

# Parents and Peers: Parental Neighbourhood- and School-Level Variation in Individual Neighbourhood Outcomes Later in Life

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## Abstract

Growing up in a disadvantaged parental neighbourhood is related to long-term exposure to similar neighbourhoods as adults. However, there are multiple socio-spatial contexts besides the residential neighbourhood to which individuals are exposed over the life course, such as households, schools, and places of work and leisure, which also influence their outcomes. For children and adolescents, the school environment is especially important. We argue that leaving these contexts out of consideration in models of neighbourhood effects could lead to a misspecification of the relevance of the residential environment in determining individual outcomes. This study examines the joint influence of the parental background, the parental neighbourhood, and a compositional measure of the childhood school environment, on individual neighbourhood trajectories later in life. We use Dutch longitudinal register data to study a complete cohort of adolescents from 1999 to 2012. We fit cross-classified multilevel models to partition the variance of schools and parental neighbourhoods over time. We find that parental neighbourhood quality strongly determines children's residential outcomes later in life. The variation in individual neighbourhood outcomes at the school level is explained by the ethnicity, parental income, and personal income of the research population, suggesting grouping of children from particular backgrounds into specific school environments.

## Introduction

There is a large body of literature on the effects of the residential environment on individual life outcomes and attainments, so-called neighbourhood effects (Ellen and Turner, 1997; Sampson, Morenoff and Gannon-Rowley, 2002; Galster, 2002, 2012; Dietz, 2002; Friedrichs and Blasius, 2003; Crowder and South, 2003; Durlauf, 2004; Wilson, 2012; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinhans, 2016). Particularly, neighbourhoods with a high percentage of low-income

residents (lowest 20 per cent incomes) are commonly assumed to have a negative impact on the life chances of their residents, with this spatial deprivation strengthening the consequences of individual disadvantages. However, an individual's neighbourhood does not necessarily represent the main and only socio-spatial context to which they are exposed in everyday life (Wheaton and Clarke, 2003; Kwan, 2012; van Ham and Manley, 2012). There are multiple contexts besides the residential environment, which unfold in parallel to one

another, in which individuals reside and interact on a daily basis, such as their households, schools, and work and leisure locations (van Ham and Tammaru, 2016; de Vuijst, van Ham and Kleinhans, 2017). These socio-spatial environments are interrelated and can affect individual lives in numerous ways (van Ham, Tammaru and Janssen, 2018). For this reason, they cannot be overlooked in a wider discussion on the reasons behind individual deprivation, poverty, and a wide range of personal outcomes over time (Buck, 2001).

The effect of a specific socio-spatial context on individual outcomes varies over time and over the life course. There is a strong belief that events in an individual's life are strongly affected by their previous experiences over time. This is a central premise in the life course approach, which purports that in addition to effects arising from multiple interrelated socio-spatial contexts, these effects can *accumulate over time* (Dykstra and van Wissen, 1999; Feijten, 2005; Feijten, Hooimeijer and Mulder, 2008). For example, it is likely that the longer or more frequent the exposure to a negative environment is, the stronger its negative effects will be on an individual (de Vuijst, van Ham and Kleinhans, 2017). Research has established that there are even intergenerational dependencies, showing a clear link between the outcomes of parents and their children over long periods of time. Socio-economic characteristics and (dis)advantage have repeatedly been shown to transfer between generations (Blanden, Gregg and Machin, 2005; Bloome, 2014), and recently, residential neighbourhood status has been shown to follow similar patterns (Sharkey and Elwert, 2011; Hedman *et al.*, 2013; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinhans, 2017). Studies from The Netherlands, Sweden, and the United States have shown that children who grew up in deprived parental neighbourhoods are more likely to reside in similarly poor neighbourhoods as adults over their life course (Sharkey and Elwert, 2011; Hedman *et al.*, 2013; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinhans, 2017).

Existing literature on the intergenerational transmission of neighbourhood characteristics from parents to their children does not explicitly account for possible effects of other socio-spatial contexts. This article contributes to this emerging body of literature by examining the *joint* influence of the parental background, the parental neighbourhood, and a compositional measure of the secondary school environment. In this study we focus on the neighbourhood careers of Dutch adolescents, up to 12 years after leaving the parental home. We argue that the secondary school (high school) environment of this young subpopulation is of particular

importance to their individual outcomes later in life, including the neighbourhoods they end up living in. The school environment is one of the settings where they have to spend the majority of their time (for a number of years) and are exposed to social networks and peers. This exposure is likely to affect their views, behaviour, and even norms and values. By examining the effects of multiple socio-spatial contexts (van Ham and Tammaru, 2016) on personal neighbourhood outcomes over time, we thus expand on previous research into the intergenerational transmission of neighbourhood characteristics.

In this study we make use of longitudinal register data provided by Statistics Netherlands, which has been geo-coded at the individual level. Using these data we were able to follow a complete cohort of young Dutch residents for a period of 13 years, from 1999 to 2012, who left the parental home in 2000. After the necessary data selections, we track 18,169 young Dutch inhabitants that attend 389 different schools and live across 10,678 different parental neighbourhoods (500 × 500-metre grids). We have complete individual neighbourhood histories available for this subpopulation, after they leave the parental home, as well as information on their school environment and core demographic and socio-economic characteristics. We were fortunate enough to have these data on education to our disposal, especially since school-related data are commonly unequivocally scarce in the field of neighbourhood effects research (Nieuwenhuis and Hooimeijer, 2016). We fit cross-classified multilevel models, to partition the variance of both socio-spatial settings, assessing their level of influence on individual neighbourhood outcomes over time. Despite the fact that we have rich population data, our data and approach also have several limitations which affect our ability to include control variables and test certain hypotheses from the literature. These limitations will be discussed in detail in the final section of the article.

## Literature Review and Background

Over their life course, people find themselves in distinct, time-ordered contexts: they move through an array of overlapping socio-spatial settings, in which they live, work, attain education, and spend leisure time (de Vuijst, van Ham and Kleinhans, 2016, 2017). Within all of these contexts or domains (van Ham and Tammaru, 2016), people have their day-to-day social interactions, and are additionally exposed to a wide range of constraints and freedoms that emerge from environmental, institutional, and geographical influences (see Galster, 2012

for an extensive discussion of these influences at the residential neighbourhood level).

According to the life course approach, all these factors emerging from multiple socio-spatial contexts jointly affect individual outcomes over time (Dykstra and van Wissen, 1999; Feijten, 2005; Feijten, Hooimeijer and Mulder, 2008). The effects of different socio-spatial contexts can accumulate and strengthen each other, but they can also partly cancel each other out. Therefore, any point in an individual's biography must be seen as part of this broader 'range' of connected events (also see de Vuijst, van Ham and Kleinhans, 2016). As such, an individual outcome in a particular period of life must be seen in relation to both foregoing and current experiences in a number of parallel individual careers, related to education, the household, housing, work, and leisure. An increasing number of authors now stress that taking into account combinations and accumulations of socio-spatial settings over the life course is important to better understand the connections between contextual factors and a given individual outcome (Sharkey and Elwert, 2011; Musterd, Galster and Andersson, 2012; Galster, 2012; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinhans, 2016, 2017). In this study we specifically investigate the combined effects of two socio-spatial domains, that both play an important role in adolescence, on individual neighbourhood careers later in life, the parental residential neighbourhood, and the secondary school environment.

### The Impact of the Residential Neighbourhood

The residential neighbourhood context is related to individual (dis)advantages. Affluent residential neighbourhoods, for instance, are positively associated with the social mobility of their residents, as well as their educational attainment and levels of income (van der Klaauw and van Ours, 2003; Simpson *et al.*, 2006; van Ham *et al.*, 2014). Deprived neighbourhoods, on the other hand, have been shown to be negatively associated with a large variety of personal outcomes, ranging from childhood achievement to delinquent behaviour (for a compilation, see Ellen and Turner, 1997; Overman, 2002; Friedrichs and Blasius, 2003; Galster, Andersson and Musterd, 2010). Most of these studies were unable to examine the effects of long-term individual neighbourhood experiences, often due to a lack of longitudinal geo-coded data (Sharkey and Elwert, 2011; Galster, 2012; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinhans, 2016, 2017). Therefore, findings of neighbourhood effects have often been based on cross-sectional measures of individuals' neighbourhood

characteristics and their instant effect on current individual outcomes (Sharkey and Elwert, 2011; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinhans, 2016, 2017). In recent years however, as data quality has improved, researchers have been able to approach the understanding of neighbourhood effects *over time* (Hedman *et al.*, 2013; de Vuijst, van Ham and Kleinhans, 2016, 2017), even spanning across generations. This has also sparked an interest in better understanding the long-term neighbourhood careers of individuals (see van Ham *et al.*, 2014), which is the focus of the current article.

A previous study on the neighbourhood histories of individuals in The Netherlands (de Vuijst, van Ham and Kleinhans, 2017) found that children from poor parental neighbourhoods were likely to live in similarly poor neighbourhoods later in life, up to 13 years after leaving the parental home (de Vuijst, van Ham and Kleinhans, 2017). This finding was in line with research conducted in Sweden and the United States (Sharkey and Elwert, 2011; Hedman *et al.*, 2013; van Ham *et al.*, 2014), which additionally showed that neighbourhood experiences over time had a strong cumulative effect on current individual residential outcomes.

The literature suggests a number of core transmission and inheritance mechanisms which explain why the parental neighbourhood is a predictor for children's individual neighbourhood outcomes later in life as adults (Vartanian, Walker Buck and Gleason, 2007; Sharkey and Elwert, 2011; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinhans, 2017). First, a large number of studies have found parental income to affect their offspring's income, which in turn influences socio-economic attainment and selection into deprived neighbourhoods over time (Becker and Tomes, 1979; Solon, 2002; D'Addio, 2007). Therefore, part of an intergenerational pattern in neighbourhood outcomes will result from intergenerational income transmissions. It is therefore important to control models for individual income and parental income. Second, from a very early age, children are exposed to norms, values, and attitudes from their parents and people in their environments, including the residential neighbourhood (Galster, 2012; de Vuijst, van Ham and Kleinhans, 2017). This affects attitudes towards education and work but also attitudes towards what is a good residential environment to live in, thus playing a role in neighbourhood outcomes later in life, partly independent to the income mechanism described above (Bisin and Verdier, 1998; for an extensive discussion, see Galster, 2012). Third, adult children often choose, or end up in, similar neighbourhoods to the ones they grew up in because of a sense of familiarity and convenience

(knowledge of the area and the housing opportunities), belonging, or proximity to their family (see [de Vuijst, van Ham and Kleinhans, 2017](#)). Children are therefore likely to end up in neighbourhoods which are similar to the neighbourhoods of their parents. Ideally we would control for distance to parents in our models, which unfortunately was not possible. We will discuss this in the final section of this article.

### The Impact of the School Environment

This article tests whether next to the effect of the parental neighbourhood on neighbourhood careers of children later in life, there is an additional effect of the school environment or whether the school environment can partly explain the effects of the parental neighbourhood as found in previous studies?

Education is one of the most important attainable resources over an individual's life course, which strongly determines future career opportunities, and subsequently affects income levels later in life. Previous research in The Netherlands has shown that educational attainment can in fact discontinue the intergenerational transmission of neighbourhood disadvantage ([de Vuijst, van Ham and Kleinhans, 2017](#)). Individuals who grew up in poor neighbourhoods, and who attained higher education, are less likely to live in concentrated poverty neighbourhoods after leaving the parental home, compared to their counterparts with a lower level of education. It is important to note that this last result primarily applied to the native Dutch individuals within the research population. For individuals from a deprived parental neighbourhood *with* a non-Western ethnic minority background, higher educational attainment did not decrease their chance of living in concentrated poverty as an adult ([de Vuijst, van Ham and Kleinhans, 2017](#)), which was substantially higher than that of the native Dutch.

In addition to the actual education gained at secondary school, the school environment and its composition also play a role in determining personal outcomes later in life. Just like the neighbourhood environment ([Galster, 2012](#); [de Vuijst, van Ham and Kleinhans, 2017](#)), also the secondary school environment is an important site of everyday interactions with peers where adolescents are exposed to the norms, values, and attitudes of other pupils. Also in the school environment, peer role models influence adolescents' educational aspirations and outcomes, but also socio-economic status aspirations and expectation later in life (see [Berndt and Ladd, 1989](#); [Hallinan and Williams, 1990](#)). Assessing the effect of the parental neighbourhood on individual

neighbourhood outcomes later in life, without taking the school environment into account, is likely to overestimate the effect of the residential environment in determining individual life outcomes.

### Hypotheses

In this study, we examine the impact of the parental background, the parental neighbourhood, *and* the composition of the secondary school environment on individual neighbourhood outcomes after leaving the parental home. We expect that individuals from a relatively poor parental neighbourhood will have a higher chance of living in deprived neighbourhoods after leaving the parental home, compared to individuals from a more affluent parental background (*H1*). Additionally, we expect that individuals who attend a secondary school in which they are exposed to high percentages of peers from a poor background (*H2*) will have a higher probability of residing in poor neighbourhoods later in life compared to those who went to a school with a higher socio-economic status. We expect that controlling for the school environment will reduce the effect of the residential neighbourhood environment (*H3*).

### Data

In this study, we used administrative register data provided by Statistics Netherlands, compiled into the longitudinal System of Social statistical Datasets (SSD hereafter) in a Remote Access facility. The SSD is an integrated database comprising various surveys and registers, which contain core demographic, socio-economic, and consistent geographical observations on the entire Dutch population tracked from 1995 to 2014. Using the SSD, we could thus distinguish this information for individuals in our selected subpopulation, and we could additionally access the characteristics of their parents and further family members ([Bakker, van Rooijen and van Toor, 2014](#)). All available registers are linked at the individual level, which allowed us to examine individual neighbourhood outcomes over time. Since 1999, the quality of the SSD registers increased in terms of the available number of socio-economic and demographic observations ([de Vuijst, van Ham and Kleinhans, 2017](#)). For the most recent years, not all registers have been released in full for public use. For these reasons, the measurement period for this study ranged from 1999 to 2012. We thus followed individuals for a period of up to 14 years.

In this study, we made a number of population selections. To establish our subpopulation, we selected

individuals from four different birth cohorts; born between 1980 and 1983. We thus restricted the selection to individuals of age 16–19 years in 1999. Further requirements entailed that individuals were not missing information on parental characteristics or residential location or had died or emigrated during the measurement period. They further had to have full demographic, socio-economic, and residential information available at the individual level and were required to be school-going and living with their parents in 1999. The individuals had to have left the parental home in 2000, starting their individual neighbourhood trajectory (de Vuijst, van Ham and Kleinhans, 2017). We used 1 year of geographical observations to define the subpopulation's neighbourhood experiences before leaving the parental home, namely 1999. As previous research has shown neighbourhood characteristics to be highly correlated throughout childhood, we do not expect this selection to have produced bias in representing the childhood neighbourhood experience (Kunz, Page and Solon, 2003; Vartanian, Walker Buck and Gleason, 2007; Manley *et al.*, 2013; de Vuijst, van Ham and Kleinhans, 2016, 2017). Finally, if the individual and their partner (registered partnership or marriage) were both present in our subpopulation, one of them was dropped at random, so as to avoid dependencies between person-records. We subsequently reorganized the data into person-year format. Table 1 provides an overview of core descriptive statistics at the individual level for our subpopulation, which consisted of 18,169 young Dutch inhabitants ( $N$ ).

In The Netherlands pupils typically attend schools that are in close proximity to their parental home. When looking at a basic summary of the number of schools per neighbourhood in our data, we see that while in one neighbourhood pupils go to nine different schools, in 22.54 per cent of neighbourhoods they go to only one; see Table 2 below. When taking a closer look at the schools per neighbourhood however, we did find that in those neighbourhoods in which young inhabitants go to more than one school, the majority still attend the same school, but at different levels, which are coded separately in the data. This results in a higher overlap between young neighbours and fellow pupils in practice than the 22.54 per cent might suggest.

The SSD provides geographical information on the individual level, most of which is highly consistent over time. We had access to a range of geographical variables, including individuals' location on the level of the municipality, neighbourhood, postal code area, and small grid cells. Standard Dutch administrative units, such as postal code areas, vary a lot in geographical size

and are relatively large and can change over time, which makes them unlikely to reflect their inhabitants' perceived neighbourhood environment. We therefore selected  $500 \times 500$ -metre grid cells to define neighbourhood boundaries in this study. Research has shown that the size of these grids is particularly likely to reflect people's perception of their direct residential environment (see Kearns and Parkinson, 2001; Wassenberg *et al.*, 2006; Musterd *et al.*, 2011). The Netherlands is composed of 34,094 inhabited  $500 \times 500$ -metre grid cells which contain 496 inhabitants on average (de Vuijst, van Ham and Kleinhans, 2017). Statistics Netherlands only allowed us to use those grids containing ten or more inhabitants. The advantage of grid cells is that we can compare equally sized, small spatial units throughout The Netherlands, the boundaries lines of which are constant over time. We argue that these grids are a suitable spatial scale at which to examine individual neighbourhood histories. Our subpopulation attended 389 different schools and lived across 10,678 different parental neighbourhoods (grids).

In our focus on neighbourhood outcomes over time, we constructed a scale to depict the concentration of poverty within a residential neighbourhood, i.e. within the grid, which served as one of our parental neighbourhood-level variables. Using economic data on the entire Dutch population, we constructed income-quintiles.<sup>1</sup> Quintile 1 contained all inhabitants who fell within the higher 20 per cent of incomes, while Quintile 5 contained those who were among the lowest 20 per cent of incomes. We subsequently constructed neighbourhood-quintiles, to define poverty concentrations based on the share of low-income neighbours (de Vuijst, van Ham and Kleinhans, 2017). Neighbourhoods in neighbourhood Quintile 1 have the lowest concentration of poverty, while those in the Quintile 5 have the highest concentration of poverty. We will refer to these latter neighbourhoods as deprived neighbourhoods hereafter. This latter neighbourhood quintile is used throughout the analyses as the parental neighbourhood predictor variable 'concentration of lowest incomes'.<sup>2</sup> We used individual incomes to construct this neighbourhood deprivation scale; although using household income would have been preferable, we were unable to derive reliable household incomes from the data, due to registration limitations in the Dutch national data. It is nonetheless important to take into consideration that poverty should ideally be measured for households.

Using a similar method, we created a compositional measure of the secondary school environment of our subpopulation in 1999, the year before leaving the parental home. Using the previously constructed



**Table 1.** Descriptive statistics of anchor population in 1999 (in the parental home), 2000 (having left the parental home), 2006, and 2012

	1999	2000	2006	2012
Age mean (standard deviation)	17.97 (0.86)	18.97 (0.86)	24.97 (0.86)	30.97 (0.86)
Share males	38.65	38.65	38.65	38.65
Ethnic background				
Dutch	86.28	86.28	86.28	86.28
Moroccan	1.23	1.23	1.23	1.23
Turkish	1.34	1.34	1.34	1.34
Surinamese	1.38	1.38	1.38	1.38
Antillean/Aruban	0.56	0.56	0.56	0.56
Other non-western	2.26	2.26	2.26	2.26
Other western	6.95	6.95	6.95	6.95
Share students <sup>a</sup>	–	97.44	24.10	1.68
Level of education <sup>a</sup>				
Low	–	67.70	22.50	9.93
High	–	32.30	77.50	90.07
Level of secondary school education				
MAVO/VMBO/HAVO	40.51	40.51	40.51	40.51
VWO/Atheneum/Gymnasium	59.49	59.49	59.49	59.49
Share with children	0.02	0.11	3.59	35.91
Share single household <sup>b</sup>	–	65.29	42.61	25.33
Share primary income from benefits	23.65	2.22	8.08	10.68
Share primary income from work	76.35	97.78	91.92	89.32
Income (1,000 EUR) mean (standard deviation)	3.38 (5.38)	8.17 (6.94)	22.01 (13.70)	40.43 (24.25)
Housing tenure <sup>c,d</sup>				
Homeowner	80.77	49.17	44.88	62.00
Rent	19.21	50.78	54.67	37.48
Residential location				
Four biggest municipalities	6.57	23.88	30.83	35.53
35 following biggest municipalities	22.65	60.05	42.13	32.59
Other municipality	70.79	16.07	27.04	31.87
N	18,169	18,169	18,169	18,169

Notes: Unless otherwise indicated, values are reported in percentages. As some variables contain missing or unknown values, not all values will sum up to 100 per cent.

<sup>a</sup>All anchors were required to be in secondary school in 1999.

<sup>b</sup>All anchors were registered as 'children within the parental home' in 1999, and the 'single household' category was therefore not applicable for this year.

<sup>c</sup>The homeowner category refers to the record of the building in the national housing registers, not the individual residing in it. Therefore, the homeowner category may include individuals who rent from a landlord/lady who did not officially declare their property to be let out to tenants.

<sup>d</sup>The housing tenure in 1999 refers to the parental home.

income-quintiles, we created school-quintiles, in which schools in Quintile 1 have a low concentration of peers from low-income parents, whereas schools in Quintile 5 have a high concentration of these pupils. The fifth quintile was again used to depict the highest concentration within the models. Additionally, as a school-level predictor variable, we included a measure indicating the educational level the pupils were enrolled in. In the Dutch educational system, the majority of schools offer several levels of education, ranging from low/middle (VMBO/MAVO/HAVO—preparing pupils for higher vocational/professional education) to high (VWO—generally

preparing pupils for university education). Nevertheless, the Dutch registers do not contain information on contact frequency between individuals or subjective measures on experiences in the school environment. By creating a measure for pupils' educational level, essentially a smaller unit within the school environment, we aim to capture the fellow pupils that individuals are likely in regular contact with, due to the fact that they will share courses and social events. In doing so, we hope to approach a peer influence mechanism which can be at play in the school environment, and which can affect later outcomes in life.

**Table 2.** School-neighbourhood connection: percentage of pupils by number of parental neighbourhoods at  $t^0$  (1999)

	Per cent
Neighbourhood sends young inhabitants to one school	22.54
Neighbourhood sends young inhabitants to two schools	16.67
Neighbourhood sends young inhabitants to three schools	13.61
Neighbourhood sends young inhabitants to four schools	10.49
Neighbourhood sends young inhabitants to five schools	9.13
Neighbourhood sends young inhabitants to six schools	7.20
Neighbourhood sends young inhabitants to seven schools	6.37
Neighbourhood sends young inhabitants to eight schools	4.65
Neighbourhood sends young inhabitants to nine schools	3.15

*Notes:* Unless otherwise indicated, values are reported in percentages. As Statistics Netherlands did not allow us to include neighbourhoods that send their young inhabitants to ten schools or more (to avoid the possibility of exposing specific residential locations and its inhabitants), not all values will sum up to 100 per cent.

## Analytic Strategy

Recent research from The Netherlands, Sweden, and the United States has shown that individuals who grew up in deprived parental neighbourhoods experienced long-term exposure to similar neighbourhoods over their life course (Sharkey and Elwert, 2011; Hedman *et al.*, 2013; van Ham *et al.*, 2014; de Vuijst, van Ham and Kleinjans, 2017). In this study, we used cross-classified multilevel models to examine how individual neighbourhood outcomes are likely to develop after leaving the parental home, given the parental background, the parental neighbourhood, and the composition of the secondary school. We argue that cross-classified models are suitable, as individuals in our data were nested in specific parental neighbourhood/school environment combinations. Therefore, they were hierarchically classified on more than one dimension (Fielding and Goldstein, 2006). Using the cross-classified models, we were able to partition the variance of both spatial settings, to assess their relative importance to individual neighbourhood outcomes over time. The dependent variable in these models was the probability of residing in a deprived neighbourhood some time after leaving the

parental home (also see de Vuijst, van Ham and Kleinjans, 2017).

The cross-classified model can be seen as a constrained three-level model, with pupils (Level 1) nested in parental neighbourhoods (Level 2) nested in a single artificial super cluster (Level 3) (Leckie, 2013). This single artificial super cluster represents the single education authority in The Netherlands encompassing all schools in the data. The 389 different schools in our data result in a 389 by 389 variance-covariance matrix. Entering the schools into the models by means of the single cluster simply sets all variances to equal, and all covariances to zero (hence, constrained model), providing us with a single random part parameter, or between-school variance component (Leckie, 2013). We fitted the cross-classified models in five steps. In Models 1 and 2 (the null or empty models), we only included the intercept, neighbourhood random effects (Model 1), and school random effects (Model 2). We thus split the total variance in residing in concentrated poverty over time into separate variance components over the levels in the models. In Model 3, we added individual-level predictor variables, and further adjusted for individual background characteristics, which will briefly be discussed below. In Model 4, we added the parental neighbourhood-level predictor variable ‘concentration of lowest incomes’, as previously discussed. And finally, in Model 5, we added the school-level predictor variable ‘share peers from low income parents’, as well as a measure indicating the educational level the pupils were enrolled in at secondary school, ranging from low to high.

Cross-classified models, as specified above, assume school and neighbourhood effects to be additive by default. However, even after controlling for neighbourhood main effects, the effect that a school environment may have on its pupils’ outcomes later in life can differ for pupils from different parental neighbourhoods: as the effects of secondary schools and parental neighbourhoods on individual neighbourhood outcomes might interact (Leckie, 2013). For this reason, to relax this additive random-effects assumption, we included a random school-by-parental neighbourhood interaction classification in all our models, allowing for school and parental neighbourhood effects to be potentially non-additive (interaction parameters not reported/discussed).

We controlled for a selection of individual, household, and school characteristics, described in Table 1 above, which were included from Model 3 onwards. In addition to the possible intergenerational and school-level determinants of residential outcomes, we have to consider that individuals’ personal and partnered/

household choices and preferences play an important role in residential outcomes. Individual and partners' annual income were included as a core socio-economic observation. We further included the individual's gender; their age; whether they were single/in a relationship; the presence of children in the household, homeownership/rent; higher education; and whether they belonged to one of the main ethnic minority groups in The Netherlands (Moroccans, Turks, Surinamese, and Antilleans/Arubans). We also adjusted for the income of the parental household, in 1999. All variables included were centred around their mean.

It would have been desirable to include more variables which according to the relevant literature affect residential choices. However, we faced two major limitations. The first is that although we had access to unique and rich population data, we were limited to information that was available in official registers and accessible for research. The second limitation relates to hardware capacity restrictions (memory and processor) on the secure servers of Statistics Netherlands. To be as efficient as possible, all models were run (repeatedly) on a random sample of 25 per cent of our subpopulation ( $N = 4,542$ ). Using the full data set in combination with a cross-classified multilevel model was not possible, and even with this smaller sample, we were limited in the number of variables we could include in our models. We also ran models on a 10 per cent sample to check whether including additional variables (presence of children, higher education, and partner's income) affected our model outcomes. On the smaller sample none of these additional variables had a significant effect on the model outcomes, and therefore, we did not include them in the final models. As a result, we continued to use the 25 per cent sample and include both parental neighbourhood and school characteristics in the model.

## Results

Table 3 shows the results from the cross-classified multilevel models on the individual probability of residing in a poverty concentration/deprived neighbourhood after leaving the parental home halfway through the measurement period, in 2006. In Model 2, we see a simple decomposition of the total variance in individual neighbourhood outcomes into separate school and parental neighbourhood variance components, respectively, estimated at 0.120 and 0.189. In comparison to Model 1, we find that the addition of the school-level variance component only moderately affects the variation in neighbourhood outcomes at the parental neighbourhood level, thus far showing distinct effects of both spatial

settings on individual neighbourhood outcomes after leaving the parental home.

In Model 3, we find that after adding a limited set of personal-level predictor variables, the between-school variance in individual neighbourhood outcomes is reduced from 0.120 to 0.060 and is no longer significant, while the between-parental neighbourhood variance is now 0.138. These results indicate that the individual characteristics have substantial explanatory power in determining neighbourhood outcomes over time, as one would expect, and further highlight that there are large disparities between the individuals in our subpopulation at the start of their independent residential neighbourhood history. Looking at the fixed part parameter estimates, the effects of the personal characteristics on neighbourhood outcomes are in line with those found in previous studies. In particular, individuals whose parental income levels are higher are less likely to reside in deprived neighbourhoods in their own residential trajectory as adults. Compared to the estimates found in Model 2, the combined effect of the personal characteristics, and parental characteristics in Model 3 (as well as the neighbourhood exposure that took place over the measurement period) explains 27 per cent ( $-0.27 = (0.138 - 0.189)/0.189$ ) of parental neighbourhood variance in individual neighbourhood outcomes over time. The school variance is no longer significant after this extension of the model. When separately assessing the personal characteristics (results not shown), we find that the predominant decrease in school-level variance was due to the addition of ethnicity, income, and parental income to the model. This suggests grouping of children from specific ethnic and parental backgrounds into similar school environments. A large percentage of variance in individual neighbourhood outcomes at the level of the parental neighbourhood has yet to be explained.

For that purpose we add additional explanatory variables in Model 4. Here we find that the parental neighbourhood-level predictor variable 'concentration of the lowest incomes' further reduces the between-parental neighbourhood variance in individual residential outcomes from 0.138 to 0.022, and it is no longer significant. This result indicates that at the parental neighbourhood level, poverty concentration is a core explanatory factor in determining children's neighbourhood outcomes after leaving the parental home. This finding reaffirms previous results in The Netherlands and demonstrates once more the importance of parental neighbourhood deprivation in explaining individual neighbourhood outcomes, even after controlling for personal characteristics and parental income. This result



**Table 3.** Cross-classified multilevel model on individual chance of residing in poverty concentration/deprived residential neighbourhood after leaving the parental home (2006)

	(1)		(2)		(3)		(4)		(5)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Male			0.473***	0.073	0.462***	0.071	0.450***	0.072	0.446***	0.072
Single			0.460***	0.073	0.451***	0.072	0.446***	0.072	0.446***	0.072
Age			-0.120**	0.044	-0.118**	0.043	-0.110**	0.044	-0.110**	0.044
Ethnic minorities (ref = no)			0.422***	0.134	0.364**	0.144	0.370**	0.143	0.370**	0.143
Rent (ref = homeowner)			0.485***	0.074	0.481***	0.073	0.478***	0.073	0.478***	0.073
Income (1,000 EUR)			-0.286***	0.046	-0.280***	0.045	-0.275***	0.045	-0.275***	0.045
Income parents (at $t^0$ )			-0.213***	0.070	-0.185**	0.070	-0.187**	0.069	-0.187**	0.069
Parental neighbourhood characteristics										
Concentration lowest incomes					0.289***	0.070	0.288***	0.070	0.288***	0.070
Concentration ethnic minorities					0.003	0.004	0.004	0.004	0.004	0.004
School characteristics										
Concentration peers poor parents							0.017	0.013	0.017	0.013
Educational level (ref = low)							-0.092	0.083	-0.092	0.083
Middle/high										
_cons	-1.003***	0.039	-1.194***	0.081	-1.140***	0.069	-1.119***	0.070	-1.091***	0.070
Random-effects parameters										
Between-school variance	-	-	0.120	0.055	0.060	0.033	0.061	0.034	0.052	0.032
Between-neighbourhood variance	0.191	0.075	0.189	0.073	0.138	0.074	0.022	0.105	0.019	0.106
N	4,542		4,542		4,542		4,542		4,542	

\*  $P < 0.05$ , \*\*  $P < 0.01$ , \*\*\*  $P < 0.001$ .

thus re-emphasizes the importance of exposure to neighbourhood deprivation *over time*, even spanning across generations, on personal outcomes. When adding parental neighbourhood characteristics in Model 4, this does not affect the school-level variance compared to Model 3, but it is important to remember that this was no longer significant after the addition of the personal characteristics in Model 3. In Model 4, we did not find a significant effect of the share of ethnic minorities in the parental neighbourhood on individual neighbourhood outcomes later in life.

In the final Model 5, we included the full range of controls and predictor variables at the parental, individual, parental neighbourhood, and the secondary school level on the individual chance of residing in a deprived neighbourhood after leaving the parental home. We did not find an effect of school characteristics on individual neighbourhood outcomes: both the share of school peers with low-income parents and the educational level of the student's class do not show significantly affect neighbourhood outcomes later in life. An LR test between Models 5 and 4 does show that the two added school-level predictors slightly improve the fit of the model. Additionally, the inclusion of the school-level variables very marginally reduces the remaining variance at both the between-school variance in individual neighbourhood outcomes and the between-parental neighbourhood variance. Extensions to these school-level predictors, such as the share of students from an ethnic minority background, did not show additional significant results (analyses not shown). The results for the full models in years towards the end of the measurement period (not shown, but available upon request) show a very similar pattern to those in 2006, suggesting a long-lasting effect of the quality of the parental neighbourhood on individual neighbourhood outcomes later in life.

## Discussion and Conclusion

In this study, we focussed on the neighbourhood outcomes of young adults in The Netherlands, after leaving the parental home. We examined the joint influence of the parental background (parental income), the parental neighbourhood, and a compositional measure of the school environment: multiple factors and socio-spatial contexts that may influence individual chances of residing in poverty concentration later in life. In doing so, we contribute to the literature in two distinct ways. First, we add to the growing body of literature that takes a dynamic, long-term perspective to neighbourhood effects. These studies show that individual outcomes are influenced not only by the current residential environment

but by neighbourhood experiences *over time*, even spanning across generations (Sharkey and Elwert, 2011; Hedman *et al.*, 2013; van Ham *et al.*, 2014; Sharkey and Faber, 2014; de Vuijst, van Ham and Kleinhans, 2017). Second, firmly inspired by the life course approach, we add to the literature by assessing the effects of multiple socio-spatial contexts on neighbourhood outcomes later in life. We argued that leaving out of consideration other possible socio-spatial contexts than the residential neighbourhood could lead to an overestimation of the importance of the residential environment in shaping individual outcomes in life.

By adding the school environment into previously established models on the intergenerational transmission of neighbourhood characteristics, we found that in The Netherlands *both* parental neighbourhood and school environments explain variance in the neighbourhood outcomes of young adults. Adding the additional school context did improve the explanatory power of the models. As also previously found by others (see for example, Hedman *et al.*, 2013; van Ham *et al.*, 2014 for Sweden), our results showed that children who grew up in poverty concentration neighbourhoods (measured at the time of leaving the parental home) are more likely than others to reside in a poor neighbourhood as adults. This finding confirms the intergenerational link in the neighbourhood histories of individuals. The variance at the level of the school environment, on the other hand, was in fact explained by a number of personal characteristics of the research population, namely, their ethnicity, parental income, and personal income as adults later in life. Once added to the model, the school-level variance was insignificant. This latter finding strongly suggested that individuals from specific ethnic and parental backgrounds were grouped within the same school environments. We did not find evidence of an additional school environment effect above and beyond the effects of the parental neighbourhood on individual outcomes later in life.

In this article we were able to use unique geo-coded longitudinal register data for the whole population of The Netherlands. These data contained detailed information on individual residential neighbourhoods over the life course, as well as information on the school environment. Although the data were very rich, there are also several limitations of the data which affected our modelling strategy. Below we will discuss some of these limitations which might affect our ability to disentangle the possible confounding mechanisms that lead to individual residential decisions over time.

First we had no information in our register data on how and why people selected certain neighbourhoods. In our data we did not have access to information on

social ties and views on intergenerational responsibilities (van der Pers and Mulder, 2015), or information on housing allocation criteria or access rules (Butler, Hamnet and Ramsden, 2013), nor did we have information on the roles played by neighbourhood reputations, social networks and residents' neighbourhood attachment, in addition to economic factors (Temkin and Rohe 1996). Although our register data do have information on some other variables, such as household composition, family formation and divorce, we were not able to include these in our models due to hardware limitations in the secure remote access facilities that we had to use. Our register data did include detailed information on individual incomes, but we were not able to derive reliable household income variables from these, partly because the register data do not allow the identification of unmarried people forming a household. Future research might especially want to focus on the relationships between family formation and educational investments as strong competing mechanisms. For example, it is likely that the secondary school environment affects choices for subsequent education, and as a result affects labour market outcomes, incomes, and hence residential outcomes. To be able to analyse these mechanisms, even richer data are needed.

Another limitation of this study relates to the possible spatial relationships in the data. In The Netherlands the majority of low-income households live in social housing provided by housing associations. Such housing is allocated through a formal allocation system. We know from the literature that lower-income and lower-educated individuals live closer to their parents than higher-income and higher-educated individuals (Dykstra *et al.*, 2006), and the spatial clustering of social housing could partly explain the intergenerational transmission of neighbourhood context from parents to children. Ideally we would have controlled our models for the geographical distance between parents and children (which is also a proxy for social networks), but this was not possible due to the aforementioned hardware limitations. We already had to run our models on a small sample of our data, and even with these smaller samples we ran into serious hardware capacity problems of the secure servers we were working on. Not being able to control for distance between the parental neighbourhood and the residential neighbourhood of their children later in life might overestimate the effect of the parental neighbourhood. It could be that children who stay closer to their parents' neighbourhood are less likely to do well in terms of their own neighbourhood outcomes later in life because of the spatial patterning of housing and neighbourhood quality. But it is likely also the case that

a range of background factors (parental, individual, and contextual) influence how far people move from their parents' neighbourhood. And these mechanisms might be related to educational choices (less advantaged young people follow further education closer to their parents), which in turn influences labour market outcomes and hence future neighbourhood trajectories.

We could also not control our models for possible spatial autocorrelation between adjacent grid cells. This thus omits the potential spatial relationships between the neighbourhood and adjacent grids (White, 1983) and could lead to an overestimation of the effects of the neighbourhood variables. Better access to data and higher capacity hardware will help future research to investigate the potential roles of these other possible factors at play. Ideally we would also have liked to include more and better neighbourhood level variables in our model. We have now measured poverty neighbourhoods by using individual incomes (see also comment on this above), and ideally we would have liked to use household income here, as contextual poverty is better measured at the household level. Ideally we would also have controlled for other contextual dimensions of neighbourhoods, for example related to the housing composition.

Another limitation of our data relates to the school data used. Our data contain school codes by educational level. So it is possible that two children go to the same school, but at a different educational level, but we are not able to observe this in the data. We expected the school environment to play a role in outcomes later in life through peer group effects and role model effects, so from that perspective it is not so problematic that we only know who follows the same classes, without information on the actual school. We did not however find a significant effect for the concentration of peers with low-income parents, or the pupils' educational level. It is important to keep in mind that when using this type of register data, there is no information on, for instance, contact regularity or frequency between peers, or the transmission of norms and values between peers or between parents and children. For this reason, the added predictors and controls in our models may not serve as sufficient proxies to cover certain types of complex intra-family and intra-peer mechanisms behind individual neighbourhood outcomes over time.

Despite the data limitations, combined, the results from this study show that there is variation in individual neighbourhood outcomes after leaving the parental home at both the parental neighbourhood and the school level, controlling for parental income and individual characteristics. Poverty concentration is shown to be at the heart of the effect of the parental

neighbourhood, reconfirming that intergenerational residence in deprived neighbourhoods negatively affects individual neighbourhood outcomes over the life course. Personal characteristics of the research population are at the heart of the effect of the school environment, which suggest grouping of children into schools based on ethnic and parental income background. To our knowledge, we are the first to combine compositional characteristics of the school environment and the parental neighbourhood environment into one model of adult neighbourhood outcomes. Despite the aforementioned limitations of the data and our approach, the results of this study reinforce previous findings on intergenerational neighbourhood patterns and support the value of a life course perspective which encourages the examination of neighbourhood effects over time *and* the need to examine additional, parallel socio-spatial contexts which make up contextual effects on individual outcomes.

### Notes

- 1 Personal income was defined as the sum of income from a variety of sources, consisting of wages, benefits, and student scholarships (see de Vuijst *et al.* 2017).
- 2 While we of course appreciate the arbitrary nature of this income quintile categorization, it eased examination and interpretation of neighbourhood-level outcomes in the scope of this study.

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