar low	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC
NA	1.003	0.987	1.043	0.873	1.207	0.379	0.918	0.785	0.590	0.192	1.368	0.523
White-collar share (k=30)	0.939	0.039	0.997	0.933	0.924	0.031	0.980	0.643	1.004	0.939	1.032	0.580
Marital status												
Single	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC
Married/in partnership	0.491	0.000	0.617	0.000	0.476	0.000	0.551	0.000	0.588	0.000	0.830	0.164
NA	0.586	0.027	0.787	0.156	0.631	0.123	0.692	0.092	0.694	0.376	1.150	0.612
Birthplace												
Not Landskrona	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC
Landskrona	0.947	0.419	0.928	0.360	0.926	0.360	0.888	0.229	0.988	0.921	1.044	0.769
NA	1.017	0.914	0.938	0.758	1.003	0.987	1.014	0.954	1.037	0.901	0.835	0.650
Household size												
Under 5	1.000	RC	1.000	RC	1.000	RC	1.000		1.000	RC	1.000	RC
5-	1.007	0.909	0.936	0.391	1.065	0.407	0.982	0.846	0.848	0.152	0.850	0.221
Parent ever missing												
Parents present always	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC
Only father	0.963	0.648	1.001	0.988	0.961	0.685	1.240	0.067	0.922	0.591	0.642	0.023
Only mother	0.851	0.361	1.247	0.259	0.710	0.152	1.080	0.773	0.989	0.969	1.503	0.149
Both missing	1.078	0.505	0.957	0.764	0.961	0.786	1.203	0.281	1.257	0.232	0.603	0.086
NA	0.966	0.802	0.937	0.700	1.078	0.651	1.186	0.385	0.747	0.251	0.623	0.180
Elementary school district												
Albanoskolan (north)	1.000	RC	1.000		1.000	RC	1.000	RC	1.000	RC	1.000	RC
Borstahusskolan (far north)	0.750	0.140	1.048	0.833	0.864	0.524	0.887	0.689	0.529	0.106	1.347	0.387
Gustav Adolf-skolan (east)	0.900	0.225	1.188	0.094	0.981	0.856	1.217	0.110	0.779	0.115	1.063	0.751
Tuppaskolan (south)	1.032	0.729	1.034	0.759	1.120	0.299	0.864	0.287	0.829	0.248	1.373	0.076
Varnaskolan (center)	1.092	0.371	1.112	0.378	1.068	0.601	1.007	0.965	1.063	0.719	1.245	0.278
Proximity to main road												
>=100m	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC
<100m	1.019	0.774	1.133	0.119	1.015	0.855	1.156	0.145	1.047	0.690	1.092	0.520
Building type												
Apartment	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC	1.000	RC
Single/chain house	1.124	0.170	0.916	0.421	1.217	0.055	0.868	0.294	0.964	0.813	1.020	0.916
Log pop. Density	1.051	0.325	0.926	0.249	1.093	0.146	0.908	0.244	0.983	0.852	0.947	0.650
Birth year	0.976	0.000	0.988	0.025	0.974	0.000	0.987	0.035	0.974	0.000	0.989	0.236
Individuals	8888		8492		8888		8492		8888		8492	
Deaths	1142		751		772		489		357		252	
Person-years	192545.9		189825.3		192545.9		189825.3		192545.9		189825.3	
LR chi2	670.2		324.7		459-2		208.7		191.5		161.0	
Prob>chi2	0.000		0.000		0.000		0.000		0.000		0.000	

3.3 Models 2 and 3 (k = 10-100; m = 100-400)

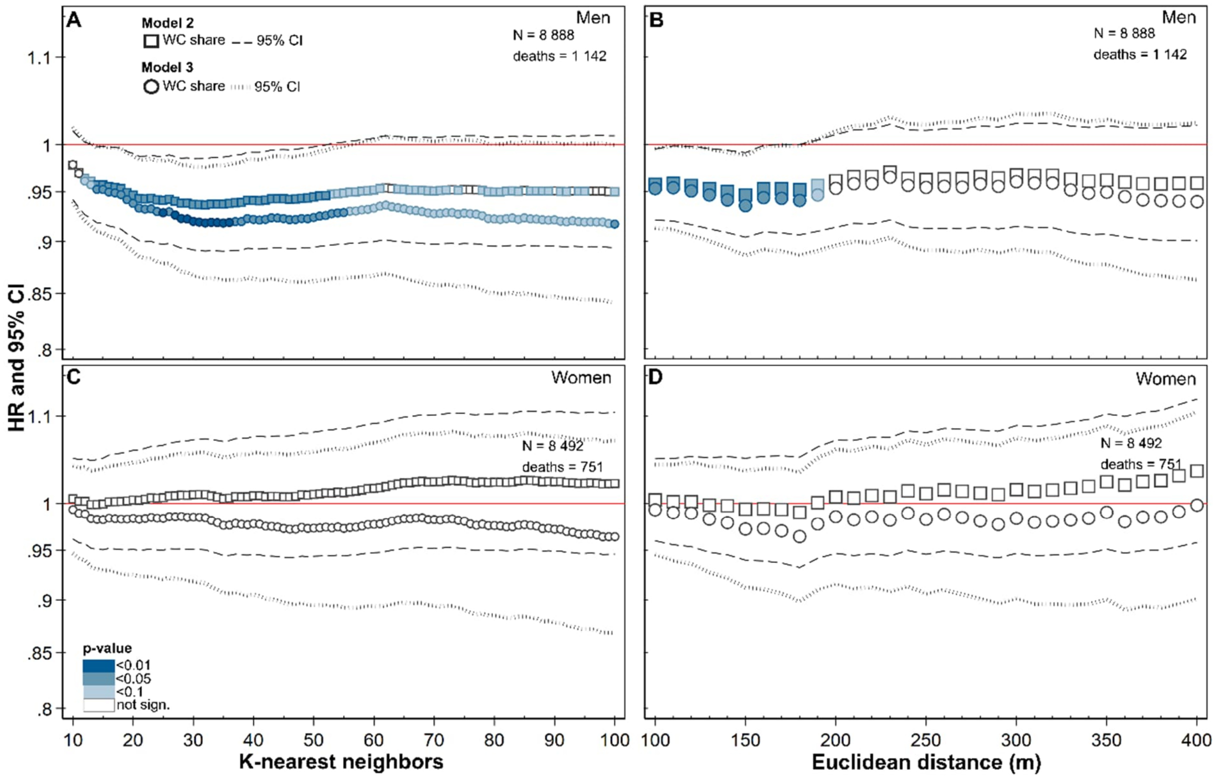

Fig. S7. Impact of childhood neighborhoods and control variables on all-cause mortality, ages 40-69, 1939 to 2015. Only the variable white-collar share and the results of models 2 and 3 are shown here. (A) k-nearest neighbors approach, men; (B) Euclidean distance approach, men; (C) k-nearest neighbors approach, women; (D) Euclidean distance approach, women.

4. Sensitivity results

4.1 Sensitivity results 1: Models with no distance decay function

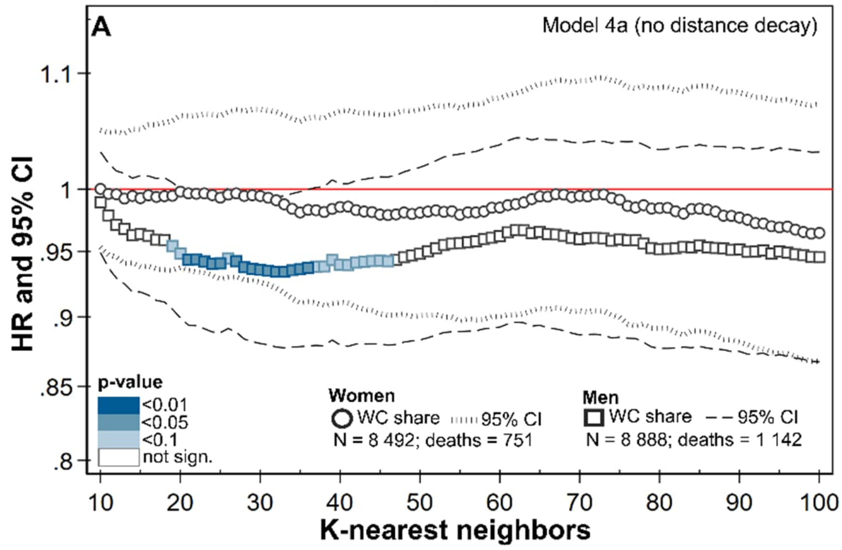

Fig. S8. Impact of childhood neighborhoods and control variables on all-cause mortality, using no distance decay function, ages 40-69, 1939 to 2015. Only the variable white-collar share is shown here. K-nearest neighbors approach.

Fig. S9 shows the differences in Bayesian Information Criterion (BIC) values between the main models using the Gaussian distance decay and the models with no distance decay (model 4a). The BIC values are obtained from the same models shown in Fig. 2 in Main Manuscript and the models in Fig. S8, estimating the effects from white-collar share of same-age (±1 year) neighbors.

A value lower than -2 indicates that the model with a Gaussian distance function may perform slightly better than its counterpart. A value higher than 2 indicates that the model using no distance decay may provide a better fit. Overall, the tests show that the two types of models provide a similar fit for both men and women, but with indications that the models without distance decay performs slightly better for men at smaller sizes of k, but worse at larger sizes of k. Hence, it may be more realistic to assume that nearby neighbors had a greater influence than neighbors residing farther away in relatively larger neighborhoods (e.g., at k = 50), whereas in smaller neighborhoods (e.g., at k = 15), the influence is similar regardless of distance.

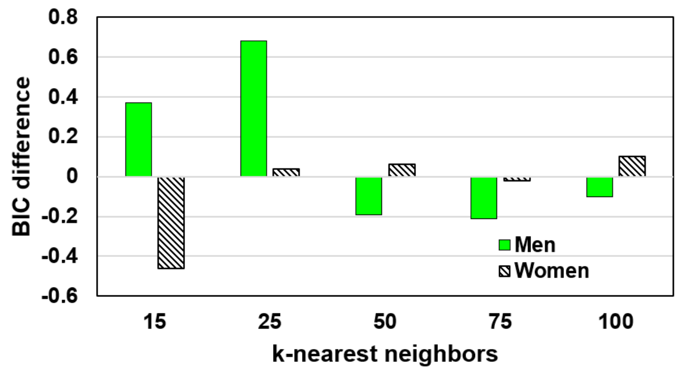

Fig. S9. Differences in BIC values between the model using the Gaussian distance decay function and the models no decay.

4.2 Sensitivity results 2: Models with surrounding neighborhoods

Fig. S10 shows the results for all-cause mortality for models 4a, 4c and 4d, using the k-nearest neighbors approach. Model 4c replaces the white-collar share of individual (local) neighborhoods with the white-collar share of surrounding neighborhoods (k = 50-100 excluding k < 50), whereas the white-collar shares of both individual and surrounding neighborhoods are included in model 4d. The models 4c and d show no significant effects of white-collar share in the surrounding neighborhoods on mortality (Fig. S10 a and b).

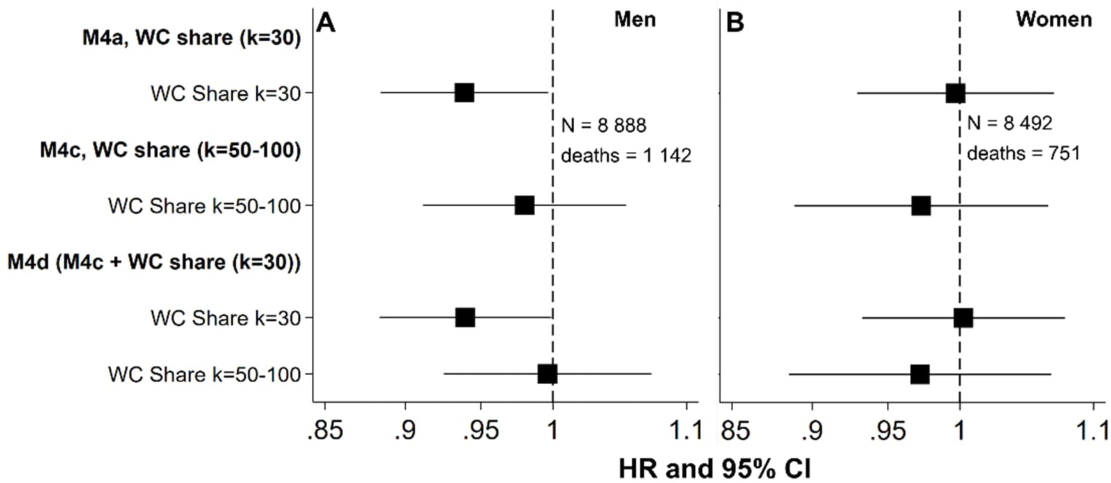

Fig. S10. Impact of childhood neighborhoods and control variables on all-cause mortality, using surrounding neighbors, ages 40-69, 1939 to 2015. Only the variable white-collar share is shown here. (A) men; (B) women.

4.3 Sensitivity results 3: Models using adults without children in the household as neighbors

Fig. S11 shows the results for all-cause mortality using model 4a. Neighbors are defined as adult individuals without children in the household. Note that a larger range of k (k = 25 (25) 500) is used here because of the higher population density of such adults compared to same-aged children. For example, the average bandwidth is 250 m at k ≈ 450 and k ≈ 60 for adult and same-age neighbors, respectively (Fig. S4, S12).

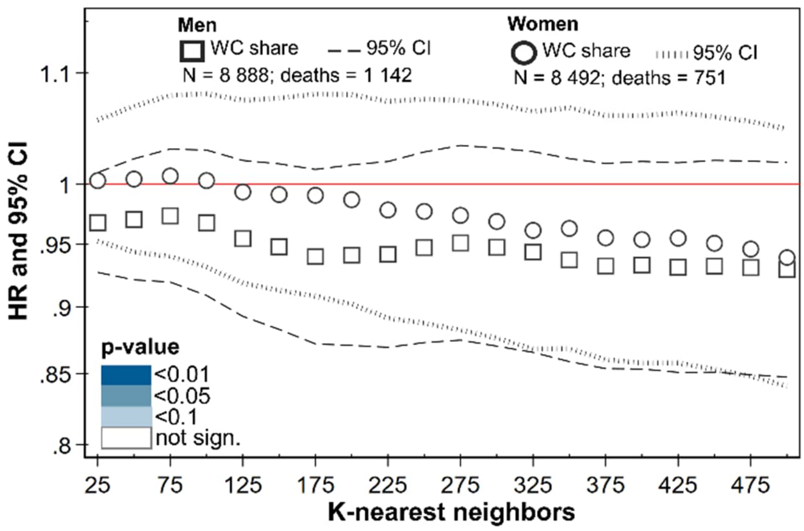

Fig. S11. Impact of childhood neighborhoods and control variables on all-cause mortality, ages 40-69, 1939 to 2015. Neighbors are defined as adult individuals without children in the household. Only the variable white-collar share is shown here. (A) men; (B) women.

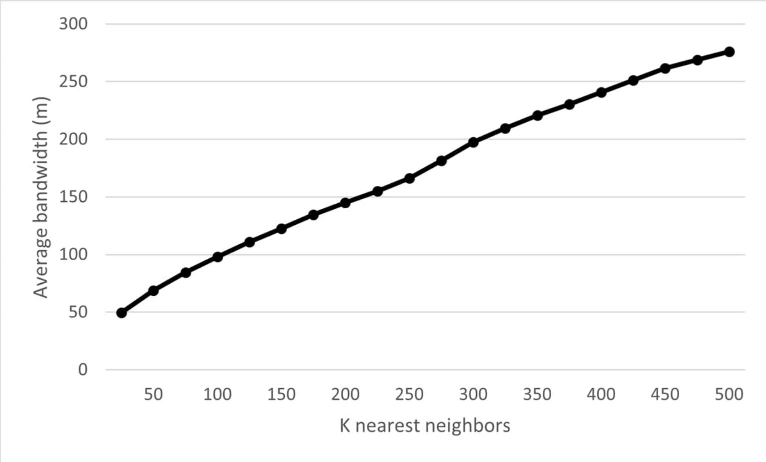

Fig. S12. Average bandwidth in meters of the individual childhood neighborhoods, k 25 (25) to 500, both women and men, 1939-1967. Neighbors are adult individuals without children in the household. The bandwidth for each individual neighborhood represents the distance to the neighbor residing farthest away when using the k-nearest neighbors approach.

4.4 Sensitivity results 4: Models including interactions between white-collar share and class origin/sex

Table S8. Impact of childhood neighborhoods on all-cause mortality, ages 40-69, Landskrona and Sweden, 1939 to 2015 (model 4a). K-nearest neighbors approach. Interactions are included between class origin and white-collar share. Only the interaction variables are shown here (reference class: White-collar high (Class origin) # White-collar share (k = 30)

	All-cause mortality: Men HR	Men P>z	Women HR	Women P>z e
Class origin				
White-collar high	1.000	RC	1.000	RC
White-collar low	0.829	0.526	1.437	0.315
Blue-collar high	0.766	0.358	1.843	0.090
Blue-collar low	0.959	0.890	1.599	0.191
NA	0.460	0.164	4.197	0.035
WC share, k = 30 (White-collar high Class origin)	0.877	0.062	1.093	0.260
Class origin ## WC share, k = 30				
White-collar low	1.070	0.411	0.908	0.308
Blue-collar high	1.108	0.208	0.883	0.205
Blue-collar low	1.019	0.834	0.921	0.397
NA	1.277	0.084	0.670	0.068
Individuals	8888		8492	
Deaths	1142		751	
Person-years	192,545.9		189,825.3	
LR chi2	674.84		328.9	
Prob>chi2	0.000		0.000	

Table S9. Impact of childhood neighborhoods on all-cause mortality, ages 40-69, Landskrona and Sweden, 1939 to 2015 (model 4a). K-nearest neighbors approach. Interactions are included between sex and white-collar share. Only the interaction variables are shown here (reference class: Women # White-collar share (k = 30).

	All-cause mortality	
	HR	**P>z**
WC share, k = 30 (Women)	1.016	0.608
Sex ## WC share, k = 30		
Men	0.914	0.014
Individuals	17380	
Deaths	1893	
Person-years	382 371.2	
LR chi2	1048.25	
Prob>chi2	0.000	

4.5 Sensitivity results 5: Models with reduced number of deaths for men

Fig. S13 shows the results for all-cause mortality using model 4a. Here, 343 men who dies in the sample are excluded. This results in N = 8 546 and deaths = 800. The effect from the white-collar share is reduced in model 1 and becomes insignificant in model 4a. Nevertheless, the pattern remains similar to the model results using the full sample of men (Main Manuscript, Fig. 4a)

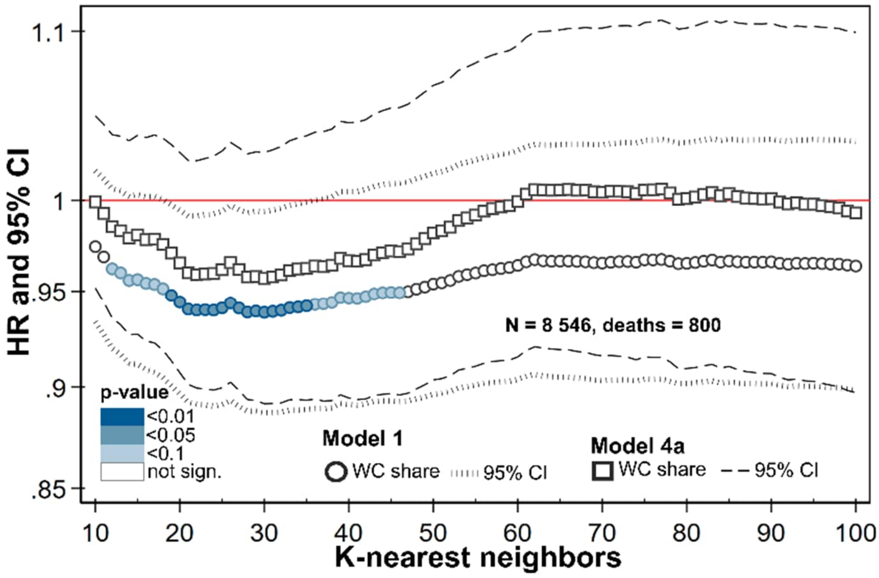

Fig. S13. Impact of childhood neighborhoods and control variables on all-cause mortality, ages 40-69, 1939 to 2015, men. K-nearest neighbors approach, k = 30. Only the variable white-collar share is shown here.

4.6 Sensitivity results 6: Models including more controls for the physical environment

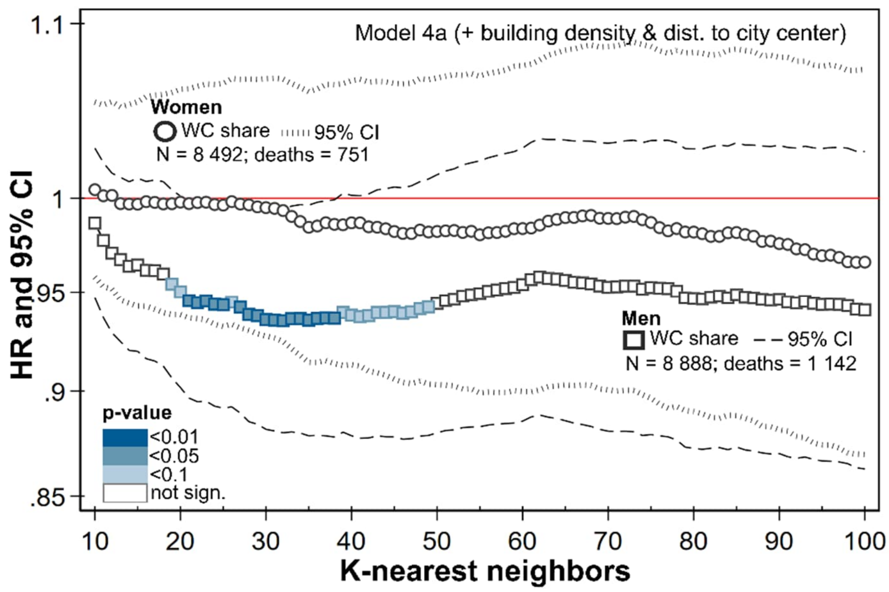

Fig. S14. Impact of childhood neighborhoods and control variables on all-cause mortality, ages 40-69, 1939 to 2015, men and women. Model 4a extended with controls for building density and distance to city center. K-nearest neighbors approach, k = 30. Only the variable white-collar share is shown here.

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