Health & Place 68 (2021) 102543

Contents lists available at ScienceDirect

Health and Place

journal homepage: http://www.elsevier.com/locate/healthplace

Longitudinal exposure assessments of neighbourhood effects in health research: What can be learned from people's residential histories?

Paulien Hagedoorn *, Marco Helbich

Department of Human Geography and Spatial Planning, Faculty of Geosciences, Utrecht University, Utrecht, the Netherlands

ARTICLE INFO

Keywords:
Long-term exposure assessment
Mental health
Register data
Neighbourhood effects
Cumulative exposure

ABSTRACT

Health research into neighbourhood effects has generally examined neighbourhoods cross-sectionally, ignoring the fact that neighbourhood exposures might accumulate over people's lives and affect health outcomes later in life. Using longitudinal Dutch register data with complete 15-year residential address histories, we examined whether health effects of neighbourhood socioeconomic characteristics differ between cumulative and current exposures. We illustrated these differences between exposure assessments using suicide mortality among middle-aged adults. All suicides aged 40–64 years between 2012 and 2016 were matched with 10 random controls in a nested case-control design. We measured neighbourhood exposures longitudinally for circular buffers around residential addresses at the current address and through three accumulative measures, each incorporating the residential address history with increasing detail. Covariate-adjusted conditional logistic regressions were used to assess associations between suicide and neighbourhood social fragmentation, population density and unemployment rate. Our results showed that total and male suicide mortality was significantly lower in highly fragmented neighbourhoods when using accumulative exposures, but not when using the current residential address. However, we observed few differences in coefficients between exposures assessments for neighbourhood urbanicity and unemployment rate. None of the neighbourhood characteristics showed evidence that detailed cumulative exposures were a stronger predictor of suicide compared to more crude measures. Our findings provide little evidence that socioeconomic neighbourhood characteristics measured cumulatively along people's residential histories are stronger predictors of suicide mortality than cross-sectional exposures.

1. Introduction

The social characteristics of people's living environment are among the determinants that affect health. Reviews suggest that poor neighbourhood conditions, such as deprivation and social disorder, threaten both physical health (Arcaya et al., 2016; Diez Roux and Mair, 2010; Riva et al., 2007) and mental health (Cairns et al., 2017; Ehsan and De Silva, 2015; Mair et al., 2008), although these associations have not always been found.

It is common practice to take the social circumstances of the current residential neighbourhood into account (Arcaya et al., 2016; Cairns et al., 2017; Diez Roux and Mair, 2010; Ehsan and De Silva, 2015). However, including neighbourhood conditions only cross-sectionally has repeatedly been called into question (Diez Roux and Mair, 2010; Helbich, 2018; Sharkey and Faber, 2014). Rather than being exposed only to the social environment where they currently reside, many people are exposed to multiple neighbourhood environments across their lives as a result of residential moving and/or changes in neighbourhood conditions themselves (Brokamp et al., 2016; Hedman, 2011; Helbich, 2018). Lingering effects of these social contexts of past neighbourhoods might have health implications later in life. For example, people might still be connected to previous neighbourhoods through maintaining social ties and social norms (Hedman, 2011). It is also plausible that neighbourhood exposures accumulate over time, implying that people do not develop health problems immediately but that effects may appear and be reinforced when people are exposed for a longer period of time (Clarke et al., 2014; Sharkey and Faber, 2014; Yang and South, 2018).

The life-course approach explicitly recognizes that exposures over time possibly have long-lasting health effects (Ben-Shlomo, 2002; Singh-Manoux et al., 2004). In addition to exposure during certain critical periods in life (Jivraj et al., 2019b), the accumulation of exposures across the life-course is thought to be related to health outcomes

* Corresponding author. Department of Human Geography and Spatial Planning Faculty of Geosciences, Utrecht University, Princetonlaan 8a, 3584 CB, Utrecht, the Netherlands.

E-mail address: p.hagedoorn@uu.nl (P. Hagedoorn).

https://doi.org/10.1016/j.healthplace.2021.102543
Received 25 November 2020; Received in revised form 17 February 2021; Accepted 19 February 2021
Available online 3 March 2021
1353-8292/

later in life (Lynch and Smith, 2005). Although it is well established that adverse individual-level social and socioeconomic conditions across the course of people's lives have negative health impacts (Ben-Shlomo, 2002; Lynch and Smith, 2005; Singh-Manoux et al., 2004), limited efforts have been made to expand place-based exposures over people's lifetimes (Helbich, 2018; Lekkas et al., 2017; Pearce et al., 2018).

Only a few studies have assessed the health effects of cumulative exposure to neighbourhood characteristics (Carson et al., 2007; Gustafsson et al., 2015; Headen et al., 2018; Helbich et al., 2020; Jivraj et al., 2019a; Pearce et al., 2018); even fewer have compared cumulative measures with those at the current address (Clarke et al., 2014; Do, 2009; Yang and South, 2018). A review of literature on long-term neighbourhood effects concluded that the accumulation of neighbourhood deprivation across the life course was associated with negative later life health outcomes (Jivraj et al., 2019a).

Furthermore, tentative results suggest that omitting exposures over the residential history is likely to lead to the underestimation of neighbourhood effects (Clarke et al., 2014; Do, 2009; Yang and South, 2018). However, these studies only used address information at a limited number of time points (e.g. time of interview), which might have biased exposure assessments as a result of residential moves or neighbourhood changes in between time-points. Instead, detailed address information across the entire residential history could allow for more precise estimations of neighbourhood effects. Yet, we are unaware of any study systematically comparing neighbourhood-health associations at the current address with multiple cumulative exposure assessments incorporating the residential address history.

To respond to this knowledge gap, we compared different operationalizations of neighbourhood exposures using unique 15-year long longitudinal and georeferenced Dutch register data. We compared cumulative socioeconomic neighbourhood exposures over people's residential histories at adulthood with conventional one-point-in-time exposure assessments. We illustrated this by examining how neighbourhood deprivation and social fragmentation correlate with suicide mortality, which is a critical public health concern (WHO, 2014). Suicide is ideal for such analyses as it develops over the lifetime (Hawton and van Heeringen, 2009). Moreover, the integrated motivational–volitional model of suicide (Connor and Kirtley, 2018) provides theoretical support that people's suicide risk is not only shaped through risk factors at the individual level, but that the neighbourhood environment may also affect suicide risk through increasing or decreasing proximal risk factors, such as mental distress or social connectedness. This is further supported by empirical evidence of neighbourhood effects on suicide (Cairns et al., 2017; Rehkopf and Buka, 2005). Finally, associations between neighbourhood characteristics and suicide mortality varied by length of residence, suggesting neighbourhood effects on suicide might accumulate over time (Hagedoorn et al., 2020).

Two hypotheses were tested: 1) that socioeconomic neighbourhood characteristics measured cumulatively across residential addresses have stronger correlations with suicide compared to traditional cross-sectional exposures at the current address; and 2) that neighbourhood measures incorporating exposures based on detailed residential histories have a better model fit and stronger associations with suicide than exposures averaged across a few time points only.

2. Materials and methods

2.1. Study design and study population

We used a population-based nested case-control study design based on longitudinal registers from the Netherlands. Details of the study design have been reported elsewhere (Helbich, 2019). Briefly, we extracted register data on the Dutch population from 1 January 1997 until 31 December 2016 from Statistics Netherlands. Registers were linked on a person-by-person basis with anonymized personal identifiers.

Officially registered suicide cases aged 40–64 years between 1 January 2012 and 31 December 2016 ($N = 5{,}047$) were extracted from the cause of death register coded as X60–X84 according to the 10th edition of the International Statistical Classification of Diseases and Related Health Problems. Previous studies have reported pronounced associations with neighbourhood characteristics in this age cohort (Agerbo et al., 2007; Hagedoorn et al., 2020). Cases who were institutionalized ($N = 419$), with an incomplete 15-year residential history ($N = 531$) or with missing individual or neighbourhood characteristics ($N = 204$) were excluded. Each case was matched based on year of birth, sex and calendar time to a random sample of 10 controls ($N = 38{,}930$) (Keogh and Cox, 2014). Controls who were institutionalized ($N = 8$), with an incomplete 15-year residential history ($N = 705$) or missing neighbourhood characteristics ($N = 333$) were excluded from the analysis. Compared to the final study population, excluded cases and controls contained a significantly larger proportion of residents who were non-Dutch, lived in institutionalized or single households and had a low individual socioeconomic position. \2. S1 in the supplementary materials summarizes the study population selection from the registers.

2.2. Residential address histories

Data on residential moving (i.e. the date of the move and the address moved to) were obtained for each case/control from the population register. All locations where cases/controls had lived from 1 January 1997 to 31 December 2016 were geocoded at an address level based on the cadastre. We used the entire residential address history per case/control in the 15 years preceding the date of suicide (cases) or matching date (controls).

2.3. Long-term exposure assessments

Three neighbourhood characteristics were included longitudinally between 1997 and 2016 for each address during a case/control's 15-year residential history. We used concentric buffers with radii of 300, 600 and 1,000 m centred on each address at which a case/control lived, as done elsewhere (Hagedoorn et al., 2020; Helbich et al., 2020). Neighbourhood characteristics (i.e. social fragmentation, unemployment rate and urbanicity) were based on register data of the total Dutch population by identifying all residents living on an address within the buffer on 1 January of each year and annually aggregating their individual-level data.

Social fragmentation reflects the level of community integration and connectedness within a neighbourhood based on the share of non-traditional households and residential turnover (Congdon, 2011, 2013; Ivory et al., 2011). It is assumed that people in more fragmented neighbourhoods experience lower levels of social support and increasing levels of neighbourhood disorder which in turn increases their risk of poor mental health (Ivory et al., 2011) and suicide (Congdon, 2013). Following Congdon (2013) we calculated the social fragmentation index as the share of adults (>18 years) who were unmarried, lived in a single-person household and had moved into the neighbourhood in the previous year. Each variable was *z*-scored and summed, with higher scores referring to higher levels of social fragmentation.

People living in disadvantaged areas might experience an increased suicide risk due to limited financial means (e.g. lack of public amenities or jobs), increased hopelessness and loss of self-efficacy (Burrows et al., 2011; Martikainen et al., 2004). We used the unemployment rate as an indicator of neighbourhood deprivation as it was available across time. Because the register has recorded employment status only since 1999, the missing unemployment rates for 1997 and 1998 were back casted through time series analysis. We fitted univariate autoregressive integrated moving average (ARIMA) models per address buffer (Hyndman, R.J. and Athanasopoulos, 2013). The best fitting ARIMA parameters were determined for each time series by minimizing the Akaike information criterion (AIC).

Finally, we used urbanicity to account for rural–urban differences in suicide mortality (Helbich et al., 2017). A few mechanisms have been suggested through which elevated vulnerability in rural areas may occur. Besides easier access to lethal means, rural living can reinforce social isolation which increases suicide risk (Hirsch and Cukrowicz, 2014). Urbanicity was captured by means of population density by aggregating the number of people per address buffer.

These three area-level characteristics were computed fourfold whereby each measure incorporated the residential history with increasing complexity (Fig. 1):

1) *One-point-in-time exposure assessment*: We measured exposures at the current residential address at the date of suicide (case) or matching date (control).
2) *Averaged exposure assessment*: To mimic a panel design, we averaged neighbourhood exposure by summing the neighbourhood characteristics of the current residential address and residential addresses 5, 10 and 15 years back in time and divided the result by 4.
3) *Cumulative exposure assessment*: We measured neighbourhood exposure cumulatively across the 15-year residential history by dividing the residential history into annual spells or by multiple spells per year if a person had several addresses that year. Each spell was then linked to the neighbourhood characteristics corresponding to the address and year of that spell. Next, we obtained relative exposure per spell by multiplying the neighbourhood characteristic by the relative time lived in each spell (i.e. the days spent in each spell divided by the total number of days in the 15-year period). Finally, we summed the exposures across all spells to obtain the cumulative exposure score across the entire residential history.
4) *Time-weighted cumulative exposure assessment:* We measured neighbourhood exposure cumulatively across the residential history with the assumption that residential spells further back in time had less influence on the overall accumulated exposure score. A similar procedure as for the third assessment was used, but we weighted each spell with a temporal decay function. We tested three functions by assuming that exposure had an exponential decay of 50% in 15 years (i.e. exposure at the address 15 years ago only accounts for 50%), an exponential decay of 50% in 5 years and a linear decay of 100% in 15 years.

To facilitate comparisons across the four exposure assessments and in line with earlier work (Hagedoorn et al., 2020), each indicator was divided into quartiles based on the sample distribution.

2.4. Individual-level confounders

We adjusted a priori for several individual-level confounders related to suicide mortality (Batty et al., 2018; Li et al., 2011). Sex and age were controlled for through the matched case-control design. Nationality was considered as a dummy variable (Dutch, non-Dutch). Marital status was categorized into married, never married or not currently married. Household type was grouped as couple with children, couple without children, single parent or other (i.e. mainly single households). Socioeconomic position was measured through employment status (employed, unemployed, non-working) and categorized standardized household income (<€20,000, €20,000–35,000, >€35,000). As a proxy for depression, we adjusted for antidepressant prescriptions (yes, no) as classified in the anatomic therapeutic chemical system (N06A). Data on nationality, marital status, household type and employment status were obtained at matching date. Household income and antidepressant prescriptions were registered annually and were obtained for the year before matching time. To adjust for the number of residential relocations and duration of residence, we classified individuals as movers (i.e. those who had relocated at least once in their residential history) or non-movers, and by the length of residence at the current address (<5 years, ≥5 years).

2.5. Statistical analyses

Descriptive statistics (e.g., mean and standard deviation [SD]) were used to summarize the variables. To assess differences in individual and neighbourhood characteristics between cases and controls, we used Chi^2 tests.

We assessed associations between neighbourhood characteristics and suicide mortality using conditional logistic regression models. Conditional logistic regressions were necessary to avoid bias arising from the matched study design (Keogh and Cox, 2014). For each of the four exposure assessments, we fitted a covariate-adjusted model including both neighbourhood-level and individual-level characteristics. Due to distinct gender differences in suicide behaviour (Turecki and Brent, 2016), we also conducted stratified analyses.

To compare cross-sectional and cumulative exposure assessments, we compared model fits based on AIC scores. Lower AIC scores indicate a better goodness-of-fit. We also tested whether the coefficients of neighbourhood characteristics differed statistically across the models by means of Wald tests. As sensitivity tests, we fitted the models with 300, 600 and 1,000 m buffers. Analyses were performed in Stata (version 16.0).

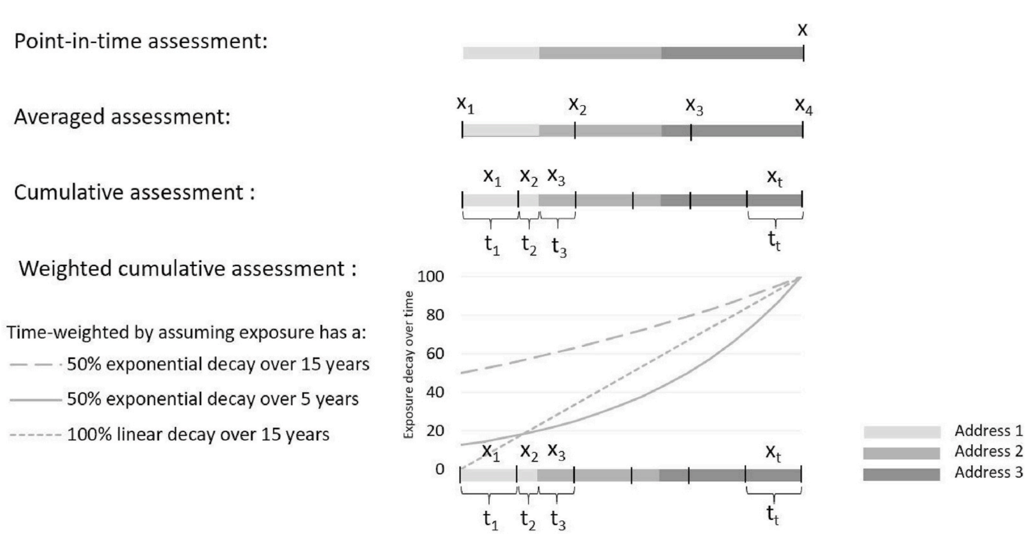

Fig. 1. Methods to assess exposure across the 15-year residential history. One-point-in-time exposure was measured at time of suicide (cases) or matching date (controls); Averaged exposure was calculated by averaging exposure every 5 years at four time points; Cumulative exposure was calculated by summing annual exposure across the residential history while weighting for the time spent in each residential spell; Weighted cumulative exposure was calculated similarly as cumulative exposure with the addition of a time-decay function.

2.5.1. *Ethics and data privacy*

In accordance with Dutch privacy legislation, anonymized microdata are non-publicly accessible without the need for informed consent for scientific research in the secure environment of Statistics Netherlands. The study protocol (Helbich, 2019) was approved by the Ethics Review Board of Utrecht University (FETC17–060).

3. Results

3.1. *Descriptive statistics of the study population*

In total, our study population consisted of 3,893 suicide cases (68.2% men, 31.8% women) and 37,884 controls (68.1% men, 31.9% women) (Table S1 supplementary materials). Compared to the controls, a higher proportion of suicides lived in neighbourhoods with high social fragmentation, high population density and high unemployment rates. Suicide cases had a higher share of individuals who were unmarried, lived in single-person households, were non-working, had low incomes and received antidepressant prescriptions. There was also a higher share of individuals with ≥5 years residence and residential move(s) during the 15-year residential history among cases. Chi^2 tests indicated that these case–control differences were statistically significant ($p < 0.05$).

3.2. *Regression-based comparison of different exposure assessments*

Results are presented for the 300 m buffers as this buffer size resulted in the lowest AIC scores across models. Table S2 summarizes the AIC across models and buffer sizes. The averaged exposure performed best for total and male suicide, while the cumulative exposure performed best for female suicide. Model fits for the time-weighted cumulative exposures were comparable across weighting methods, but the exponential decay of 50% in 5 years resulted in the overall lowest AIC score and is therefore presented in the following.

Fig. 2 shows the associations between suicide and social fragmentation, urbanicity and unemployment rate across the four exposure assessments for total, male and female suicide. Corresponding coefficients can be found in Tables S3–S6. The models showed a negative association with total and male suicide for social fragmentation when using accumulated exposures, but not when using one-point-in-time exposure. In addition, the Wald test indicated significant differences between coefficients of current and accumulated exposure assessments for the highest quartile of social fragmentation (Table S6). For women, none of the exposure assessments showed a difference in suicide risk by social fragmentation.

Further, the models showed a lower suicide rate among residents of densely populated neighbourhoods. These negative associations were significant for total and female suicides in both the one-point-in-time and accumulated exposures (Fig. 2). Among males, suicide was only significantly associated with urbanicity when using the one-point-in-time exposure. The Wald test showed few significant differences in coefficients between exposure assessments (Table S6).

For total and male suicide, we observed an overall trend of lower suicide mortality in neighbourhoods with high unemployment (Fig. 2). This negative association was only significant in the averaged and the one-point-in-time exposure for total and male suicide, respectively. Corresponding coefficients were significantly different only for the 3rd quartile of unemployment (Table S6).

For robustness tests, we re-estimated the models with 600 and 1,000 m buffers. Tables S7 and S8 summarize the numeric results. Exposure assessments for social fragmentation and population density were similar across buffer sizes, although the negative association of total and male suicide with neighbourhood unemployment was only observed at the 300 m buffers.

4. Discussion

4.1. *Key findings*

Using a large population-based case control study with complete 15-year residential address histories, we assessed correlations between spatiotemporal neighbourhood socioeconomic characteristics and suicide mortality. Models incorporating accumulated exposures resulted in the highest goodness-of-fit. There was, however, little evidence that accumulated exposures performed better than current exposures,

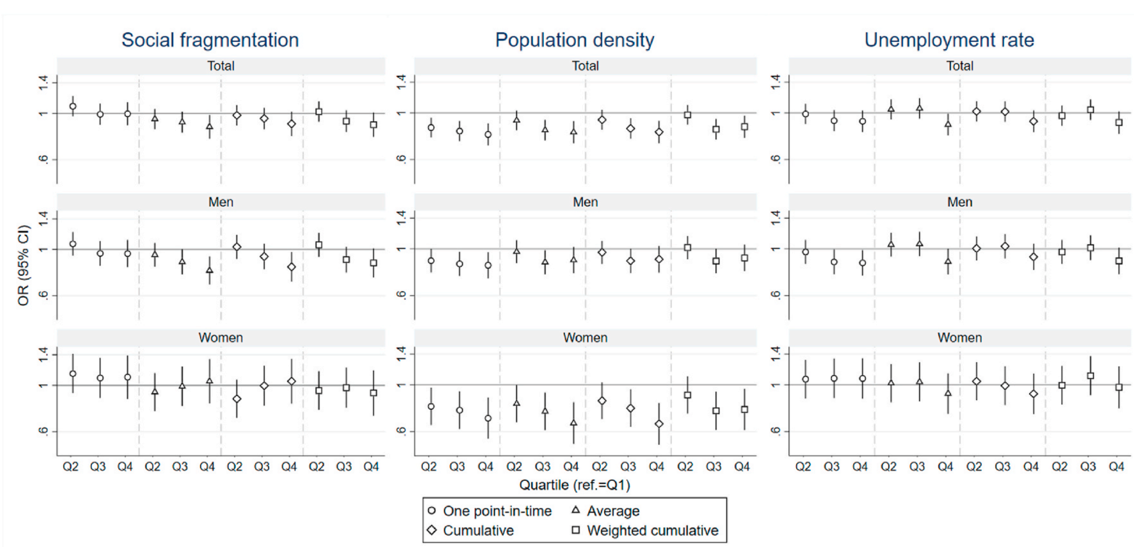

Fig. 2. Odds ratios (ORs) and 95% confidence intervals (CIs) for exposure quartiles at the 300 m buffers associated with male, female and total suicide mortality. All estimates are relative to the reference category (i.e. quartile 1 [Q1]). The models were adjusted for area-level characteristics (i.e. social fragmentation, population density, unemployment rate) and person-level factors (i.e. nationality, marital status, household type, employment status, income, antidepressant use, length of residence, moving).

refuting our first hypothesis Social fragmentation was significantly and negatively associated with total and male suicide when using accumulated exposures, but not when incorporating exposures at the current residential address. Coefficients for unemployment rate remained comparable across exposures and showed insignificant associations with suicide mortality. Urbanicity was negatively associated with total and female suicide across all four exposure assessments; it was negatively associated with male suicide only for exposure at the current address. Wald tests indicated that only a few coefficients differed significantly across the four tested exposure assessments. Furthermore, accumulative exposures using detailed residential histories had similar associations with suicide as more crude exposures measured at a few time points. We therefore also must reject our second hypothesis.

4.2. Other available evidence

Studies on long-term neighbourhood deprivation and health suggest that neighbourhood exposure accumulates over the life course (Jivraj et al., 2019a). We too observed significant associations between cumulative neighbourhood social and socioeconomic characteristics and suicide mortality. However, with some exceptions for social fragmentation, we found little evidence to suggest that these cumulative effects differed from effects at the current address. Although previous studies on physical health found that cross-sectional exposure assessments underestimated neighbourhood effects compared to cumulative exposures (Brokamp et al., 2016; Clarke et al., 2014; Do, 2009; Yang and South, 2018), our results for mental health remained inconclusive.

The context of our study might be an explanation for these inconclusive results. Earlier research has reported stronger neighbourhood effects on depression (Mair et al., 2008) and suicide (Rehkopf and Buka, 2005) in the USA compared to European countries. Residential moves and neighbourhood change might therefore have less pronounced effects on differences between exposures over time in more egalitarian contexts such as the Netherlands.

The minor differences between exposure assessments might also be a consequence of our population's long-term residence combined with little neighbourhood change. Although 60% of our study population had moved at least once during their 15-year residential history, the vast majority (i.e. 77% of the cases and 82% of the controls) had lived at their current address for at least five years. In addition, neighbourhood characteristics for non-movers had remained relatively stable over time. Exposure differences over time might thus not be large enough to result in substantial differences in exposure quartiles. Our findings might imply that the current residential address is representative of neighbourhood exposures over longer time spans for long-term residents; however, additional empirical verification is needed.

Finally, cumulative exposures possibly mask larger variances in neighbourhood exposures and neighbourhood trajectories (Do, 2009). For example, annual variations in cumulative deprivation might average out for persons moving from a highly deprived to a highly affluent neighbourhood halfway through their residential history. Almost 60% of our study population moved at least once during the study period. Half of these moves were to neighbourhoods with similar characteristics, while upward or downward residential moves each consisted for about 25% of moves. Persistent exposures to highly deprived neighbourhoods and downward mobility have been associated with adverse health outcomes (Clarke et al., 2014; Riva and Curtis, 2012), while upward mobility seems to have protective effects (Headen et al., 2018). In contrast, a study from New Zealand, albeit an ecological one, reported only a few differences in neighbourhood effects on health when considering the current address compared to upward or downward residential trajectories (Pearson et al., 2013). Future research might shed more light on the health effects of neighbourhood trajectories and how this compares to exposures at the current address.

4.3. Strengths and limitations

To our knowledge, this was the first study to systematically compare the health effects of social and socioeconomic neighbourhood characteristics measured at the current address and cumulatively over time. A major strength of this study is the availability of detailed, population-wide register data that includes people's residential histories. This allowed us to accurately assess socioeconomic changes over a 15-year period as a result of both residential moving and due to changes in the residential environment itself. An analytical strength compared to previous studies (Clarke et al., 2014; Yang and South, 2018) is that our neighbourhood data were available at an address level (Hagedoorn et al., 2020). This allowed us to assess neighbourhood effects over time using personalized buffers on different scales, avoiding several limitations related to the use of administrative areas (Flowerdew et al., 2008; Helbich, 2018). The registers ensured a neighbourhood assessment of similar high quality over time. Due to our large dataset, the statistical results were well powered.

As Dutch registers have been systematically compiled only since 1995, we were unable to obtain residential histories across people's entire life-courses, including childhood and early adulthood. Nevertheless, while neighbourhoods early in life might be important for later health outcomes, their effects are often attenuated by neighbourhoods later in life (Jivraj et al., 2019a). Moreover, registers are intrinsically constrained by the number of variables available over time (e.g. green space, air pollution). However, earlier studies found no significant suicide–green space associations across people's 10-year residential histories (Helbich et al., 2020), while associations with air pollution were insignificant for the Netherlands (Helbich et al., 2020). As individual characteristics were not incorporated longitudinally, we cannot exclude that the accumulation of individual-level socioeconomics may have influenced our findings, especially for accumulated neighbourhood exposures. However, previous research observed robust effects of long-term neighbourhood poverty on health, also after adjusting for long-term personal income (Do, 2009). Finally, we cannot rule out reverse causalities and neighbourhood self-selection; the latter was found to be a minor source of bias in health studies (James et al., 2015).

5. Conclusion

Our longitudinal case-control study found no clear evidence that cumulative neighbourhood effects (i.e. social fragmentation, unemployment rate, urbanicity) along people's 15-year residential histories result in substantial differences in suicide mortality compared to current neighbourhood exposures. Nor did we find evidence that exposures based on comprehensive residential histories result in stronger associations with suicide than exposures averaged across a few time points. Further research is needed in populations with more inequality and neighbourhood change to verify our findings and to shed more light on long-term neighbourhood effects on mental health.

Funding

The research leading to this paper received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No 714993). The funders played no role in study design, data collection, data analysis, data interpretation, or writing of the article. Both authors had full access to the data and had final responsibility for the decision to submit for publication.

CRediT authorship contribution statement

Paulien Hagedoorn: Conceptualization, Methodology, Analysis, Data curation, Writing - Original Draft, Visualization. **Marco Helbich:** Conceptualization, Methodology, Resources, Writing - Review & Editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors have no conflict of interest to declare.

Acknowledgements

This study made use of the Open Data Infrastructure for Social Science and Economic Innovations (ODISSEI) in the Netherlands. We thank the editor and the anonymous reviewers for their suggestions to improve the original draft of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2021.102543.

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