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DISCUSSION PAPER SERIES

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ABSTRACT

The Temporal Dynamics of Neighborhood Disadvantage in Childhood and Subsequent Problem Behavior in Adolescence

Research on neighborhood effects has increasingly focused on how long children have lived in a deprived neighborhood during childhood (duration), but has typically ignored when in childhood the exposure occurred (timing) and whether circumstances were improving or deteriorating (sequencing). Using Dutch register data, we applied sequence analysis to simultaneously capture duration, timing, and sequencing of exposure to neighborhood (dis)advantage in childhood. Compared to children who lived in a deprived neighborhood throughout childhood, we found that children who were exposed to neighborhood deprivation only during adolescence were equally likely to become a teenage parent and were more likely to drop out of school. Unexpectedly, children who lived in an affluent neighbor-hood throughout childhood were most likely to engage in delinquent behavior.

JEL Classification: I30, J60, P46, R23

Keywords: neighborhood effects, temporal dynamics, childhood, adolescence, problem behavior, sequence analysis

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INTRODUCTION

It has repeatedly been shown that children who grow up in a deprived neighborhood are more likely to engage in several types of problem behavior during adolescence than children growing up in more affluent neighbourhoods (for reviews, see Ginther et al., 2000; Jencks & Mayer, 1990; Gaias et al., 2017; Pebley & Sastry, 2004; Sampson et al., 2002). For example, previous studies have found neighborhood effects on high school dropout rates (Crowder & South, 2003, 2011; Harding, 2003; Overman, 2002; Wodtke et al., 2011, 2016), juvenile delinquency (Damm & Dustmann, 2014), adolescent substance use (Kulis et al., 2007), and teenage childbearing (Crane, 1991; Harding, 2003; South & Crowder, 2010; Wodtke, 2013). Yet, while there is extensive empirical evidence supporting the existence of neighborhood effects on adolescent development and behavior, a recurring issue is that the estimated effects are often relatively weak. Moreover, when family socioeconomic status, school contextual variables, and parenting practices are controlled for, the estimated impact of the residential neighborhood typically becomes even smaller (Nieuwenhuis & Hooimeijer, 2016). This has led several researchers to be sceptical about the importance of neighborhood context in shaping young people's life perspectives (Ellen & Turner, 1997).

One reason for why in general only weak neighborhood effects are observed could be that previous research has often neglected or not adequately addressed the temporal dynamics of children's neighborhood context (Sharkey & Faber, 2014). Until recently, research has almost exclusively relied on single point-in-time indicators of children's neighborhood characteristics (e.g., Brooks-Gunn et al., 1993; Crane, 1991; Sucoff & Upchurch, 1998). These measures have been criticized for the fact that children's neighborhood characteristics may change over time, either because families move to a different neighborhood or because neighborhoods themselves change over time (Kleinepier & van Ham, 2017a). The increasing availability of longitudinal data has enabled more recent studies to develop more dynamic measures of children's neighborhood experiences. Most of these studies have focused on the *duration* of exposure to poor and nonpoor neighborhoods during childhood, showing that measures of cumulative exposure exert a stronger effect on outcomes in later life than point-in-time measures of neighborhood (dis)advantage (Crowder & South, 2011; South & Crowder, 2010; Wodtke et al., 2011).

However, while researchers have increasingly focused on the amount of time children spend living in poverty neighborhoods during childhood, little attention has been paid to examining whether the *timing* of exposure (e.g., early childhood vs. adolescence) to neighborhood (dis)advantage has differential effects on adolescent outcomes. At the same time, both theory and empirical research suggest that the consequences of living in a deprived neighborhood may vary across different developmental periods in childhood (Anderson et al., 2014; Wheaton & Clarke, 2003; Wodtke, 2013; Wodtke et al., 2016). The few prior studies that have investigated timing effects of neighborhood (dis)advantage have typically estimated the effect of neighborhood deprivation at one stage in childhood on some dependent variable while controlling for neighborhood deprivation at other stages (e.g., Wodtke, 2013; Wodtke et al., 2016). A disadvantage of this approach is that it does not differentiate between children who live in a poor neighborhood throughout childhood, those who move into poor neighborhoods, those who move out of poor neighborhoods, and those who move in and out of poor neighborhoods. In other words, these studies do not take into account the *sequencing* of exposure to neighborhood deprivation during childhood. Although results are somewhat inconsistent, several studies suggest that moving to a poorer neighborhood during childhood is related to problem behavior of youth, highlighting the need to focus on sequencing of neighborhood poverty during childhood as well (Goldsmith et al., 2016; Kessler et al. 2014).

In this paper, we apply sequence analysis (Abbott & Tsay, 2000) to simultaneously capture children's duration, timing, and sequencing of exposure to neighborhood disadvantage during childhood. Although sequence analysis has increasingly been used in the field of neighborhood studies, its application has so far mainly remained limited to visualization purposes (e.g., Coulter & van Ham, 2013; de Vuijst et al., 2017; van Ham et al., 2014; but for exceptions see Kleinepier & van Ham, 2017b; Lee et al., 2016). We go one step further and use optimal matching followed by cluster analysis to empirically categorize children into a limited number of groups on the basis of similarities in terms of duration, timing, and sequencing of exposure to neighborhood deprivation. The primary aim of this study is to examine how and to what extent such different patterns of exposure to neighborhood disadvantage during childhood are related to three types of problem behavior in adolescence, viz. teenage childbearing, school dropout, and delinquent behavior.

We make use of rich longitudinal microdata from the Dutch population registers which cover the entire population of the Netherlands. These register data provide detailed geocoded information on each individual's residence as well as a range of socioeconomic and demographic characteristics for every individual over a long period of time, allowing us to reconstruct children’s complete neighborhood histories. All children born in the Netherlands in 1995 are observed for a period of 20 years, i.e. from birth in 1995 up until age 19 in 2014 (N=168,645). We estimate a series of logistic regression models to assess how different patterns of exposure to neighborhood (dis)advantage in childhood affect the aforementioned problem behaviors in adolescence.

BACKGROUND

A large literature suggests that neighborhood disadvantage in childhood is associated with a range of adolescent outcomes such as deviant behavior, educational attainment, and cognitive development (Pebley & Sastry, 2004). Traditionally, studies linking neighborhood disadvantage during childhood to outcomes in later life have investigated the effects of single point-in-time measurements of neighborhood context on individual outcomes. For example, Crane (1991) defines teenagers’ neighborhood environments based on their places of residence in 1970. Similarly, Brooks-Gunn et al. (1993) and Sucoff and Upchurch (1998) measure children’s neighborhood characteristics specifically at age 14. However, recent research indicates that there is substantial variation over time in children’s neighborhood characteristics, particularly among those who moved (Kleinepier & van Ham, 2017a). This means that cross-sectional measures of children’s neighborhood characteristics do not provide an accurate representation of the experiences of deprivation that they endure in the long run. It has been argued that understanding the importance of children’s residential context requires a life-course perspective that takes into account complete neighborhood histories (Sharkey & Faber, 2014). In response, researchers have developed more dynamic conceptions of children’s neighborhood environments. We explain different approaches with a hypothetical example of five children who experience distinctive patterns of exposure to neighborhood deprivation (as indicated by shading) in Figure 1.

<<<Figure 1 about here>>>

Duration of Exposure

A common approach to measure children's neighborhood experiences longitudinally has been to focus on the duration of exposure to poverty neighborhoods during childhood, often referred to as 'cumulative exposure' models (Anderson et al., 2014). The assumption here is that children who are consistently exposed to neighborhood deprivation may be influenced more than those who experience socio-spatial disadvantage for only a short period of time. In fact, most theories on neighborhood effects assume, at least implicitly, that people have been exposed to a neighborhood for a medium to long period of time (Galster, 2012). For example, a long stay in a neighborhood where social norms prevail which devalue education and condone crime might lead to lower educational attainment or delinquent behavior, whilst a brief period in such a neighborhood is likely not enough for the local values and behaviors to become internalized (Friedrichs & Blasius, 2003; Wilson, 1987). Likewise, the extent to which individuals are harmed by the physical conditions of a neighborhood (e.g., air pollution) strongly depends on the time spent in the neighborhood (Schwartz, 2006).

In line with this, several studies showed that measuring duration of exposure to neighborhood poverty during childhood yields stronger effects on outcomes in later life than measuring neighborhood characteristics at a single age in childhood (Crowder & South, 2011; South & Crowder, 2010; Wodtke et al., 2011; Wodtke, 2013; see also Timberlake, 2007). As regards the example in Figure 1, if it is indeed primarily the duration of exposure to neighborhood disadvantage driving problem behavior among youth, we would expect Person A to be affected strongest by neighborhood disadvantage because it lasts longest (i.e., throughout the entire childhood life course) and Person D and E to suffer the least consequences from their neighborhood deprivation.

Timing of Exposure

However, by solely focusing on the duration of exposure to neighborhood disadvantage during childhood, one would for example fail to recognize the obvious difference between Person B and C – both have lived in a deprived neighborhood for a duration of 10 years, but never at the same age (Figure 1). This brings us to a rather small body of research in which the importance of timing of exposure to disadvantaged neighborhoods during childhood is emphasized. There are two competing lines of reasoning in this regard. One line of reasoning argues that neighborhood disadvantage is particularly detrimental if experienced early in the childhood life course. This argument stems from developmental and brain research pointing to early childhood as the key period for cognitive development (Heckman, 2006) and a period of 'unique vulnerability to environmental influences' (Anderson et al., 2014: 125). Because children's cognitive skills develop by building upon prior knowledge and experiences, early childhood neighborhood disadvantage may place children on disadvantaged life-course trajectories and eventually lead to problem behavior in adolescence.

In somewhat indirect support of this, McCulloch and Joshi (2001) find that neighborhood poverty has a strong negative effect on test scores for children aged 4-5 years, a relatively weak effect for children aged 6-9 years, and no effect among children aged between 10-18 years. Furthermore, Wheaton and Clarke (2003) showed that exposure to neighborhood poverty in early childhood had larger effects on mental health in early adulthood than neighborhood disadvantage in adolescence or early adulthood. Finally, a study by Anderson et al. (2014) suggests that living in a neighborhood with more affluent residents in early childhood, but not adolescence, is associated with higher reading abilities in adolescence. Thus, several studies suggest that exposure to neighborhood disadvantage in early childhood, as opposed to other developmental periods in childhood, is most important for educational achievement and problem behavior of youth. If so, one would expect Person A, B, and D in Figure 1 to affected strongest by the neighborhood deprivation.

The second line of reasoning argues that neighborhood deprivation has stronger effects if it is experienced later in childhood (i.e., in adolescence). This argument is based on the fact that parents grant more autonomy to their children as they grow older. Consequently, adolescents have greater exposure to extrafamilial influences, including peers in the neighborhood and at school (Prinstein & Dodge, 2008). Indeed, the influences of peers on problem behavior have been found to be particularly strong during adolescence, likely because of increases in the amount of time spent with peers, the importance of peer relationships, and greater susceptibility to peer influences (Prinstein & Dodge, 2008). Additionally, children in adolescence are more aware of their potentially disadvantaged circumstances than young children which, in turn, might influence their academic aspirations (Wagmiller et al., 2006). Consistent with this reasoning, previous research showed that exposure to neighborhood poverty during adolescence has a stronger negative effect on high school graduation (Wodtke et al., 2016) and a more positive effect on teenage childbearing (Wodtke, 2013) than exposure earlier during childhood. In view of these theoretical propositions and empirical findings, we would expect that Person A, C, and E are harmed most by neighborhood deprivation (Figure 1).

Sequencing of Exposure

Importantly, however, as the latter example points out, an exclusive focus on the timing of neighborhood deprivation does not take into account the fact that Person A has lived in a deprived neighborhood throughout childhood, whereas Person C and E have moved into poverty neighborhoods during adolescence. Yet another line of argumentation emphasizes such changes in neighborhood circumstances, i.e., the sequencing of neighborhood deprivation. Research on the sequencing of neighborhood deprivation has mainly been concerned with children moving from a poor neighborhood to a more affluent neighborhood. For instance, the Moving To Opportunity (MTO) program in the US sought to relocate poor families out of high-poverty neighborhoods by providing housing vouchers. Studies on the MTO experiment portray a rather mixed picture, with some finding positive effects (Chetty et al., 2016) some finding negative effects (Kessler et al. 2014), and still others finding no effects at all (Ludwig et al., 2013) on adolescents' schooling and behavioral outcomes. A recent study using Dutch data showed that adolescents moving to a more affluent neighborhood are more likely to have increased levels of depression, social phobia, aggression, and conflict with their parents (Nieuwenhuis et al., 2017). Other research in the UK, however, found that downward movers had more mental health problems than those moving upward in neighborhood hierarchy (Tunstall et al., 2012). Regarding the example in Figure 1, if as some studies suggest that moving into poverty neighborhoods is most harmful for child development, we would expect Person C and E to be most likely to engage in problem behavior. However, if moving to a more affluent neighborhood leads to problematic behavior as other studies suggest, then Person B and D are in the least favorable position.

The Current Study

As the above sections have made clear, previous studies on the temporal dynamics of neighborhood disadvantage during childhood and outcomes in later life are inconclusive in their verdict. Our study addresses this ambiguity in two important ways. First, to our knowledge, this is the first study to simultaneously capture the duration, timing, and sequencing of exposure to neighborhood disadvantage in childhood and to use the different patterns of exposure to predict children's outcomes in later life. This allows for a direct test of the competing theoretical hypotheses outlined above (cf. Wagmiller et al., 2006). Second, because an important reason for inconsistent findings across studies may be the use of different outcome variables in these studies, we focus on three commonly studied types of adolescent problem behavior: teenage parenthood, school dropout, and delinquent behavior. In other words, the use of three different outcome variables allows us to examine whether different patterns of exposure to neighborhood (dis)advantage in childhood correspond differently to different types of problem behavior in adolescence.

DATA AND METHODS

This study uses longitudinal, geocoded administrative microdata derived from the Dutch population registers: the System of Social statistical Datasets (SSD; Bakker et al., 2014). The SSD, hosted by Statistics Netherlands, allows for combining data from various administrative sources for statistical purposes. The different administrative registers, including the municipal population register and tax registers, provide a wide range of demographic, socioeconomic, and geographic information on every legal inhabitant of the Netherlands for the period 1995–2014. We selected all children who were born in the Netherlands in 1995 and follow them from birth (in 1995) up until age 19 (in 2014). Children who themselves and/or whose both parents died or emigrated during the observation period were excluded from the analysis (N=23,107; 12%). This leaves us with a total research population of 168,645 children that are observed throughout their entire childhood.

Dependent Variables

We rely on three dependent variables covering different types of problem behavior in adolescence: (a) teenage parenthood, (b) school dropout, and (c) delinquent behavior. In Table 1, we show the percentage of children who exhibited each of the three types of problem behavior across ages 12-19 (none of the problem behaviors were observed before age 12). In line with previous research (Prinstein

& Dodge, 2008), Table 1 shows that problem behavior is most prevalent during late adolescence. Because only very few children engaged in problem behavior more than once, all three dependent variables were coded as dichotomous variables indicating whether or not the child has engaged in the problem behavior (0=no, 1=yes).

Teenage parenthood thus indicates whether the individual had become a parent before the age of 20. *School dropout* indicates whether the individual had left education without having obtained a start qualification before age 20. A start qualification is defined as a higher general or pre-university secondary school diploma ('havo' or 'vwo' graduate) or an intermediate vocational education diploma ('mbo' level 2 graduate). *Delinquent behavior* indicates whether the child had been sent to 'Bureau Halt'. Youth between the ages of 12 and 17 arrested by the police for having committed certain minor offences are referred to Bureau Halt. If the person carries out the Halt sanction satisfactorily, no further prosecution takes place and no entry is made in the criminal records.

<<<Table 1 about here>>>

Independent Variables

Our key independent variable is children's exposure to neighborhood disadvantage over the 20-year study period, i.e., from birth up until 19 years of age. This variable was constructed in several steps. The first step was to define the neighborhood boundaries. We opted to use 500x500 meter grids (based on geographical coordinates) for this because, in contrast to standard administrative units such as postal codes, grid cells are equally sized and their boundary lines are consistent across time. The latter is particularly important for longitudinal research, because it prohibits neighborhoods to change over time as a result of administrative boundary changes. Yet, a disadvantage of grid-defined neighborhoods is that they ignore physical barriers, such as a major highway or river.

The second step was to classify neighborhoods into different types. Although we recognize that neighborhood disadvantage can be measured with a wide-variety of indicators, we use the average income in the neighborhood due to its close relationship with the underlying social processes thought to be responsible for neighborhood effects (Wodtke, 2013). Specifically, we use data on the full population to compute the average individual income in each neighborhood for each year of observation[1]. Subsequently, we create quintiles based on the neighborhoods' average income from the poorest to the wealthiest of tracts. We treat the top 20 percent of the neighborhood income distribution as affluent, the bottom 20 percent as deprived, and the remaining 60 percent as middle-income neighborhoods. We thus break down each child's neighborhood history into a set of 20 discrete time units (one for each age) that can take three possible values: D (deprived), M (middle-income), or A (affluent). As an example, consider the sequence:

[D–D–D–D–D–D–D–D–D–D–M–M–M–M–M–A–A–A–A–A]

This individual started in a deprived neighborhood at birth, moved to a middle-income neighborhood at the age of 10 to live there for a period of five years, and subsequently moved to an affluent neighborhood at age 15 to live there for the remainder of the observation period. This is just one example of the many possible neighborhood histories. In fact, the number of possible sequences (i.e., 3^{20}) is too large to compare the sequences directly.

The third and last step was aimed at reducing complexity by creating an empirical typology of children's neighborhood trajectories. In order to arrive at this typology, we first computed distances between all individual sequences. We opted for the optimal matching (OM) metric which measures sequence dissimilarity in terms of three edit operations – insertion, deletion, and substitution (see Abbott & Tsay, 2000; Gabadinho et al., 2011). In our case, insertion/deletion costs were set at 1 and substitution costs were defined as the inverse of the transition rates. This replicates the approach used most widely in the literature (e.g., Aassve et al., 2007; Kleinepier et al., 2015; Widmer & Ritschard, 2009). Once the OM distances were calculated, we applied partitioning around medoids cluster analysis in order to classify children into more-or-less homogeneous groups on the basis of similarities in their neighborhood histories. We tested a range of cluster solutions (2-20 cuts) and determined the quality of the partitions with the Average Silhouette Width (ASW) criterion. The 7-cluster solution was determined to be optimal (ASW=0.57). The 'Results' section starts off with a detailed description of these neighborhood trajectory subtypes.

[1] Because income data were not available for the years earlier than 1999, we use the average neighborhood income in 1999 to determine the quality of the neighborhoods for the period 1995-1998. Previous research has shown that neighborhood change is a slow process (Zwiers et al., 2016), implying that this should introduce only limited bias in our analyses.

Importantly, not every individual that engaged in problem behavior did so specifically at age 19 (see Table 1). This could potentially be problematic because, for some children, neighborhood exposure thus partly occurred later in time than the dependent variable. We therefore also constructed a 7-cluster typology using the following age ranges: 0–17, 0–15, and 0–12. Reassuringly, the clusters based on the complete age range and the restricted age ranges were very similar and were found to overlap substantially, with respectively 97, 92, and 86 percent being grouped in the same cluster. Thus, if we would model children's neighborhood trajectories up to occurrence of problem behavior, the typology would be very similar to the current classification. We prefer to cluster children's neighborhood trajectories using the full age range, however, because comparing and clustering sequences of unequal lengths is problematic (Billari, 2001).

<<<Table 2 about here>>>

Control Variables

We estimate a series of binary logistic regression models to assess the effect of exposure to poor and nonpoor neighborhoods in childhood on three types of problem behavior in adolescence. For each dependent variable, two models were fitted. In the first model, we included only the different types of neighborhood trajectories. In the second model, we added a range of control variables. The control variables are measured as follows. *Ethnicity* of the child is based on the mother's country of birth or the father's country of birth in case the mother was born in the Netherlands. We distinguish the following six ethnic minority groups: (1) Turkish, (2) Moroccan, (3) Surinamese, (4) Antillean, (5) other non-Western, and (6) Western ethnic minorities. Children with both parents born in the Netherlands are classified as native Dutch and serve as the reference group. *Sex* is a dummy variable (0=female, 1=male). *Educational level* of the child is based on the track placement in the first year of secondary school, around the age of 12. We distinguish between the following three categories: (1) pre-vocational secondary education (vmbo'), (2) higher general secondary education ('havo') and (3) pre-university education ('vwo').

Parental educational level is measured for both parents separately with a dummy variable indicating whether the father / mother obtained a degree in higher education (i.e. bachelor degree or higher). Unfortunately, we have no information on degrees obtained abroad or before 1986. We therefore include an additional dummy variable for cases missing data on parental educational attainment. *Parental employment status* is based on the period from 1999 onwards because data on employment and income were not available for the period 1995-1998. We divide the total number of years the father / mother was employed during the period 1999–2014 by 16 (i.e., total years of observation). *Household income* is also based on years 1999–2014 for reasons of data availability. For each of these years of observation, we determine the total household income of each child and correct all values for inflation relative to the base year 1999. We then adjust household income for household size by dividing the household income in each year by the square root of household size in the given year. This 'square-root equivalence scale' presumes that, for example, a household of four persons has needs twice as large as one composed of a single person (OECD, 2013). Finally, we take the natural logarithm of the average equivalent household income over the years 1999–2014 to account for its right-skewed distribution.

Residential mobility is measured with a set of dummy variables indicating the number of times the child changed residences during the observation period: (1) no moves, (2) one move, (3) two moves, and (4) three or more moves. *Household size* is a linear variable indicating the number of people living in the same household as the child in 1995 (including the child). *Parental union* status is distinguished into four categories: (1) parents remained together, (2) parents never lived together after child was born, (3) parents divorced, separated, or one parent died during observation period, and (4) parents started living together after initially living apart. *Age difference with parents* is measured in years as two continuous variables (for the father and mother separately). Table 2 provides descriptive statistics for all variables used in the regression analyses.

RESULTS

Children With Similar Neighborhood Trajectories

Using optimal matching and cluster analysis, we have grouped all individual sequences into seven broader types of neighborhood trajectories. Figure 2 shows the sequence index plots for each of these seven trajectory types. In sequence index plots, each individual is represented by a separate horizontal line that is colored according to the type of neighborhood at each chronological age – red for deprived, yellow for middle-income, and green for affluent neighborhoods. We thus visualize the longitudinal succession of neighborhood types for each individual as well as, through the length of each color segment, the duration spent in each neighborhood type. Moreover, we report the medoid sequence (smallest sum of pairwise distances to all other sequences in the group) as the most characteristic sequence within each cluster (see Aassve et al., 2007; Gabadinho et al., 2011).

<<<Figure 2 about here>>>

Cluster 1 (consistent deprivation) accounts for 11% of the sample and has the medoid sequence D/20, which stands for a trajectory in which a person has lived in a deprived neighborhood during the complete observation period, i.e. from birth up until age 19. The sequences in this cluster are thus characterized by long-term exposure to a deprived neighborhood during childhood. This does not necessarily mean that individuals in this cluster had never changed residences during the observation period, but if they moved, they typically moved from one deprived neighborhood to another. The trajectories in Cluster 2 (early deprivation) are characterized by the medoid sequence D/6–M/14. Individuals who experienced such a trajectory were born in a deprived neighborhood and moved towards a middle-income neighborhood at the age of 6 to live there for the remainder of the observation period. Cluster 3 (late deprivation) includes those who followed the opposite path: they were born in middle-income neighborhoods, but moved towards deprived neighborhoods as they grew older. The medoid sequence (M/7–D/13) suggests that these moves occurred around the age of 7. Clusters 2 and 3 each cover about 8% of the total sample.

Cluster 4 (consistent middle-income) compromises by far the largest group of the sample (46%) and has the medoid sequence M/20, reflecting a sequence in which an individual has lived in a middle-income neighborhood throughout the entire childhood life course. Cluster 5 (early affluence), accounting for about 8% of the sample, mainly includes children who were living in an affluent neighborhood during early childhood and in a middle-income neighborhood during adolescence. This is reflected in the medoid sequence of A/6–M/14. Cluster 6 (late affluence) is the smallest cluster of the sample (7%) and has the medoid sequence M/8–A/12. This cluster is thus the opposite of Cluster 5, with exposure to middle-income neighborhoods during early childhood and exposure to neighborhood affluence in adolescence. Finally, Cluster 7 (consistent affluence) contains trajectories that are characterized by living in an affluent neighborhood throughout childhood (medoid = A/20).

Neighborhood Trajectories and Problem Behavior

Now that we have described each of the trajectory types, we examine how and to what extent they are related to three types of adolescent problem behavior: teenage parenthood, school dropout, and delinquent behavior. We generated six dummy variables that compare the effect of membership in clusters 2-7 to the effect of membership in cluster 1. In Table 3, we present the odds ratios (OR) and standard errors (SE) of a series of binary logistic regression models relating the three outcome variables to these dummy variables. For each dependent variable, two models were estimated. In the first model, (under Model 1) we included only the dummy variables for the different trajectory types. In the next set of models (under Model 2), we added a range of control variables to assess the extent to which the measured 'neighborhood effects' are attributable to other observed characteristics in the data. All standard errors were corrected for the clustering of persons in the neighborhood at birth.

Models 1a-c (Table 3) show that children in clusters 2 and 4-7 all have a significantly lower likelihood to engage in any of the behavioral problems than children who were consistently exposed to neighborhood deprivation (cluster 1). Especially children who had lived in an affluent neighborhood throughout childhood (cluster 7) are much less likely to engage in any type of problematic behavior. Interestingly, while children who were exposed to neighborhood deprivation only early in their childhood (cluster 2) are less likely to demonstrate problem behavior than children in the consistent deprivation group (cluster 1), children who only lived in a deprived neighborhood in adolescence (cluster 3) do not differ significantly from the reference group in terms of teenage parenthood and delinquency. This suggests that neighborhood deprivation during adolescence has a stronger influence on problem behavior than neighborhood deprivation early in childhood, highlighting the importance of timing of exposure. Furthermore, although the differences are rather small, we find that children who only lived in a deprived neighborhood in adolescence (cluster 3) are significantly more likely to drop out of school than those who had consistently lived in a deprived neighborhood (cluster 1), suggesting that the sequencing of neighborhood deprivation is important as well.

We proceed by describing the results obtained when including the control variables in Models 2a-c in Table 3. Regarding teenage parenthood and school dropout, we find that the effects of the neighborhood trajectory types become substantially attenuated in Models 2a and 2b (except for cluster 3), but they remain statistically significant and the direction of the effects remains consistent across the two models. With regard to delinquent behavior, however, the results portray a different picture. Whereas the effects of membership in clusters 2, 4, 5, 6, and 7 are all negative and statistically significant in Model 1c, the effects of clusters 2 and 5 lose statistical significance after including the control variables in Model 2c. The effects of clusters 4, 6, and 7 remain statistically significant, but change from negative in Model 1c to positive in Model 2c. Somewhat counterintuitively, we find that after controlling for various individual and parental background characteristics, especially children who had lived in an affluent neighborhood throughout childhood (cluster 7) are more likely to engage in delinquent behavior than children who had consistently lived in a deprived neighborhood during childhood (cluster 1).

Finally, in order to assess which control variables are primarily responsible for the changes in the coefficients associated with the neighborhood trajectory in Table 3, we applied the KHB decomposition method (Karlson et al., 2012). The results (not in table) showed that particularly educational level and household income have a strong attenuating effect for all neighborhood trajectory types. Put differently, compared to children who were exposed to neighborhood deprivation throughout childhood (cluster 1), children with other neighborhood trajectories (clusters 2 and 4-7) are less likely to engage in behavioral problems, but this difference is for an important part attributable to the fact that children in cluster 1 on average have lower educational levels and household incomes. For the clusters characterized by a change in neighborhood context (i.e., clusters 2, 5, and 6), residential mobility was found to be an important mediator as well, but working in the opposite direction. Specifically, we found a so-called ‘suppression effect’ in which the negative effect of membership in clusters 2, 5, and 6 compared to cluster 1 became more negative when the number of residential moves was included in the regression model.

<<<Table 3 about here>>>

DISCUSSION

There is a persuasive theoretical basis for the view that neighborhood effects on children's life chances depend on duration, timing, and sequencing of neighborhood deprivation during childhood (Sharkey & Faber, 2014). However, empirical studies addressing the temporal aspects of neighborhood effects have predominantly only focused on how long children have been exposed to neighborhood disadvantage over their childhood (duration). As such, research on the impact of exposure to neighborhood disadvantage at different stages in childhood (timing) and changes in children's neighborhood circumstances over time (sequencing) is still limited and, moreover, does not yield consistent results. In this study, we applied sequence analysis to simultaneously capture children's duration, timing, and sequencing of exposure to poor and nonpoor neighborhoods during childhood, providing a much more comprehensive measure of their neighborhood experiences.

The sequence analysis identified seven substantively different types of neighborhood trajectories in childhood. In three of these types, children had lived in a deprived neighborhood at some point during childhood, but differed in terms of duration, timing, and sequencing of exposure. Some children experienced neighborhood disadvantage throughout childhood (consistent deprivation), while other children were exposed to a deprived neighborhood either only early in childhood (early deprivation) or only during adolescence (late deprivation). In three of the four remaining trajectory types in our classification, children had lived in an affluent neighborhood with a similar threefold distinction in terms of patterns of exposure: throughout childhood (consistent affluence), only early in childhood (early affluence), or only during adolescence (late affluence). The last remaining trajectory type included children who had lived in a middle-income neighborhood throughout childhood (consistent middle-income).

The next step in the analysis was to examine the extent to which the identified trajectory types were related to three types of behavioral problems in adolescence: teenage parenthood, school dropout, and delinquent behavior. We found that children who had consistently lived in a deprived neighborhood during childhood (i.e., consistent deprivation group) were more likely to become a teenage parent and/or to drop out of school than children who were exposed to more advantaged neighborhood circumstances. The only exception here were children who had lived in a deprived neighborhood only in adolescence (i.e., late deprivation group) – they did not differ from the consistent deprivation group in terms of teenage parenthood and were even more likely to drop out of school. These results first of all underscore the importance of adolescent exposure to neighborhood disadvantage on subsequent problem behavior (Wodtke, 2013; Wodtke et al., 2016). The finding that the late deprivation group was more likely to drop out of school than the consistent deprivation group suggests that the sequencing of neighborhood deprivation is important as well. The finding is in line with previous research on family poverty showing that children whose family income declines are at greater risk of problem behavior than children who experience stable but disadvantaged economic circumstances (Moore et al., 2002).

Our findings with regard to delinquent behavior were interestingly different from those discussed above. Whereas the direction of effects of the trajectory types was similar to that for teenage parenthood and school dropout on the bivariate level, the results changed substantially after accounting for various individual and parental background characteristics. More precisely, we found that after holding all control variables constant, particularly children who were exposed to neighborhood affluence throughout childhood (i.e., consistent affluence group) and those exposed to an affluent neighborhood only in adolescence (i.e., late affluence group) were most likely to engage in delinquent behavior. A possible explanation for this somewhat counterintuitive finding may be that there are higher levels of community surveillance and more frequent reporting of suspicious behaviors to the police in more affluent neighborhoods (Varano et al., 2009). Another explanation could be that unobserved characteristics of the children's parents make the parents in affluent neighborhoods more likely to report their child(ren) to the police if they realise or suspect any signs of criminality. Future research may more specifically test these conjectures.

The sequence analysis approach that we employed delivered results that would not have been uncovered by more conventional approaches for assessing children's exposure to neighborhood deprivation, such as single point-in-time and cumulative measures of exposure. Nevertheless, our findings suggest that point-in-time measures of neighborhood quality introduce only limited bias in the analyses as long as they are measured during adolescence. Indeed, point-in-time measures of neighborhood quality in adolescence conflate the effect of long-term neighborhood advantage or disadvantage in childhood (i.e., consistent affluence / deprivation) with the effect of more recent exposure to neighborhood affluence or deprivation (i.e., late affluence / deprivation). However, this may be less problematic than previously thought, because we hardly find differences between consistent and adolescent exposure to neighborhood (dis)advantage. Even so, longitudinal measures are to be preferred because they are less sensitive to random noise or transitory fluctuations in children's neighborhood status (Jackson & Mare, 2007; Wodtke, 2013). Moreover, while we found no noteworthy differences in the effects of consistent and adolescent exposure to neighborhood deprivation on adolescent problem behavior, such differences may well exist for other outcomes of children's lives, such as cognitive development and (psychological) health.

This study has several limitations. Especially regarding delinquent behavior, it is important to bear in mind that we used administrative data which obviously only provide information on registered delinquency. It is well known that a large proportion of crimes are not reported to the police (and thus remain unregistered), especially so with regard to minor offences. More importantly, reporting practices have been found to vary across different types of neighborhoods (Varano et al., 2009). Furthermore, because in some cases the identity of the biological father may be unknown, registration effects may also play a role in the accuracy of our measure of teenage fatherhood, but it is unlikely that this has seriously biased our results. Another limitation of this study is that our data lack information on several potentially important variables, such as such as parenting styles and cultural values. Consequently, we are unable to fully account for the self-selection of parents into specific types of neighborhoods, which may partly explain the associations that we have observed. Finally, although sequence analysis provides a much more complete measure of children's experiences of neighborhood deprivation than other approaches, it does not allow for the inclusion of time-varying variables. Time-varying covariates such as household income and parental employment status influence selection into different neighborhoods, but may themselves also be affected by past neighborhood conditions (Wodtke, 2013). We cannot take into account these dynamics using sequence analysis, which possibly leads to an underestimation of neighborhood effects. Yet, we believe that the underestimation will not be very large as previous research suggests that neighborhood effects on individual socioeconomic outcomes are small or even trivial (Miltenburg, 2017).

In spite of the limitations, this study enhances the current literature on neighborhood effects on children. Theoretically, we provide new insights on the importance of exposure to neighborhood (dis)advantage across different developmental stages in childhood, pointing to adolescence as the most crucial period. Empirically, we regard our study as a first step in class-based trajectory modelling of neighborhood exposures to predict outcome variables. Future research may elaborate on our work by using other data and/or outcome variables. For example, using the Swedish register data which go back further in time, future studies can track individual neighborhood trajectories from birth all the way up to middle adulthood and identify patterns of exposure to neighborhood (dis)advantage for more stages across the human life span. Another potentially interesting avenue for future research would be to use multichannel sequence analysis to simultaneously take into account the duration, timing, and sequencing of exposure to disadvantage in multiple spheres of life, such as neighborhoods, schools, and households. This is a complex task for further research.

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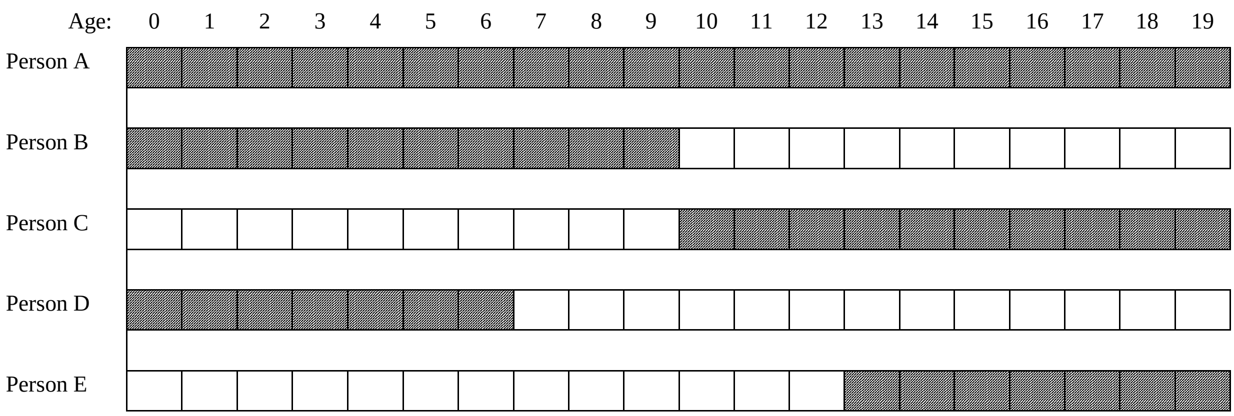

Figure 1. A hypothetical example of five different patterns of exposure to neighborhood deprivation (as indicated by shading) in childhood

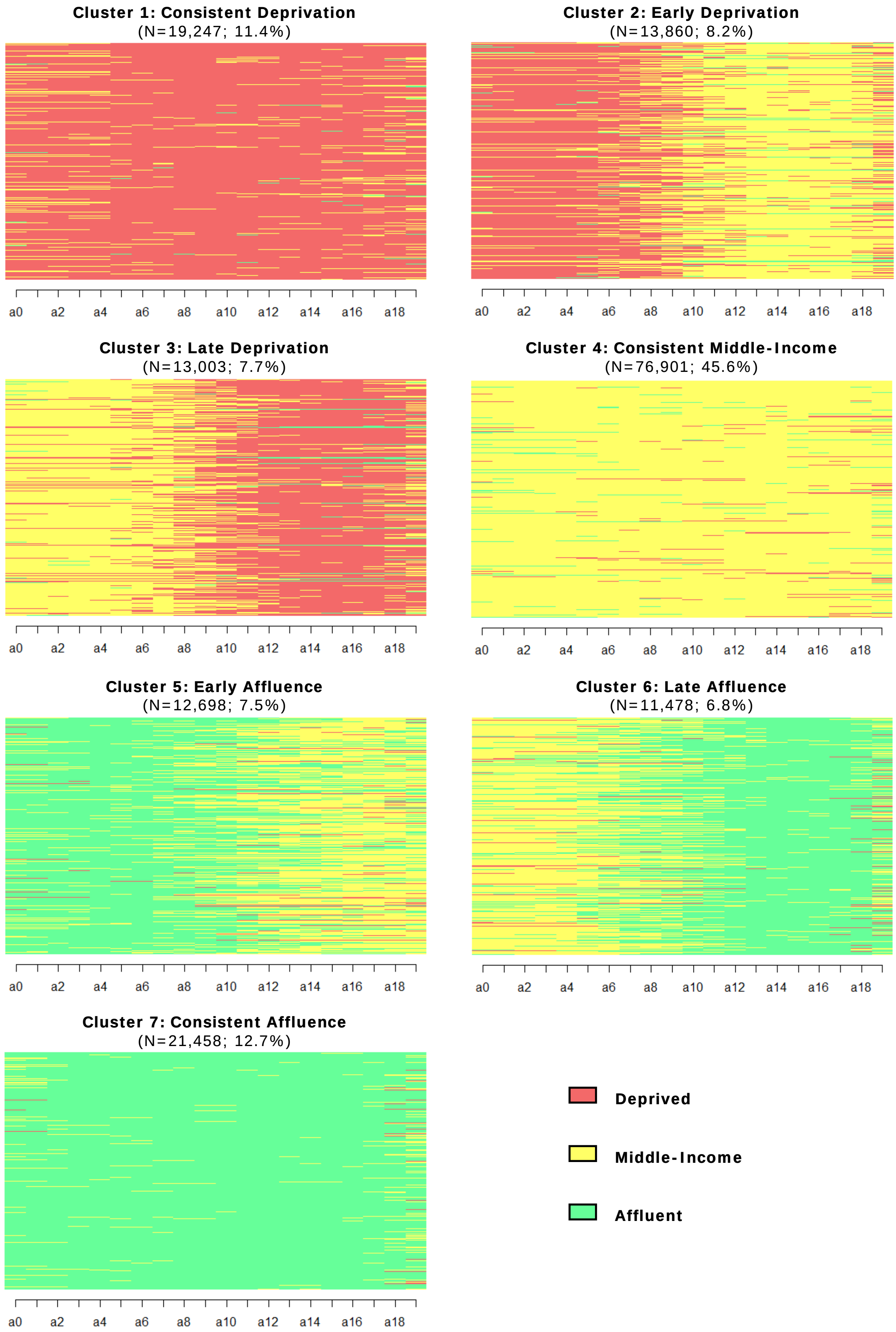

Figure 2. Sequence index plots of seven clusters of children’s neighborhood trajectories

Table 1. Percentage distribution of the three problem behavior variables across ages 12-19

	Teenage parenthood		School dropout		Delinquent behavior	
Age	%	Cumulative %	%	Cumulative %	%	Cumulative %
12	0.00	0.00	0.02	0.02	0.02	0.02
13	0.00	0.00	0.04	0.06	1.01	1.03
14	0.00	0.00	1.00	1.06	1.75	2.78
15	0.01	0.01	1.00	2.06	1.78	4.56
16	0.03	0.04	1.49	3.55	1.79	6.35
17	0.08	0.12	3.70	7.25	2.44	8.79
18	0.18	0.29	3.28	10.53	0.00	8.79
19	0.69	0.98	2.12	12.65	0.00	8.79

Source: System of Social statistical Datasets (SSD).

Table 2. Descriptive statistics of dependent, independent, and control variables used in the regression analyses

Variable	Category	% in Each Category or Mean (SD)
Dependent variables		
Teenage parenthood	Yes	1.0
School dropout	Yes	11.3
Delinquent behavior	Yes	8.1
Independent variable		
Neighborhood trajectory	Cluster 1. Consistent deprivation	11.4
	Cluster 2. Early deprivation	8.2
	Cluster 3. Late deprivation	7.7
	Cluster 4. Consistent middle-income	45.6
	Cluster 5. Early affluence	7.5
	Cluster 6. Late affluence	6.8
	Cluster 7. Consistent affluence	12.7
Control variables		
Ethnicity	Native Dutch	83.8
	Turkish	2.7
	Moroccan	2.9
	Surinamese	2.1
	Antillean	0.7
	Other non-Western	2.9
	Western	5.0
Sex	Male	51.2
Educational level	Pre-vocational	53.0
	Higher general	20.6
	Pre-university	26.4
Father’s educational level	Low	23.3
	High	14.5
	Missing	62.2
Mother’s educational level	Low	26.8
	High	15.1
	Missing	58.1
Father’s labor force participation	Mean (SD)	0.88 (0.24)
Mother’s labor force participation	Mean (SD)	0.68 (0.35)
Household income (logged)	Mean (SD)	7.48 (0.48)
Residential mobility	0 moves	33.4
	1 move	32.1
	2 moves	18.4
	≥3 moves	16.1
Household size	Mean (SD)	4.33 (0.99)
Parental union status	Stable union	77.8
	Dissolution	17.2
	Never lived together	3.2
	Started living together	1.8
Age difference with father	Mean (SD)	32.98 (5.05)
Age difference with mother	Mean (SD)	30.34 (4.40)

Note: Percentages may not total 100 due to rounding.

Source: System of Social statistical Datasets (SSD).

Table 3. Logistic regression models of cluster membership influencing three types of problem behavior in adolescence

	Teenage parenthood				School dropout				Delinquent behavior			
	Model 1a		Model 2a		Model 1b		Model 2b		Model 1c		Model 2c	
	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Neighborhood trajectory (ref=cluster 1. consistent deprivation)												
Cluster 2. Early deprivation	0.67***	0.06	0.78*	0.08	0.76***	0.02	0.90**	0.03	0.80***	0.03	0.96	0.04
Cluster 3. Late deprivation	1.03	0.11	1.00	0.12	1.08*	0.04	1.11*	0.05	0.97	0.05	0.99	0.05
Cluster 4. Consistent middle-income	0.46***	0.03	0.78***	0.06	0.68***	0.02	0.94**	0.02	0.79***	0.02	1.09**	0.03
Cluster 5. Early affluence	0.43***	0.04	0.71**	0.07	0.66***	0.02	0.87***	0.03	0.80***	0.03	1.05	0.05
Cluster 6. Late affluence	0.30***	0.02	0.55***	0.08	0.59***	0.02	0.88**	0.03	0.69***	0.03	1.13**	0.04
Cluster 7. Consistent affluence	0.15***	0.02	0.55***	0.09	0.53***	0.02	0.82***	0.03	0.66***	0.03	1.22***	0.05
Ethnicity (ref=native Dutch)												
Turkish			0.27***	0.05			1.18***	0.05			1.27***	0.06
Moroccan			0.51***	0.08			1.39***	0.06			1.94***	0.09
Surinamese			1.67***	0.20			1.11*	0.06			1.39***	0.08
Antillean			2.47***	0.50			1.23*	0.12			1.28*	0.14
Other non-Western			0.76	0.11			1.04	0.05			1.20***	0.06
Western			1.08	0.12			1.17***	0.04			1.21***	0.05
Male			0.19***	0.01			1.46***	0.02			2.69***	0.06
Educational level (ref=pre-vocational)												
Higher general			0.35***	0.04			0.30***	0.01			0.59***	0.02
Pre-university			0.12***	0.02			0.16***	0.01			0.37***	0.01
Father's educational level (ref=low)												
High			0.83*	0.08			0.91**	0.03			0.94*	0.03
Unknown			0.94	0.06			0.98	0.02			0.98	0.02

Table 3. (cont'd)												
	Teenage parenthood				School dropout				Delinquent behavior			
	Model 1a		Model 2a		Model 1b		Model 2b		Model 1c		Model 2c	
	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE	OR	SE
Mother's educational level (ref=low)												
High			1.02	0.09			0.93**	0.02			0.94	0.03
Unknown			0.97	0.06			0.94**	0.02			0.89***	0.02
Father's labor force participation			0.58***	0.06			0.62***	0.02			0.63***	0.03
Mother's labor force participation			0.55***	0.04			0.68***	0.02			1.05	0.03
Household income (logged)			0.67***	0.05			0.93***	0.02			0.90***	0.02
Residential mobility (ref=0 moves)												
1 move			2.00***	0.19			1.14***	0.03			1.05*	0.03
2 moves			3.30***	0.32			1.35***	0.04			1.15***	0.03
≥3 moves			5.37***	0.50			1.95***	0.05			1.37***	0.04
Household size			1.20***	0.03			0.97***	0.01			0.99	0.01
Parental union status (ref=stable union)												
Dissolution			1.42***	0.10			1.53***	0.03			1.42***	0.04
Never lived together			1.78***	0.21			1.87***	0.09			1.75***	0.10
Started living together			1.25	0.19			1.59***	0.09			1.48***	0.09
Age difference with father			0.98*	0.01			1.00*	0.00			0.99*	0.00
Age difference with mother			0.97**	0.01			0.99***	0.00			0.99*	0.00
Pseudo R^2	0.02		0.18		0.01		0.10		0.01		0.07	
-2 Log Likelihood	-8883.45		-6971.67		-59050.48		-51113.67		-47461.15		-42674.27	

*Note *** p <.001; ** p < .01; * p <.05. The standard errors have been corrected for clustering of individuals in neighborhoods in 1995.*

Source: System of Social statistical Datasets (SSD)