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ABSTRACT

Cumulative Exposure to Disadvantage and the Intergenerational Transmission of Neighbourhood Effects

Studies of neighbourhood effects typically investigate the instantaneous effect of point-in-time measures of neighbourhood poverty on individual outcomes. It has been suggested that it is not solely the current neighbourhood, but also the neighbourhood history of an individual that is important in determining an individual's outcomes. The effect of long-term exposure to poverty neighbourhoods on adults has largely been ignored in the empirical literature, partly due to a lack of suitable data. Using a population of parental home-leavers in Stockholm, Sweden, this study is innovative in investigating the effects of two temporal dimensions of exposure to neighbourhood environments on personal income later in life: the parental neighbourhood at the time of leaving the home and the cumulative exposure to poverty neighbourhoods in the subsequent 17 years. Using unique longitudinal Swedish register data and bespoke individual neighbourhoods, we are the first to employ a hybrid model, which combines both random and fixed effects approaches, in a study of neighbourhood effects. We find independent and non-trivial effects on income of the parental neighbourhood and cumulative exposure to poverty concentration neighbourhoods. The intergenerational transmission and exposure effects suggest the need for a more dynamic formulation of the neighbourhood effects hypothesis which explicitly takes temporal dimensions into account.

JEL Classification: I30, J60, R23

Keywords: neighbourhood effects, cumulative exposure, intergenerational transmission, poverty concentration, hybrid model, bespoke neighbourhoods

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Introduction

Over the last few decades, a large literature has developed which investigates neighbourhood effects and the hypothesized negative effect of living in poverty concentration neighbourhoods on various individual outcomes such as employment, earnings, school performances and "deviant" behaviour (see for a review Ellen & Turner, 1997; Galster, 2002; Dietz, 2002; Durlauf, 2004; van Ham & Manley, 2010). Within this literature, there is substantial debate with little apparent agreement on the causal mechanisms which produce these hypothesized effects, their relative importance in shaping individual's life chances compared to other external influences, and the circumstances or conditions under which they are most important (van Ham et al., 2012a). The neighbourhood effects debate is not only academically intriguing, but is also highly policy relevant as a strong belief in neighbourhood effects is guiding urban renewal programmes all over Europe which aim to artificially create mixed neighbourhoods (Musterd and Andersson, 2005; van Ham and Manley, 2010).

Despite a growing body of literature on neighbourhood effects, one crucial dimension of neighbourhood effects is largely overlooked: the temporal dimension (Quillian, 2003; Sharkey and Elwert, 2011; Musterd et al., 2012). Most studies of neighbourhood effects investigate the instantaneous effects of single point-in-time measurements of neighbourhood environments on individual outcomes. However, it has repeatedly been suggested that most theories of neighbourhood effects assume medium to long-term exposure to poverty neighbourhoods for there to be an effect (Quillian, 2003; Hedman, 2011; Musterd et al., 2012; Galster, 2012). It seems obvious that more severe negative effects can be expected from living in a poverty concentration neighbourhood your whole life, than exposure to such a neighbourhood for only a short period of time. However, the effects of long-term exposure to poverty neighbourhoods has largely been ignored in the empirical literature. More research on these temporal dimensions was recently advocated by Briggs and Keys (2009).

Two small, but growing, bodies of literature are especially relevant for this study. The first investigates the long term exposure to poor neighbourhoods. To our knowledge only a few studies have investigated long term exposure, and they argue that neighbourhoods should not be treated as static entities linked to individuals at single time points, but that they should be characterised as dynamic interactions between people and places over the life course. A surprising finding has been that there is, in fact, great continuity in individual neighbourhood histories over the life course, and even across generations. Quillian (2003) uses longitudinal data from the US Panel Study of Income Dynamics (PSID) to test the spatial entrapment hypothesis. He finds that most African Americans will live in a poor neighbourhood over a 10 year period, compared to only 10 per cent of whites. He also found that African Americans are more likely than whites to re-enter a poor neighbourhood following a previous exit. Sharkey (2008) also used PSID data to show that in the US inequalities in neighbourhood environments persist across generations (see also Vartanian et al., 2007). He found that 70 per cent of black children who grow up in the poorest American neighbourhoods still live in such neighbourhoods as adults, compared to 40 per cent of whites. Intriguingly, van Ham and colleagues (2012b) found very similar evidence of intergenerational transmission of neighbourhood status for ethnic minorities in Sweden. In their study they also analysed the cumulative exposure to poverty concentration neighbourhoods over an 18 year period after leaving the parental home. They found that this exposure is strongly related to the parental neighbourhood, ethnicity, and housing tenure (van Ham et al., 2012b).

This strong evidence of continuity of neighbourhood poverty across both generations and the individual life course leads to the important question whether neighbourhood effects should also be conceptualised in a dynamic life course context. This is the focus of a second small literature which investigates the effects of the temporal dimensions of exposure to neighbourhood environments on individual outcomes. Several studies investigated the effects of exposure to poverty neighbourhoods for children or adolescents. Negative effects associated with increased exposure were found on high school graduation (Aaronson, 1998; Crowder and South, 2011; Wodtke et al., 2011), verbal ability of children (Sampson et al., 2008), welfare use (Vartanian, 1999), high school attainment and earnings (Galster et al., 2007), health outcomes (Phuong Do, 2009), and cognitive ability (Sharkey and Elwert, 2011). One of the few studies which investigates the effects of exposure (over a 4 year period) to poor neighbourhoods for adults is by Musterd and colleagues (2012) who found for Sweden that cumulative exposure yields stronger associations on individual income than temporary exposure.

This study contributes in several ways to the very recent body of literature on the temporal dimensions of neighbourhood effects. Using a population of parental home leavers in Stockholm, Sweden, this study investigates the combined effects of two temporal dimensions of exposure to neighbourhood environments on personal income: the parental neighbourhood at the time of leaving the parental home and the cumulative exposure to poverty neighbourhoods in the subsequent 17 years. By combining these temporal dimensions we cover the whole period of exposure from childhood to adulthood. This study is one of the few to focus on outcomes for adults and to use such a long exposure period. The study uses unique longitudinal Swedish register data which allows us to investigate a whole cohort (not a sample) of parental home leavers. Instead of using administrative neighbourhoods, we constructed bespoke individual neighbourhoods by measuring the characteristics of the nearest 500 working-age individuals for each person in our dataset. We are the first to employ a hybrid model, which combines both random and fixed effects approaches, in a study of neighbourhood effects. This approach allows us to estimate unbiased parameters while still including all time-invariant characteristics in the model.

Towards a dynamic neighbourhood effects framework

Galster (2012) used the metaphor of a drug to think about how neighbourhoods can influence individual outcomes. He argued that to understand the effect of a drug on a human body it is necessary to know about (among other things) the dosage (strength) administered, the frequency of the administration and the duration of the administration. The same issues could be true in understanding how a neighbourhood can influence individual outcomes. Most existing studies use simple point-in-time measures of neighbourhood by linking the neighbourhood of residence to individual outcomes in the same year, or sometimes lagged at best 4 years previously (Musterd et al., 2012). Such a research design assumes an instantaneous effect of neighbourhood on individual outcomes and completely ignores the fact that a stay in a poverty concentration neighbourhood can be a very temporary state, but can also be a state which lasts for many years and even decades. In line with Galster's metaphor we argue that it is important to take into account how long people have been exposed to poor neighbourhoods and in which stage of their lives.

To our knowledge there is only one study which in detail investigated individual neighbourhood histories for adults over a longer period of time. Van Ham and colleagues (2012b) used Swedish register data to investigate the neighbourhood histories of young adults leaving the parental home between the ages of 16 and 25 and then followed their independent housing and neighbourhood careers over an 18 year period. For every year after leaving the parental home the type of neighbourhood in which people lived was recorded, based on the percentage of poor residents in that neighbourhood (poor being defined as belonging to the 20 percent poorest residents). Next they used innovative visualisation methods (based on Coulter and van Ham, 2012b) to construct individual neighbourhood histories, which were made visible through colour coded life lines. It was demonstrated that the socioeconomic composition of the neighbourhood children lived in before they left the parental home is strongly related to the status of the neighbourhood they live in 5, 12 and 18 years later. Children living with their parents in high poverty concentration neighbourhoods are very likely to end up in similar neighbourhoods much later in life. The parental neighbourhood is also important in predicting the cumulative exposure to poverty concentration neighbourhoods over a long period of adulthood. Ethnic minorities were found to have the longest cumulative exposure to poverty concentration neighbourhoods. The findings imply that for some groups, disadvantage is both inherited and highly persistent (van Ham et al., 2012b). What was striking from the visualisations of individual neighbourhood histories was that within a single person's history, there is great variation in neighbourhood types over the years. Even individuals who were brought up in a relatively affluent neighbourhood are likely to spend a significant period of time in poorer neighbourhoods, especially during the period immediately after they leave home (and are often engaged in full time education). For many, their subsequent moves see them climb the neighbourhood hierarchy, although there are often 'bumps' downwards, before continuing on their upwards trajectory. Conversely, van Ham and colleagues (2012b) also found that many people who start lower down the hierarchy rarely move upwards, and remain in the poorest neighbourhoods.

We argue that the above findings are crucial for our understanding of neighbourhood effects. There is very little consistency in the outcomes of studies of neighbourhood effects (see critiques by Oreopoulos, 2003; Bolster et al., 2007; van Ham and Manley, 2010) and one of the reasons might be that most studies completely ignore the neighbourhood histories of people. Many of the mechanisms that are thought to be responsible for neighbourhood effects will require a certain period of exposure before any effect is likely to be seen (Quillian, 2003; Hedman, 2011; Musterd et al., 2012; Galster, 2012). Also the route into a poverty concentration neighbourhood might be relevant. For example, it is unlikely that someone who moves into cheap rental accommodation in a poverty concentration neighbourhood following a divorce, and subsequently moves to a better neighbourhood one year later will experience negative effects on their earning capacity during the rest of their life. On the other hand, someone who was brought up in a poverty neighbourhood and lived there his or her whole life might be at greater risk of experiencing negative consequences. Many people will have neighbourhood histories in between these extremes with shorter or longer periods of exposure to poverty neighbourhoods, and this paper aims to get more insight into the effects of these varying exposures.

So what is our theory of exposure? There is not a single theory of neighbourhood effects and in most studies (including this one) the causal mechanisms of the hypothesised neighbourhood effects are effectively contained within a black box. Quantitative research is generally not able to identify exactly which mechanisms are at play, and more in depth, qualitative studies using ethnographic methods would be needed to identify these causal mechanisms (Small and Fieldman, 2012). This is not a justification for ignoring the possible causal mechanisms, so we briefly outline the most important ones below. Galster (2012) has identified 15 distinctive causal mechanisms linking individual outcomes to the neighbourhood environment from the literature. He grouped these into four categories: social-interactive mechanisms, environmental mechanisms, geographical mechanisms, and institutional mechanisms. Social-interactive mechanisms refer to social processes endogenous to neighbourhoods, which are generally seen as the core of the neighbourhood effects argument (social contagion, collective socialisation, social networks, social cohesion and control, competition, relative deprivation, and parental mediation). It can be argued that in all these cases it can be expected that the longer one is exposed to a poverty concentration neighbourhood, the more detrimental the effect will be on your income. For example, a longer stay in a poor neighbourhood where social norms prevail which are less supportive of regular employment might lead to lower income, whereas a brief period in such a neighbourhood is likely not to be sufficient to lead to different behaviours or beliefs. Environmental mechanisms are thought to operate through natural and human-made attributes of neighbourhoods that may affect directly the mental and/or physical health of residents without directly affecting their behaviours (exposure to violence; physical surroundings; and toxic exposure). A longer exposure to poor neighbourhoods with greater incidence of crime and violence might lead to stresses inhibiting an individuals' ability to concentrate on studies or work and again lead to a lower income (Galster et al., 2007). Geographical mechanisms refer to effects of the relative location of neighbourhoods (spatial mismatch of jobs and workers and a lack of quality public services). Again, it can easily be argued that living for a longer period of time in a poor neighbourhood, with poor quality services, such as job centres, can lead to a lower income. And finally institutional mechanisms, which are related to the behaviour of actors external to neighbourhoods, who control the resources available and access to housing, services and markets for neighbourhood residents (stigmatisation, local institutional resources, and local market actors). Growing up in a poor neighbourhood, and subsequently staying there longer periods of time can be expected to lead to stigma and reduced job and earning opportunities.

Being exposed to a poverty concentration neighbourhood during childhood can be expected to have an additional negative effect on income. Norms and beliefs are largely formed during childhood and these can have a long lasting effect on labour market behaviour and employment opportunities. Growing up in a poor neighbourhood can also affect incomes through the quality of schools in the neighbourhood and the (lack of) peer support to do well in school and the labour market (Galster et al., 2007). Based on the above we hypothesise that a parental poverty concentration neighbourhood can have a long lasting negative effect on incomes of children as adults.

Data and methods

The data used for this study are derived from GeoSweden, a longitudinal micro-database containing the entire Swedish population tracked from 1990 to 2008. The database is constructed from a number of different annual administrative registers and includes demographic, geographic and socio-economic data for each individual living in Sweden. Within this database, it is possible to follow people over a 19 year period and construct their labour market and neighbourhood histories. In this study we have restricted our selection to people living in the Stockholm metropolitan region[1] during the entire period of study. This was to ensure that the definition of 'neighbourhood' was as consistent as possible. It is clear that neighbourhoods in the highly rural far north of Sweden are very different from inner city neighbourhoods, while two neighbourhoods within the Stockholm metropolitan region are more likely to be of similar size. To identify home leavers, we restricted the selection to individuals who were between 16 and 25 years old and living with their parents in 1990, and who had left the parental home by 1991. These selections resulted in a total of 13,526 parental home leavers for whom we can construct neighbourhood histories. It is important to note that the analysis uses the full population of Stockholm parental home leavers in 1990-1991, not a sample.

[1]The Stockholm metropolitan region includes the municipalities of Stockholm and Solna, along with municipalities of the Stockholm labour market region which are areas where the majority of the commuting flow is into either Stockholm or Solna.

Neighbourhood is defined using bespoke individualized units containing the nearest 500 working-age (20-64) people to a residential location, constructed from 100x100m geo-coordinates (the smallest geographical coding available in the dataset). These calculations were carried using Equipop software (see Östh, Malmberg and Andersson, forthcoming, for a description of the software) which combines individuals based on their 100x100m geo-coordinates[2]. Each person therefore has their own personal neighbourhood made up of their 500 nearest working-age neighbours. The advantage of this definition, compared with using standard administrative neighbourhoods, is that the resulting neighbourhood characteristics are a better representation of the residential environment surrounding each individual. This process also reduces the risk of creating biased neighbourhood estimates because of boundary effects. We measured the socio-economic status of the individualized neighbourhoods using the percentage of low income people in the personal neighbourhood, where income is defined as personal income from work[3]. Low income was coded by categorising income for all working-age Swedish individuals into quintiles, with individuals in the lowest quintile identified as having a "low income". The neighbourhood percentage of low income individuals is, therefore, the summation of low income individuals within the 500 working-age neighbours over the total number of these neighbours who are of working age. These shares of low income individuals in each neighbourhood in the Greater Stockholm region were then categorised into *neighbourhood* quintiles where Quintile 1 represents the lowest share of low income neighbours and Quintile 5 the highest. The neighbourhood quintiles were calculated for every year 1990 - 2008 and attached to the relevant individuals in the GeoSweden database (by using each individual's annual geo-coordinates). Thus, we can identify the neighbourhood income quintile each person lives in for each year of their 19 year neighbourhood history. To emphasize differences caused by residential moves (as opposed to neighbourhood change whilst an individual remains in situ), the neighbourhood income quintiles are only allowed to change in individual histories after an actual residential move event occurs. This decision is justified further by the fact that neighbourhoods change relatively little over time (Hedman et al., 2011; Meen et al., 2012). Descriptive statistics of the five neighbourhood quintiles can be found in Table 1.

<<<Table 1 about here>>>

The main interest of this paper is exposure to quintile 5 neighbourhoods with the highest share of low-income people. We refer to these neighbourhoods using the short-hand "poverty concentration neighbourhoods" and consequently, when we discuss exposure to poverty concentration neighbourhoods, we refer to the number of years spent in neighbourhoods belonging to quintile 5. We used two variables to measure exposure to poverty concentration neighbourhoods. The first measures whether people were exposed to a poverty concentration neighbourhood in 1990, the year before they left the parental home. Although it could be argued that measuring childhood experience using a point-in-time measure of parental neighbourhood only gives a partial indication of childhood experience, previous research by Kunz and colleagues (2003) from the US has shown that point-in-time neighbourhood measures are reasonable proxies for childhood experiences as there is great continuity in neighbourhood status over the life course of a child (see also Geist et al., 2008).

[2]The calculations stop when the number of neighbours exceeds 500. Since the software only includes full sets of coordinates, the total number of neighbours is often slightly higher than 500.

[3] Income from work is calculated as the sum of: salary payments, income from active businesses, and tax-based benefits that employees accrue as terms of their employment (including sick or parental leave, work-related injury or illness compensation, daily payments for temporary military service, or giving assistance to a disabled relative).

Since our data starts in 1990, we cannot test whether this assumption of continuity is also valid for our cohort of Swedish parental home leavers. We therefore took a cohort of Stockholm home leavers from 1996 (otherwise similarly defined as in our data set) and found that 64 per cent of those leaving the parental home in 1996 had stayed in the same neighbourhood with their parents 1990-1995 and 72 per cent had at least three years of exposure. It is thus very likely that our measure of parental neighbourhood environment is a reasonable measure of childhood neighbourhood experience. Our measure of childhood experience probably underestimates the real effect of the parental neighbourhood on children's income later in life, as parents are likely to improve the status of their residential neighbourhood over time. It is reasonable to assume that many children lived in neighbourhoods with lower average incomes earlier in their childhood than at the time of leaving the parental home.

The second variable measures cumulative exposure to poverty concentration neighbourhoods in every year after leaving the parental home. The maximum value for this cumulative exposure is 17 years since we included cumulative exposure up to t-1 for each year after leaving the parental home. We included three different exposure variables in our models because we hypothesised that exposure just after leaving the parental home has different effects on income later in life than exposure later on. Later exposure is symptomatic of being 'trapped' in poverty concentration neighbourhoods, while early exposure may be the result of spending time in full-time education. Cumulative exposure is measured 1) between 1991 and 1996; 2) between 1997 and 2002; and 3) between 2003 and 2007.

Modelling strategy

To understand the effect that prolonged exposure to concentrations of poverty can have on an individual's income we adopt two different modelling strategies. Neighbourhood effect research has frequently made use of standard ordinary least squares (OLS) regression models but this approach has been subjected to a number of important criticisms not least a lack of controls for selection mechanisms or omitted variable bias, both of which are known to invalidate many neighbourhood effects studies (van Ham and Manley, 2010).

A common strategy in the econometric literature to overcome these problems is "using fixed effects models that better control for the fact that neighbourhood selection is non-random as well as the fact that outcomes are often related to unobserved family background characteristics" (Vartanian and Buck, 2005). In this paper we used a fixed effects approach which models the deviation from the mean for each variable (see also Allison, 2009) to give the within person variation. The model can be represented as follows:

$$(y_i - \bar{y}_{ij}) = \beta_0 + \beta_1(x_{1i} - \bar{x}_{1i}) + \varepsilon_{0i} \quad (1)$$

Where y_{ij} is the global mean for the dependent variable, and y_j is the individual mean, β_0 is a constant and $\beta_i(X_{1i} - X_{1i})$ represents the coefficient for the first of the time varying individual variables with an individual mean subtracted from the global mean (for the original notation see Jones and Subramanian, 2012, p.209). The term ε_{0i} is a normally distributed residual. This operation is carried out on both the predictor and the outcome variables and the regression is run on the demeaned outcome and using the de-meaned predictors. Allison (2009) and others demonstrate that the output of this model is equivalent to including individual dummies for each individual in the data. In practice we use the 'xtreg' function in STATA 11 with the 'fe' (fixed effects) option.

The fixed effects approach is appealing for a number of reasons. The most important one is that by controlling out the time invariant variables, the model accounts for biases that occur with omitted and unobserved variables, such as non-random neighbourhood selection.

As a result, any remaining effect of a neighbourhood characteristic being significantly related to an individual's income is likely to be a 'true causal' effect (or at least an effect which comes closer to a true causal effect in comparison with the OLS estimate). A further advantage of the fixed effects approach is that the model is "largely neutral as to the initial level of income ... so the estimated coefficients can therefore to a large extent be seen as reflecting general 'all worker' effects" (Korpi et al., 2011, p.1062). The fixed effects approach is the first modelling strategy employed in this paper.

Unfortunately, the power of the fixed effect approach results in an undesirable consequence: time invariant information that is measured, such as gender, ethnicity, prior educational attainment, and crucially for this application, parental neighbourhood at the time of leaving the parental home is also lost from the model (Galster, 2008). A common solution to the fixed effects problem is to adopt a random effects approach. However, the random effects model does not control for the unobserved variables and therefore reintroduces the problem associated with the OLS which we originally wanted to overcome. More importantly, the fixed effects models are actually modelling very different data structures to the random effects models as a random effects models use information about both variation within individuals (over time) as well as information about the variation between individuals. This is in contrast to the fixed effects approach which completely discards the between individual variation. "This is a sacrifice of efficiency in modelling terms to ensure that we achieve a reduction in bias" (Allison, 2009, p.27).

The literature tends to depict the fixed effects versus random effects debate as highly polarised with the Hausman test portrayed as a means to identify which technique is the most appropriate. However, Mundlak proposed a correction to the fixed effects model and stated that "the whole approach which calls for a decision on the nature of the effect whether it is random or fixed is both arbitrary and unnecessary" (Mundlak, 1978, p.70). Jones and Subramanian (2012) outlined the Mundlak correction in detail and demonstrated that it provides a method by which it is possible to incorporate both the time invariant variables with the demeaned coefficients from the fixed effects model and at the same time use the framework of a random effects model (hence a hybrid model). Adopting the notion of Jones and Subramanian (2012, p.210) the form of the model is very similar to the model above and we include the group mean in the model:

$$y_{ij} = \beta_0 + \beta_1(x_{1ij} - \bar{x}_j) + \beta_2\bar{x}_j + (u_{0j} + \varepsilon_{0i}) \tag{2}$$

As in the fixed effects model, the within estimate β_1 is not biased because of between individual variations which is now modelled in β_2 (this is the time invariant characteristics that were omitted from the fixed effects model in equation 1 above). Including independent variables that have not been demeaned, means we also have addition variables to account for the variation that the fixed effects model bundles up as error. The residuals $(u_{0j} + \varepsilon_{0i})$ are assumed to be normally distributed. Adopting this approach, we suggest that combining the time invariant characteristics with fixed effects parameters is a non-trivial point and merits fuller exploration with respect to neighbourhood effects. The fact that both the within individual variation (from the fixed effects) and the between individual variation can be obtained in one model is important: there is no reason to assume that the within and between individual variation are the same. Substantively there may be different processes occurring as a result of neighbourhood context which could affect individuals in different ways. This would not be apparent in the fixed effects world. Thus, this model uses both the random and fixed effects approaches together and as such allows a much more complex picture to be built up as a result of the modelled outcomes and is the second modelling approach adopted in this paper.

In the hybrid model, the parameters for the demeaned variables should provide similar (if not completely identical) estimates from the fixed effects approach. Given that the degrees of freedom will change between the models (greater for the hybrid model than the fixed effects model), the hybrid model will also be more conservative in the attribution of significant relationships. A comparison of the hybrid model and the fixed effects model will thus leave us confident that we have effectively controlled for bias that is due to time invariant individual characteristics.

The dependent variable in our models is income from work (as defined above). Both models use the same control variables, measuring demographic characteristics, household characteristics, ethnicity, socio-economic status and tenure. Household characteristics are measured by two different variables, whether the individual is single or lives in a registered couple (married/registered partner or is cohabiting with a common child[4]) and whether the individual has any children below 18 years of age. The socio-economic variables include whether the individual is currently studying, the highest completed level of education (where "medium" refers to a high school degree while a "high" education refers to a university degree), whether the individual is employed, and whether the individual receives social benefits. Finally, we also control for housing tenure. All above variables are measured at t-1 relative to the year (t) when we measure income from work (our dependent variable). This procedure increases the chance that we measure causal effects. In the hybrid model, we also add the time invariant parameters sex, ethnicity, age when leaving the parental home and parental neighbourhood exposure. Ethnicity is measured using country of birth, separating Swedish born from those born in Western (OECD) and Non-western countries. In our analyses, we focus on the Non-western born (in relation to the Swedish and Western born), from here on referred to as "ethnic minorities". Parental neighbourhood is measured as a dummy which indicates whether the neighbourhood the individual lived in the year before leaving the parental home was a poverty concentration neighbourhood or not. Finally, to take into account improvements in income that are due to time (and correlated factors) we control for calendar year, inserted as a set of dummy variables, one for each year. Descriptive statistics for all variables for the full panel data set are found in Table 2.

<<<Table 2 about here>>>

Results

The results from the fixed effects model are presented in Table 3. The dependent variable is the log of income in each year after leaving the parental home. Dummy variables for each year are included in the model but not shown for presentation purposes; they do however show a positive linear pattern which is expected since incomes tend to increase over time. The results from the fixed effects model provide support to our assumption that the effect of exposure depends on when this exposure took place. We find that cumulative exposure to poverty concentration neighbourhoods during the 12 years immediately after leaving the parental home has no effect on individual earnings; the coefficients are positive but small and insignificant. The absence of a negative effect of cumulative exposure to poverty concentration neighbourhoods on income in the first period after leaving the parental home might be explained by the fact that most young people start their independent housing careers in poverty concentration neighbourhoods (see van Ham et al, 2012b). Neighbourhood experiences in poor neighbourhoods in these early years do not necessarily reflect structural

[4] Cohabiting individuals with no common children are coded as single in the Swedish data files.

poverty, but might be a temporary situation when young adults are enrolled in full-time education and building up their labour market career. However, while early exposure does not seem to matter, we find that exposure during the later period, 2003-2007, has a significant *negative* effect on income from work. Thus, remaining in a poverty concentration neighbourhood after the first years of the independent housing career is negatively associated with income development, in line with the arguments of Musterd and colleagues (2012).

The control variables perform as expected; income from work is positively associated with a higher level of education, while negatively associated with having children, receiving social welfare, being a student, and living in rental dwellings.

<<<Table 3 about here>>>

It is at this point that many studies of neighbourhood effects conclude that an unbiased model has been reached which efficiently estimates neighbourhood effects in income. However, as discussed above, we argue that individual outcomes are the consequence of much more complex systems and a significant flaw of the fixed effects model is that the controlling of selection and omitted variable bias has been at the expense of not including time invariant factors such as sex, ethnicity and, in our case, parental neighbourhood. There is an extensive literature that shows that females earn less than males, and that there are links between lower income from work and belonging to an ethnic minority group. Similarly, van Ham and colleagues demonstrated that there was significant evidence of neighbourhood disadvantage being transmitted intergenerationally. Using a random effects model allows these factors to be included in the modelling process whilst the Mundlak correction enables the inclusion of the unbiased fixed effects parameters to show how parental neighbourhood and cumulative exposure are related to individual income. Because of the nature of the model, the hybrid model includes both a within individual variation part (from the fixed effects part, denoted in Table 4 by deviation from individual mean at the top of the table) and a between individual variation part (from the random effects part denoted by individual means of time variant variables).

The first important finding to note in Table 4 is that the coefficients in the top part of the table (within individual variation) are virtually identical to the coefficients in the fixed-effects model (Model I, Table 3), albeit with some differences in significance. As such, we can observe that the random effects model with the Mundlak correction is performing as expected and provides unbiased terms for cumulative exposure (as in the fixed effects model). The conclusion that cumulative exposure to poverty concentration neighbourhoods later in life has a negative effect on incomes holds. The only difference with the fixed effects model is that in the hybrid model the very small positive effects of exposure in the early years after leaving the parental home are now just significant (at the 0.05 level). We suggest that this positive effect of exposure reflects the fact that many young people experience both rapid increases in income and exposure to low income neighbourhoods in the early years after leaving the parental home.

What the fixed-effects model could not show us, but what we can observe in the hybrid model, is that there is also an effect of parental neighbourhood on children's income as adults (see the time invariant part of the model in Table 4). Individuals who lived with their parents in a poverty concentration neighbourhood experience an extra income penalty in addition to the negative effects associated with the number of years spent in such a neighbourhood during later years of adulthood. This additional effect of the parental neighbourhood is equivalent to spending 4.5 years in a poverty neighbourhood during the years 2003-2007.

The hybrid model also reveals strong negative effects for being female or a non-western immigrant on income. It is important to note that the coefficients for these variables are much larger than the coefficients for the cumulative exposure, indicating that they have a larger impact on individual income inequality. In Model II, Table 4, we interact the effect of the parental neighbourhood with being a non-western immigrant. The results show that for immigrants there is a strong income penalty for growing up in a poverty concentration area; the effect is much stronger than the cumulative exposure effects. Adding the parental neighbourhood to the model thus reveals substantial neighbourhood effects on income which could not be shown using a fixed effects model.

<<<Table 4 about here>>>

The second finding to note from Table 4 is that the random effects parameters (representing the between individual variation) in the bottom half of the table are not identical to those in the top half of Table 4: the within individual (from the fixed effects model) and between individual (from the random effects coefficients) variation are not the same. Conceptually, this tells us something about the variation structure in the data. We find that there is greater variation between individuals than occurs within a single individual's trajectory. The between individuals effects of cumulative exposure to poverty concentration neighbourhoods shows a strong negative effect of cumulative exposure between 2003-07 (parameter of -0.128) on income. Interestingly in the between individuals part there is a negative (but not significant) effect of exposure in earlier years.

A major advantage of the hybrid model is the ability to include time invariant variables to obtain additional information about the relationship between neighbourhood and individual characteristics. This information was completely hidden in the fixed effects model. We suggest that neighbourhood effects researchers should not be content to "throw the baby out with the bath water" (Beck and Katz, 2001) in the pursuit of unbiased estimates when there is an alternative to the fixed effects model in the hybrid model. We argue that the information the fixed effects model discards is non-trivial in nature. For instance, the fact that there is a highly significant effect of belonging to a non-western ethnic group is important, but also that this effect is much larger than the effect of the neighbourhood level characteristics. Both were invisible in the fixed effects model. In short, by using the hybrid approach we are able to answer not only the question whether the parental neighbourhood has an effect on incomes, but also to answer it in the context of the relative importance of other intervening factors including individual characteristics.

Conclusions

This paper has made three substantial contributions to the literature. This is one of the first studies which investigated the effects of neighbourhood histories on individual outcomes for adults. We innovatively included both childhood experiences (through the parental neighbourhood) and cumulative exposure to poverty concentration neighbourhoods in our models of income later in life. Our models demonstrated clearly that those who lived with their parents in a poverty concentration neighbourhood, experienced significant negative effects on their income later in life, even 17 years after they have left their parental home. This is a very important finding as it indicates that there is intergenerational transmission of neighbourhood effects from parents to children, and that these effects are long lasting. We also found that cumulative exposure to poverty concentration neighbourhoods after leaving the parental home has important effects on income later in life. Exposure in the first 12 years after leaving the parental home has no, or very small positive effects on incomes. This is probably caused by the fact that young people often start their housing career at the bottom of the housing and neighbourhood hierarchy (see van Ham et al., 2012) while at the same time they advance their labour career, which is associated with income gains. Exposure to poverty neighbourhoods at a later stage in life (13-17 years after having left the parental home) has a strong negative effect on incomes later in life. There are two possible explanations. The first is that only more recent experiences have significant effects and the second is that effects are only significant for those who (still) live in poverty neighbourhoods later in life. Our results are unique as we are not aware of any other neighbourhood effects paper that has investigated the effects of exposure over such a long period of time for an adult population (Jackson and Mare, 2007; Crowder and South, 2011, and Wodtke, Harding and Elwert, 2011, have done so for children).

The second contribution is that we have made use of bespoke neighbourhoods to represent individual neighbourhoods. Only few studies have done so previously (for an exception see Bolster et al., 2007). We used bespoke neighbourhoods to overcome some problems associated with the use of standard administrative boundaries, most importantly boundary and scale issues. Creating bespoke neighbourhoods based on the nearest neighbours mean that we are in direct control of the geographic extent of the neighbourhood scale. Furthermore, because each individual is placed centrally within their bespoke neighbourhood we are able to avoid the problem that arises when an individual lives near to a boundary of an administrative neighbourhood or spatial unit.

The third contribution of this paper arises from the modelling framework we have adopted. To our knowledge we are the first neighbourhood effect study to combine a fixed effects approach with a random effects hybrid model with a Mundlak (1978) correction. The hybrid model allows a very useful extension of the fixed effects model with the inclusion of time invariant characteristics effectively enabling us to ‘have our cake and eat it’. As such we have the advantage of reducing selection bias and omitted variable bias from our estimates while also getting additional information about the impact of time invariant individual characteristics.

In conclusion, this paper is a major step forward in the neighbourhood effects literature by combining theoretical and methodological innovations. We have demonstrated that the fixed effects versus random effects choice is not the binary that is frequently presented in the literature and that it is possible use a relatively simple combination of the two models. We argue that taking such an approach should be the empirical gold standard when using longitudinal data. We have also demonstrated that the neighbourhood context has long lasting, and even intergenerational, effects on individual incomes. The fact that prolonged exposure matters more than brief exposure, if taking place later in life, has particular policy relevance. It demonstrates that brief episodes of residence in poverty concentrations are not problematic. Low income neighbourhoods provide cheap housing which has an important role for, for example, students and new (international) arrivals. Exposure to poverty concentrations is problematic when it is long lasting and occurs later in life. Exposure to poverty concentration neighbourhoods is also problematic when it runs over several generations. So policy efforts should be directed at assisting individuals who experience long stays in poverty concentrations and should seek to assist intergenerational socio-spatial mobility.

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Table 1. Descriptive statistics of the five neighbourhood quintiles in 1990 and 2008.

	1990						2008					
	% low income neighbours		% ethnic minorities		% public rentals		% low income neighbours		% ethnic minorities		% public rentals	
Neighbourhood quintile	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.	Mean	Std Dev.
1	.101	.015	.022	.020	.067	.170	.096	.014	.064	.053	.046	.137
2	.132	.007	.038	.036	.202	.283	.123	.006	.072	.061	.089	.194
3	.155	.007	.052	.046	.343	.356	.145	.007	.083	.069	.119	.228
4	.181	.009	.072	.059	.483	.399	.174	.011	.097	.081	.149	.259
5	.241	.054	.189	.153	.615	.397	.248	.062	.163	.151	.264	.360

Table 2: Descriptive statistics (Log of income from work is measured 1992-2008. All other variables are measured 1991-2007, i.e. at t-1)

	Mean	**Std. Dev.**	**Min**	**Max**
Log of income from work (at time t)	2.682	1.121	-4.610	7.563
Cumulative exposure to quintile 5 neighbourhood 91-96	2.419	2.291	0.000	6.000
Cumulative exposure to quintile 5 neighbourhood 97-02	1.102	1.795	0.000	6.000
Cumulative exposure to quintile 5 neighbourhood 03-07	0.261	0.825	0.000	5.000
Have children (ref = no children)	0.472	0.499	0.000	1.000
Medium education (ref = low)	0.388	0.487	0.000	1.000
High education (ref = low)	0.119	0.324	0.000	1.000
Single (ref = couple)	0.552	0.497	0.000	1.000
Receive social welfare (ref = no)	0.042	0.201	0.000	1.000
Student (ref = no)	0.107	0.309	0.000	1.000
Live in cooperative (ref = home ownership)	0.268	0.443	0.000	1.000
Live in private rental (ref = home ownership)	0.204	0.403	0.000	1.000
Live in public rental (ref = home ownership)	0.184	0.387	0.000	1.000
Year (same descriptive statistics for all years 1992-2007, ref = 1991)	0.059	0.235	0.000	1.000
Female (ref = male)	0.513	0.500	0.000	1.000
Non-western immigrant (ref = Swedish or western immigrant)	0.041	0.198	0.000	1.000
Parental neighbourhood = quintile 5 (ref = other quintile)	0.115	0.319	0.000	1.000
Age when leaving parental home (in 1991)	22.039	2.185	17.000	26.000

Table 3: Fixed Effect Model: Log of income from work controlling for individual exposure to quintile 5 neighbourhoods. Year dummies are included in the model but not shown.

	Coef.	Std. Err.	Sign.
TIME VARIANT VARIABLES (DEVIATION FROM INDIVIDUAL MEAN)			
Cumulative exposure to quintile 5 neighbourhood 91-96	0.008	0.004	
Cumulative exposure to quintile 5 neighbourhood 97-02	0.005	0.003	
Cumulative exposure to quintile 5 neighbourhood 03-07	-0.018	0.005	***
Have children (ref = no children)	-0.150	0.011	***
Medium education (ref = low)	0.067	0.019	**
High education (ref = low)	0.660	0.024	***
Single (ref = couple)	0.014	0.010	
Receive social welfare (ref = no)	-0.323	0.019	***
Student (ref = no)	-0.725	0.011	***
Live in cooperative (ref = home ownership)	-0.011	0.009	
Live in private rental (ref = home ownership)	-0.043	0.012	***
Live in public rental (ref = home ownership)	-0.070	0.013	***
Constant	2.255	0.011	***
N	230,010		
R2 (within)	0.271		
R2 (between)	0.057		
R2 (overall)	0.158		

Note: *p<0.05; **p<0.01; ***p<0.001

Table 4: Random Effects Model with Mundlak Correction: Log of income from work controlling for individual exposure to quintile 5 neighbourhoods and parental neighbourhood (and other time-invariant characteristics). Year dummies are included in the model but not shown.

	Model I			Model II		
	Coef.	**Std. Err.**	**Sign.**	**Coef.**	**Std. Err.**	**Sign.**
TIME VARIANT VARIABLES (DEVIATION FROM INDIVIDUAL MEAN)						
Cumulative exposure to quintile 5 neighbourhood 91-96	0.008	0.003	**	0.008	0.003	**
Cumulative exposure to quintile 5 neighbourhood 97-02	0.005	0.002	*	0.005	0.002	*
Cumulative exposure to quintile 5 neighbourhood 03-07	-0.018	0.003	***	-0.018	0.003	***
Have children (ref = no children)	-0.150	0.007	***	-0.150	0.007	***
Medium education (ref = low)	0.067	0.010	***	0.067	0.010	***
High education (ref = low)	0.661	0.013	***	0.661	0.013	***
Single (ref = couple)	0.014	0.007	*	0.014	0.007	*
Receive social welfare (ref = no)	-0.323	0.010	***	-0.323	0.010	***
Student (ref = no)	-0.725	0.006	***	-0.725	0.006	***
Live in cooperative (ref = home ownership)	-0.010	0.006		-0.010	0.006	
Live in private rental (ref = home ownership)	-0.042	0.007	***	-0.042	0.007	***
Live in public rental (ref = home ownership)	-0.069	0.008	***	-0.069	0.008	***
TIME INVARIANT VARIABLES			***			***
Female (ref = male)	-0.300	0.010	***	-0.301	0.010	***
Non-western immigrant (ref = Swedish or western immigrant)	-0.187	0.025	***	-0.124	0.031	***
Parental neighbourhood = quintile 5 (ref = other quintile)	-0.081	0.015	***	-0.064	0.016	***
Parental nbd = quintile 5 * non-western immigrants				-0.179	0.051	***
Age when leaving parental home	-0.002	0.002		-0.002	0.002	
INDIVIDUAL MEANS OF TIME VARIANT VARIABLES						
Cumulative exposure to quintile 5 neighbourhood 91-96	-0.002	0.003		-0.002	0.003	
Cumulative exposure to quintile 5 neighbourhood 97-02	-0.004	0.006		-0.004	0.006	
Cumulative exposure to quintile 5 neighbourhood 03-07	-0.128	0.015	***	-0.127	0.015	***
Have children (ref = no children)	0.161	0.026	***	0.159	0.026	***

Medium education (ref = low)	0.264	0.012	***	0.263	0.012	***
High education (ref = low)	0.536	0.021	***	0.535	0.021	***
Single (ref = couple)	0.046	0.027		0.041	0.027	
Receive social welfare (ref = no)	-2.421	0.048	***	-2.416	0.048	***
Student (ref = no)	-1.822	0.041	***	-1.823	0.041	***
Live in cooperative (ref = home ownership)	0.001	0.019		0.001	0.019	
Live in private rental (ref = home ownership)	0.005	0.020		0.006	0.020	
Live in public rental (ref = home ownership)	0.006	0.022		0.007	0.022	
Constant	2.528	0.060	***	2.528	0.060	***
N	230,010			230,010		
R2 (within)	0.271			0.271		
R2 (between)	0.432			0.432		
R2 (overall)	0.340			0.340		

Note: *p<0.05; **p<0.01; ***p<0.001