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Contextual Effects on Educational Attainment in Individualized Neighborhoods: Differences across Gender and Social Class

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CONTEXTUAL EFFECTS ON EDUCATIONAL ATTAINMENT IN INDIVIDUALIZED NEIGHBORHOODS; DIFFERENCES ACROSS GENDER AND SOCIAL CLASS

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ABSTRACT: The idea that neighborhoods affect the future life course of young people has over the years, stimulated an impressive amount of empirical work. We propose a method for constructing contextual variables based on scalable, individualized neighborhoods to capture neighborhood effects. What is an appropriate neighborhood size to capture effects on adolescents? Here role models, norms and peer effects could be suggested to emanate from the closest 50, 100 or 400 neighbors. We use an extensive, register-based, geo-coded, longitudinal data set. A cohort of adolescents born in 1980 is analyzed as regards their educational achievements by 2010, when the cohort had reached the age of 30. Earlier studies using the same research design show significant but small effects on education from administratively set neighborhoods. Our results show effects three times greater. Also, scale-dependent effects of marginality as well as significant interaction effects with gender and educational background were found.

Key words: contextual effects, neighborhood effects, context, EquiPop, adolescents, education

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INTRODUCTION

In 2012, two books with strikingly different ideas about the role of neighborhood processes in urban development were published. On the one hand, there was Robert Sampson's *Great American City: Chicago and the Enduring Neighborhood Effect,* arguing that neighborhood processes are of fundamental importance for the working of a modern city. On the other hand, there was *Neighbourhood Effects Research: New Perspectives* edited by Van Ham et al., essentially arguing that neighborhood effect studies are at an impasse and that further progress will require radical rethinking of both theories and changes in research methodology. Together, these two books provide a good summary of the current state of neighborhood effect studies. Both bear witness to the continuing interest in neighborhood effects, but they also make it clear that this has become a field of research that, in spite of a growing number of empirical studies, is characterized by considerable controversy.

One possible reason for the controversy is that although there is a strong theoretical argument—backed up by considerable qualitative evidence—there is meager quantitative evidence for an influence of neighborhood context on life outcomes at an individual level. And it is clearly frustrating for a social scientist to have such a discrepancy between one's best theories and what it is possible to demonstrate empirically.

In this paper, we will argue that problems associated with the measurement of neighborhood context could be one reason for the lack of clear-cut results in neighborhood effect studies. Up to now the main approach in this field of study has been to measure context using aggregate values for administratively defined areas. This implies that neighborhood effect studies have, to a considerable degree, ignored the argument put forward by Openshaw (1984) and others that such aggregate measures will be plagued by indeterminacy. Certainly researchers have been aware that their measures have been far from perfect (see e.g. Putnam (2007), but there seems to have been a widespread belief that values that have been aggregated using fixed areal units can serve as good approximation, given a lack of feasible alternatives. Statistical theory, however, says that measurement errors in explanatory variables will have strong negative effects on one's ability to obtain good estimates of the parameters of a statistical model. Therefore, it is possible that disappointing results in neighborhood effect studies are simply a reflection of weakness in the empirical design (Galster, 2008; Sampson, Morenoff and Gannon-Rowley, 2002).

The solution that we propose in this paper is to measure neighborhood context using aggregates for individualized, egocentric neighborhoods. These neighborhoods will be constructed as buffers around the residential location of the individuals under study in such a way that the buffer for each location will include the same number of nearest neighbors. In this way, the modifiable areal unit problem will be circumvented since the measurement of context will become independent of any statistically given areal subdivision. By constructing buffers of different size, this approach also makes it possible to measure neighborhood context using different scale levels.

The question we will address using this new methodology is how educational achievements are influenced by neighborhood context. Education is a determinant of individual income, health, and welfare and it also plays a key role in the transfer of social status from parents to children. Therefore, contextual effects on educational achievements can be an important lever for equality and inequality.

NEIGHBORHOOD EFFECTS ON EDUCATIONAL ACHIEVEMENT

Neighborhood effects is a research area which over time has grown to become vital in many disciplines. Key references are found particularly in American research and in studies of poor neighborhoods (Crane, 1991; Crowder and South, 2003; Ludwig, 1999). One prominent scholar typically cited is William Julius Wilson (1987). He shows how poverty spreads in American poor, black areas where the middle class has moved from the area. Those still living there find it difficult to get jobs and they are also deprived of their social networks to find work.

European research on neighborhood effects is a somewhat later phenomenon, but has, similarly to research from the U.S., dealt with the issue of access to jobs, income (Galster, Andersson, Musterd and Kauppinen, 2008), the effects of concentrations of poverty (Friedrich, 1998) and effects on education (Kauppinen, 2007, Leckie, 2009; Sykes, 2011). An early study by Andersson (2001) used longitudinal individual data from Statistics Sweden to analyze contextual effects on educational outcomes. The study demonstrated the contextual effects of the socio-economic composition of so-called SAMS areas on individual future education (Andersson, 2004). In a study by Andersson and Subramanian (2006), neighborhood effects were found on years of education from socio-economic resources and demographic stability. Using data for individuals, several studies of educational issues have been conducted on, for instance, neighborhood effects on school commuting (Andersson, Malmberg and Östh, 2012), and school segregation as a consequence of choice reforms (Östh, Andersson and Malmberg, 2013). Another Swedish study in this field is Brännström's dissertation (2006). In his first counterfactual study of young people in Stockholm in the 1950s, he showed that neighborhood effects could not be detected (2004). Children who grew up in poor areas were not affected in any other way than children who grew up in affluent areas. Since these studies, the Swedish research on neighborhood effects has continued with several valuable studies such as Sundlöf's (2008) on young people's socio-economic careers in Stockholm, Bergsten's (2010) study of young people in Örebro, Västerås and Linköping, and Trumberg's (2011) study on school choice in Örebro. Both Sundlöf and Bergsten found contextual effects on educational achievements. Swedish researchers in the field of neighborhood effect research have benefited greatly from the quantitative material, such as registry data, available from Statistics Sweden.

The review above is intended to show neighborhood effect studies have become a large field of research that focuses on the analysis of different outcomes. Researchers have measured contextual effects on education, but also health, employment and income. Most studies indicate the existence of neighborhood effects, which are distinct from individual and household characteristics of the measured outcomes. The effects measured are relatively low compared to household effects, and some studies find no support for neighborhood effects.

FROM CRITICISM TO INDIVIDUALIZED NEIGHBORHOODS

In recent years, increasing criticism has been directed at the neighborhood effect studies (methods) and also the phenomenon as such (Hedman 2011). Criticism has touched on: the stability of effects over time, subjects of cross-sectional studies, and the fact that measured effects are quite small or non-existent (Brännström, 2004; Hedman, 2011). In the same vein, different groups of inhabitants in a neighborhood might be influenced differently, which has not been researched sufficiently (Bergsten, 2010; Galster, Andersson and Musterd, 2010; Sykes and Kuyper, 2009). The policy of mixing population and mixing housing (tenure forms) has been criticized for not being an effective policy against segregation because neighborhood effects are not satisfactorily assessed. The fact that researchers critically examine concepts and methods is justified, but this discussion can also be seen as a sign of declining enthusiasm. This is an idea taken from qualitative research, namely that where we live is very important when growing up and for our subsequent socioeconomic career.

There are several reasons that neighborhood effects still remain a large research area and a matter of political interest and debate. One reason is that qualitative research, as well as lived experiences, show people that there is greater importance to where they have been growing up than has been proved scientifically. A second reason is that inequality of outcomes in e.g. education due to where adolescents live is against the expectations and goals set by welfare states and against national policies of education. In the US, for example, segregated schools were declared unconstitutional because of their detrimental effect on educational equality (Brown v. Board of Education, 1954; Clark, 1987; Coleman, 1966). A third reason is that mixing residential areas and schools is a direct policy and planning measure that is in constant debate. Mixing strategies are questioned and need scientific support if continued in (especially) times of economic crisis (Galster, 2007; Holmqvist and Bergsten, 2009). However, planning mixed residential areas and schools is far more direct than targeting individual and family behavior to equalize outcomes.

MEDIATING MECHANISMS AND PROCESSES

Articles measuring neighborhood effects (Ainsworth, 2002; Andersson, 2004; Andersson and Subramanian, 2006; Crane, 1991; Evans, Wells and Moch, 2003; Immergluck, 1998; Ludwig, 1999; South, Baumer and Lutz, 2003) have in common a quantitative approach where the richness and quality of material are vital. Additionally, they have in common that contextual effects are significant for the specified outcomes. However, the question of *how* area effects are transferred seems to be a topic where research is rare and where qualitative empirical work could enrich the research field, (Galster, 2012; Galster and Santiago, 2006).

Mechanisms that transfer influences between individuals and their surroundings are called *mediating processes/mechanisms*. Exploring these mediating processes is, in other words, exploring *how* neighborhood effects work. Mediating processes such as collective socialization, social control, social capital, perception of opportunity and institutional characteristics are among other researchers proposed by Ainsworth (2002) and Galster (2007).

Collective socialization as a concept is used to explain how neighborhood characteristics influence children and adolescents. Collective socialization is a process where youths are exposed to role models among adults, and adapt to those to varying degrees. It is then important who these role models are. Are they from mainstream society? One could easily imagine a context wherein homework and studying were not considered the 'coolest' things, but also the opposite: a neighborhood where homework and reading were taken seriously by most parents and children. Wilson (1987) claimed that neighborhoods where most adults have steady jobs foster behaviors and attitudes that value success at both school and work. Wilson also discusses gender roles and family types to be influenced by the context, for instance more lone mothers in distressed areas. The theory of socialization is important to many scholars in the field of neighborhood effects. Most of them use the theory to explain influences on children or adolescents but some state that the effects just do not disappear at a certain age; instead, they can also be observed in adults (Andersson, 2000).

In addition to collective socialization processes, neighborhood level *social control* may also influence outcomes. Social control is the monitoring and sanctioning of deviant behavior of youths and others. If there are fewer adults around and if they do not spend time with youths, youths may shape their own norms. These norms can be more influential than those transferred from the parental group (Ainsworth, 2002).

Another mediating process is that of *social capital* or social networks that exist in a given community (Putnam, 1993). Children and adolescents living in advantaged neighborhoods are more likely to be exposed to helpful social networks. In advantaged neighborhoods, children are more likely to meet adults who can provide positive recourses in the form of information and other things that may be beneficial in the future (personal computers, job opportunities, help with advanced homework etc.). Poor or disadvantaged people have limited social networks and social capital according to some scholars (Friedrichs, 1996) while others state that this is not evidently so (Van Kempen, 1998).

The *perception of opportunity* is an important mediating mechanism in structuring the lives of youths. If youths succeed in school because they believe in a pay-off in the form of a good job, and then see discrimination, they may question the value of educational achievements. Youths in stigmatized neighborhoods are likely to encounter discrimination and perceive few opportunities. Stigmatization may also result in reduced flows of resources to an area, according to Galster (2007).

These mediating mechanisms will not be measured in this study, but they explain why we expect a relationship to exist between the neighborhood or context and educational outcomes.

EMPIRICAL DESIGN

The design of the study is straightforward; we follow a cohort born in 1980 from 1995 to 2010. Neighborhood context is observed in 1995 and educational outcome is observed in 2010. With this longitudinal design we face less problem with selection bias than studies that observe neighborhood context and outcome in the same period (Galster et al., 2007; Sampson, Morenoff and Gannon-Rowley, 2002). We allow for a five-year exposure period between the ages of 14 and 18. Our hypothesis is that these adolescents are influenced by their childhood/adolescent surroundings, and the majority of the population lived in the same area from early childhood and onwards. To ensure a minimum number of years of exposure a restriction of two km mobility is set to certify a possible influence from the residential environment in the studied cohort; see Figure 1. However, we assume most children stayed in the same area for a longer time because infrequent moves in the Swedish population is reported in some studies, e.g. Fischer and Malmberg (2001), and a general pattern of infrequent moves for families with children in other studies, e.g. Warnes (1992). Built into the design is also the fact that although the voucher system was put in place in 1992, the Swedish school choice reform did not take off until later. This means most children in the 1980s cohort went to the school closest to home, which included the neighboring children.

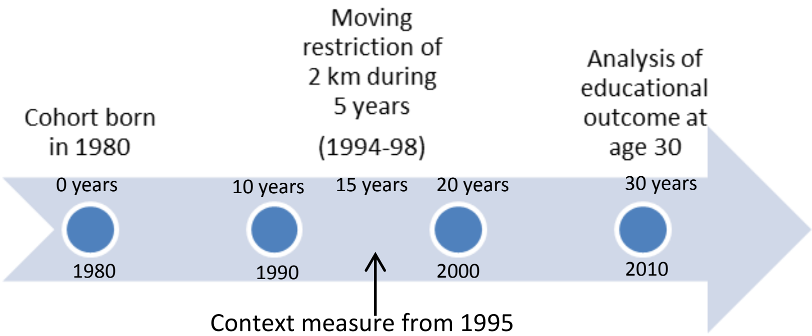

FIGURE 1. THE COHORT AND ITS AGE AT DIFFERENT STAGES OF ANALYSIS.

The design then includes the constructed individualized neighborhoods to measure the significance of context. The size of the context is also varied from the 12 closest neighbors to the 25 600 closest neighbors.

DATA AND METHODS

In order to estimate contextual effects on educational level we employ a logistic regression using educational level (dummy of university education) as a dependent variable with individual background variables and contextual variables as explanatory variables. The data originates from PLACE, a database delivered by Statistics Sweden located at Uppsala University. The contextual variables are factor scores based on contextual measurements from individualized, egocentric neighborhoods.

In the following text, two types of data and their use are described in more detail.

INDIVIDUAL LEVEL, COHORT AND HOUSEHOLD DATA

For our study we choose to use a cohort of individuals born in 1980, living in Sweden from 1995 to 2010. The main limitation on the sample was a non-mobility criterion during five years (1994, 1995, 1996, 1997, and 1998) because the individuals in the sample were to be affected by the same surroundings during the five years. The limit for mobility was set to two km. The sample was reduced by 15% by this criterion. Reductions were also made due to missing variables for parents. From 102 592 individuals born in 1980 we had a population of 74 648 individuals in our final sample.

It is possible that removing movers can affect the results we obtain. Movers, for example tend to come from households with fewer resources than stayers. Thus, among movers there is a higher share having unemployed, lower educated, foreign born, low income, and visible minority parents. Movers also to a larger extent come from households that obtained social allowances in 1995. There is a literature discussing unobserved characteristics that might bias the apparent neighborhood effects, see e.g. Galster et. al. (2007) for a research design similar to ours or Sampson (2012).

The dependent variable of education was measured by the existence of a university or university college degree, as shown in Table 1 below. Most children in Sweden start school at seven years of age and attend compulsory education for nine years; see Table 1. Upper secondary school is now three years and prepares many students for university or university college.

TABLE 1. THE SWEDISH SCHOOL SYSTEM. NUMBER OF YEARS IN SCHOOL AND THE AGE OF STUDENTS AND PROPORTION OF EDUCATIONAL ACHIEVEMENTS IN OUR 1980 COHORT.

	Compulsory Education									Upper secondary school			University or University College				PhD programs
School years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16/17	≥20/21
Age of student	7	8	9	10	11	12	13	14	15	16	17	18	>18				
Share of students in our sample								1	6		7	35		14		37	5
Share of students in our sample												49	51				

Furthermore, we included individual level variables. There are a number of variables often used in contextual effect studies of education concerning individual, and importantly, parental characteristics. We included a similar, standard set of variables (see Table 2) containing: the sex of the individual, and for parents of the individuals, whether one or both belonged to a visible minority in the Swedish context, whether one or both parents were foreign-born, if the household received social allowance, if either parent had a university degree, if either parent was non-employed, if the household type was 'single mother', and lastly, if the parents' income belonged to the top decile of incomes among parents in the 1980s cohort (the parents with the highest salaries were ranked in percentiles).

In Table 2, descriptive statistics for the cohort show the proportion of individuals having single mothers to be 15 percent. Among the individuals in the cohort, 51 percent had a university education in 2010, whereof 43 percent were men and 60 percent women. Furthermore, 41 percent among parents had a university education and about 2 percent of the parents were from a visible minority in the Swedish context and close to 17 percent were foreign-born. The proportion of parents that had received a social allowance was 10 percent, which was slightly higher than the national average due to the fact that these were households with children. A total of 25 percent of the parents were unemployed: probably a high number due to the serious recession starting in 1991 and having consequences even in 1995.

TABLE 2. INDIVIDUAL LEVEL VARIABLES.

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Sex	74649	1	1	2	1.48	0.499
Single mothers	74649	1	0	1	0.15	0.354
Univ. education 2010	74649	1	0	1	0.51	0.500
Parent with univ. education	74649	1	0	1	0.41	0.492
Parent in visible minority	74649	1	0	1	0.02	0.145
Parent with social allowance	74649	1	0	1	0.10	0.299
Parent foreign-born	74649	1	0	1	0.17	0.378
Parent non-employed	74649	1	0	1	0.25	0.432
Disposable income decile	74649	100	0	100	50.78	28.465

CONTEXTUAL MEASUREMENT

With respect to the use of individual background variables the empirical design of this study is conventional. This is not the case, though, with our approach to context measurement. Here, instead, our study introduces two important novelties: first, and most importantly, we introduce contextual measures that are based on individually defined and scalable neighborhoods. Second, we introduce a factor-analysis based representation of the spatial variation in a socio-demographic context as a means to manage the wealth of information resulting from scalability. Last in this section, and as means of comparing this work with earlier studies, we present the often used Swedish areal division of so called SAMS areas.

INDIVIDUALLY DEFINED AND SCALABLE NEIGHBORHOOD

Thus, in this study we measure neighborhood population compositions using individual centered neighborhoods of fixed population size. Thus, we have used register data containing information of individual residential location to compute contextual variables based on the population composition among an individual's nearest 12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, and 25600 neighbors for 1995 (for the population older than 25 years *and* the total population, depending on variables).

In order to measure the population composition in individually defined neighborhoods we have used a spatial analysis program developed in 2011 by John Östh (Östh, Malmberg, and Andersson 2011). EquiPop was first developed in order to address the modifiable areal unit problem, MAUP, in segregation measurement. As shown in Östh, Malmberg, and Andersson (forthcoming), traditional measures of segregation such as the isolation index are strongly dependent on the size of the statistical units for which the segregation index has been computed. In many cases, variation in segregation values is more influenced by varying areal subdivisions than by variation in residential patterns. In the EquiPop software, the individualized neighborhoods are obtained by expanding a circular buffer around each residential location until the population encircled by the buffer corresponds to the population threshold chosen. When this threshold is reached, the program computes aggregate statistics for the encircled population of a selected socio-economic variable.

EquiPop requires that the input data is geocoded on a detailed level. We have used data from the PLACE (Population Labor Market Chorology Data) database of Uppsala University. This data contain register-based, individual level data for the population in Sweden from 1990 to 2010 with geocodes of the residential location by 100 meter squares. From this data, seven different socio-demographic indicators have been extracted and used as input for EquiPop; see Table 3.

TABLE 3. CONTEXT VARIABLES RUN IN EQUIPOP FOR K NEAREST NEIGHBORS IN 1995.

Variable	Description	Year	Population	Number of neighbors (k)
Education	1 = university/college, 0 = not university/college	1995	>25 years	12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600
Social allowance	1 = social allowance	1995	all	12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600
Family type	1 = single mother	1995	>25 years	12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600
Disposable income	percentiles	1995	>25 years	12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600
Born abroad	1 = born abroad (not Sweden)	1995	all	12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600
Unemployed	1 = non employed 0 = employed	1995	>25 years	12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600
Housing	1 = Single owner occupied housing, 0 = other types of housing	1996	All	12, 25, 50, 100, 200, 400, 800, 1600, 3200, 6400, 12800, 25600

FACTOR-ANALYSIS BASED REPRESENTATION OF CONTEXTUAL VARIATION

With seven different socio-demographic indicators and 12 different levels of neighborhood scale we obtain a total of 84 different contextual variables. Clearly, such a large number of contextual variables cannot be included, without problems, as explanatory variables in a regression of educational achievement. Moreover, many of the indicators are strongly correlated, for example, contextual indicators based on the same socio-economic indicator but computed for different neighborhood sizes. Therefore, in order to make the analysis manageable we have subjected the contextual indicators to a factor analysis that compresses the 84 original indicators to 10 orthogonal factors that jointly capture more than 79% of the original variation. The factor analysis was based on covariances, and the number of principal components to be rotated was selected based on them having eigenvalues higher than one. The factors were rotated using varimax method.

Some factors influence a small number of neighbors (k) as contextual variables, and other factors influence a large number of neighbors. This result of the factor analysis is clearly of interest since it provides an opportunity to analyze the scale dependence of contextual effects. Table 4 shows the descriptive names of factors one to ten and indicates the scale of interest.

TABLE 4. CONTEXT DESCRIBED BY INDIVIDUALIZED NEIGHBORHOODS FOR 1995.

Factor no.	Factor name
Factor 1	Elite areas
Factor 2	Low employment in adjacent areas
Factor 3	Foreign-born
Factor 4	Marginal nearby
Factor 5	Marginal intermediate scale
Factor 6	Single family housing
Factor 7	Low employment, small scale
Factor 8	Low employment, medium scale
Factor 9	Marginal, medium scale
Factor 10	Non-academic elite

Figure 2 shows diagrams of what the different factors represent. This interpretation is important since we are going to include factor scores as explanatory variables in the logistic regression of educational achievement. Without an interpretation of the different factors it will be difficult to interpret the regression results. Our interpretation of the factors is given below.

Factor 1 **Elite areas**. High values for this factor in a location result in a high proportion of people with tertiary education, high disposable income, and a low proportion of unemployed.

Factor 2 **Low employment in adjacent areas**. High values for this factor result in a high level of non-employment at neighborhood scales beyond 100 persons. The same areas are also characterized by low disposable income.

Factor 3 **Foreign-born**. High values for this factor implies a high proportion of foreign-born residents, and to some extent, social allowances.

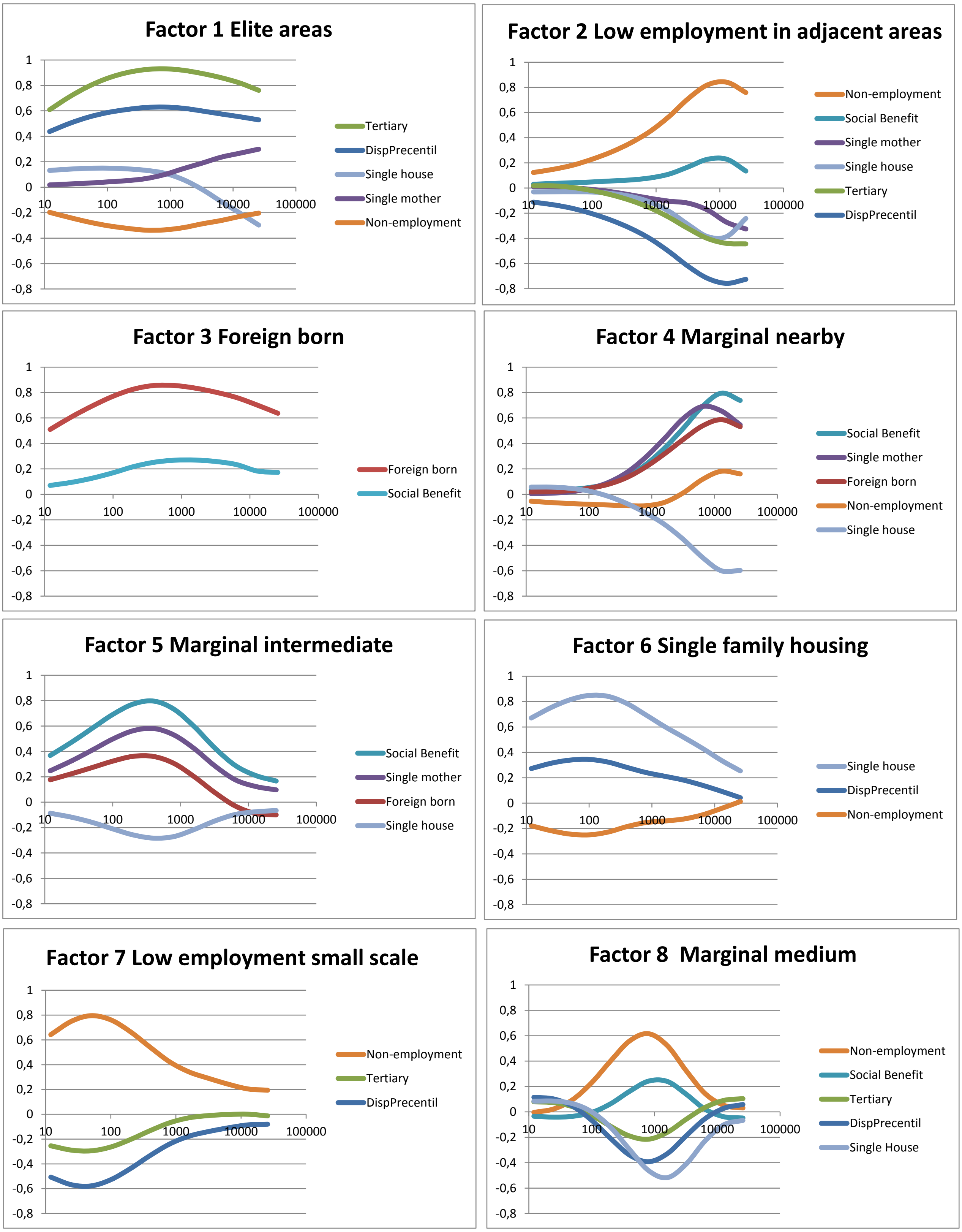

FIGURE 2. FACTORS AND LOADINGS. (TO REDUCE CLUTTER, THESE GRAPHS ONLY SHOW FACTORS THAT FOR AT LEAST ONE *K-LEVEL* HAVE A LOADING HIGHER THAN 0.2 OR LOWER THAN -0.2.)

Factor 4 **Marginal nearby**. High values for this factor result in low levels of single family housing, a high proportion of single mother households, households with social allowances, and foreign-born residents at neighborhood scales above 800 persons.

Factor 5 **Marginal intermediate**. Factor 5 is similar to Factor 4 with the difference that Factor 5 has an effect mainly on neighborhood scales below 800 persons.

Factor 6 **Single family housing.** This factor contributes to a high proportion of the population living in single-family houses, high disposable income and a low proportion of non-employed.

Factor 7 **Low employment, small-scale**. Factor 7 is similar to Factor 2 with the difference that Factor 7 has an effect mainly on neighborhood scales below 1000 persons.

Factor 8 **Low employment medium**. Factor 8 is similar to Factor 2 with the difference that Factor 8 has an effect mainly on neighborhood scales of around 1000 persons.

Factor 9 **Marginal medium**. Factor 9 is similar to Factor 4 with the difference that Factor 9 has an effect mainly on neighborhood scales of around 1600 to 6400 persons.

Factor 10 **Non-academic elite**. High values on Factor 10 are associated with high levels of disposable income but not with a high proportion of tertiary education.

SAMS AREAS AS CONTEXT

The residential differentiation according to the Small Area Market Statistics, SAMS, classification scheme is a national subdivision in homogenous residential areas (more than 9 000). SAMS was developed by Statistics Sweden in collaboration with the municipalities, and is a social division according to building characteristics and tenure form. Originally, for publicity purposes and municipal planning, SAMS was formed to include a certain target group. Some SAMS-areas are uninhabited and accordingly the number of inhabitants and sizes of SAMS vary. Our study makes use of 7 704 SAMS areas (see Table 5 for individuals from the 1980s cohort) and varies in population size between 1 and 207 individuals. The average number of individuals from our sample is 10 per SAMS-area.

TABLE 5. DESCRIPTIVE STATISTICS FOR SAMS-AREAS IN 1995 INHABITED BY THE 1980S COHORT.

	N	Range	Minimum	Maximum	Mean	Std. Deviation
Social allowance	7704	1	0	1	0.06	0.066
Foreign-born	7704	1	0	1	0.08	0.080
Single mother	7704	0	0	0	0.03	0.023
Single family housing 1996	7678	1	0	1	0.57	0.319
Non-working	7704	1	0	1	0.44	0.101
Residents	7704	206	1	207	9.69	10.718

RESULTS

Below we present the estimates of four logit models with university education in 2010 as the dependent variable. Model 1 uses only individual level variables. Model 2 adds contextual variables based on individualized neighborhoods to the individual level variables. Model 3 is similar to model 2 but uses context variables based on administrative units, SAMS areas. Finally, model 4 is based on model 2 but adds individual-contextual interaction variables.

MODEL COMPARISON

As explained below, the *individual* level variables including parental characteristics are the most important consideration when predicting educational achievements for adolescents. Further below we do however focus on the *contextual* level variables using both individualized neighborhoods and SAMS areas.

The first logistic regression (model 1) shows the strongest individual level effects for university education for adolescents with university-educated parents, and for girls; see Table 6. Significant but weaker effects are found for adolescents with parents receiving social allowances and those with non-employed parents. These results are supported by earlier research on Swedish data (Andersson and Subramanian, 2006). Model 2, Table 6 includes both individual as well as contextual level variables. Here too university-educated parents are strongly and positively associated with an adolescents' university education in 2010. Also comparable with the model including individual level variables only, is negative effects from non-employed parents and parents receiving social allowances. In addition, being a girl or a boy strongly affects the existence of a later university education. Finally for models 3 and 4 in Table 6, results from individual level variables are generally the same; having parents with university education, and whether one was a boy or a girl, are important factors in determining whether adolescents achieve a university education.

TABLE 6. PARAMETER ESTIMATES FROM FOUR MODELS FOR UNIVERSITY EDUCATION IN 2010.

	Model 1 Parameter estimates individual level for tertiary education in 2010.				Model 2 Parameter estimates individual level and contextual level for university education in 2010.				Model 3 parameter estimates individual level and SAMS-area level for tertiary education in 2010.				Model 4 Parameter estimates individual level, contextual level and interactions for university education in 2010.			
Term	**Estimate**	**Std Error**	**ChiSquare**	**Prob>ChiSq**	**Estimate**	**Std Error**	**ChiSquare**	**Prob>ChiSq**	**Estimate**	**Std Error**	**ChiSquare**	**Prob>ChiSq**	**Estimate**	**Std Error**	**ChiSquare**	**Prob>ChiSq**
Intercept	0.465	0.034	189.24	<.0001	0.012	0.019	0.36	0.5459	0.407	0.034	140.44	<.0001	0.011	0.019	0.35	0.5527
Parent with univ. education	0.634	0.009	5302.70	<.0001	0.605	0.009	4697.70	<.0001	0.625	0.009	5061.90	<.0001	0.604	0.009	4663.40	<.0001
Parent visible minority	-0.076	0.029	6.70	0.0096	-0.166	0.059	7.84	0.0051	-0.070	0.030	5.68	0.0172	-0.168	0.059	7.99	0.0047
Parent social allowance	-0.290	0.015	360.91	<.0001	-0.526	0.031	281.07	<.0001	-0.265	0.016	290.33	<.0001	-0.526	0.031	281.08	<.0001
Parent foreign born	0.008	0.012	0.47	0.4907	0.111	0.025	20.26	<.0001	0.021	0.012	3.08	0.079	0.110	0.025	19.99	<.0001
Parent non employed	-0.121	0.010	141.75	<.0001	-0.222	0.020	117.47	<.0001	-0.115	0.010	126.88	<.0001	-0.222	0.020	117.66	<.0001
Disposable income decile	-0.007	0.000	553.27	<.0001	0.007	0.000	518.70	<.0001	-0.006	0.000	399.60	<.0001	0.007	0.000	513.94	<.0001
Single mothers	0.427	0.024	322.62	<.0001	-0.387	0.025	247.71	<.0001	0.390	0.024	256.76	<.0001	-0.386	0.025	246.45	<.0001
Sex	0.391	0.008	2337.90	<.0001	0.394	0.008	2350.30	<.0001	0.392	0.008	2342.90	<.0001	0.397	0.008	2337.20	<.0001
1. Elite areas					0.006	0.000	304.21	<.0001					0.006	0.000	285.41	<.0001
2. Low employment in adjacent areas					0.003	0.000	166.40	<.0001					0.003	0.000	154.60	<.0001
3. Foreign born					-0.003	0.000	159.77	<.0001					-0.003	0.000	149.66	<.0001
4. Marginal nearby					-0.001	0.000	32.66	<.0001					-0.001	0.000	30.22	<.0001
5. Marginal intermediate scale					-0.001	0.000	17.15	<.0001					-0.001	0.000	16.64	<.0001
6. Single family housing					0.003	0.001	17.85	<.0001					0.003	0.001	19.00	<.0001
7. Low employment. small scale					-0.002	0.001	8.33	0.0039					-0.002	0.001	8.39	0.0038
8. Low employment medium scale					0.002	0.000	24.74	<.0001					0.002	0.000	24.51	<.0001
9. Marginal medium scale					0.001	0.000	62.07	<.0001					0.001	0.000	59.91	<.0001
10. Non-academic elite					-0.002	0.001	12.78	0.0004					-0.002	0.001	11.38	0.0007
SAMS_Factor1									0.046	0.009	26.83	<.0001				
SAMS_Factor2									-0.045	0.009	24.21	<.0001				
SAMS_Factor3									-0.083	0.009	89.80	<.0001				
Factor 1 -1.01825)*Sex[2]													-0.0003	0.000	0.88	0.3473
Factor 2 -5.74404)*Sex[2]													-0.0003	0.000	1.97	0.1606
Factor 3 -9.90044)*Sex[2]													-0.0003	0.000	2.18	0.1394
Factor 6 +3.4295)*Sex[2]													0.0011	0.000	5.83	0.0158
Factor 1 -1.01825)*Parent_Edu.[1]													0.0005	0.000	2.65	0.1036
Factor 2 -5.74404)*Parent_Edu.[1]													0.0001	0.000	0.54	0.4615
Factor 3 -9.90044)*Parent_Edu.[1]													-0.0004	0.000	3.00	0.0835
Factor 1 -1.01825)*Parent_Edu.[1]*Sex[2]													-0.0009	0.000	9.56	0.002
Factor 2 -5.74404)*Parent_Edu.[1]*Sex[2]													-0.0005	0.000	5.25	0.0219
Factor 3 -9.90044)*Parent_Edu.[1]*Sex[2]													0.0006	0.000	7.25	0.0071

As stated above, individual level variables were found to be the most important for adolescents' future educational achievements, which is in accordance with earlier research. However, identifying the contextual effect is the aim of this paper, and is important since it is a subject of policy debate and can be changed directly, unlike family conditions. In order to compare the usefulness of contextual measure variables for educational achievements we compare the log likelihood across our four models; see Figure 3.

An important discovery using individualized neighborhoods as a measure is a drastic increase of measurable context effects on adolescents' educational achievements between models 3 and 2, Figure 3; that is, between the model using SAMS areas and the model using individualized neighborhoods (EquiPop).

Compared to model 1 with individual level variables, the contextual level variables in model 3 add another 4.2% to the overall log likelihood. This addition is considerably larger than the additional explanation captured by the SAMS areas; see Figure 3. An interpretation of why this comparably larger contextual effect is found is the measurement. The measurement is *individualized* in that it measures every individual's context in the 1980s cohort year in 1995. In addition, it captures different numbers of closest neighbors; therefore seizing different *scales* simultaneously. Compared to the traditional use of administratively set SAMS areas the result could be expected.

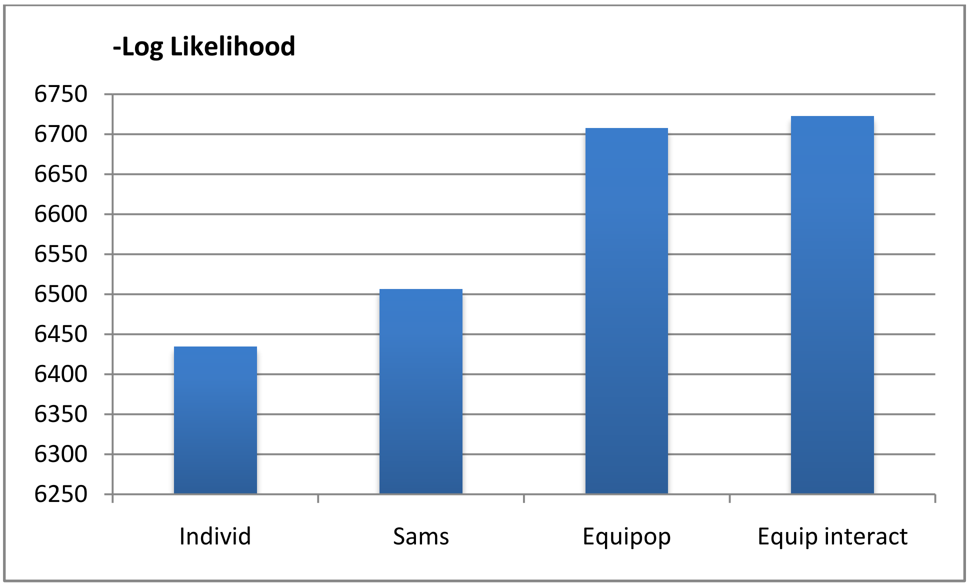

FIGURE 3. -LOG LIKELIHOOD COMPARISON BETWEEN FOUR MODELS; INDIVIDUAL LEVEL VARIABLES, MODEL THAT ADDS SAMS AREAS AS CONTEXT, MODEL THAT ADDS INDIVIDUALIZED NEIGHBORHOODS (EQUIPOP), AND LASTLY THE EQUIPOP MODEL WITH INTERACTION VARIABLES. (NOTE BASELINE OF -LOG LIKELIHOOD OF 6250 IN FIGURE).

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CONTEXTUAL FACTORS

As shown in Table 6, model 2, it is the first three contextual factors that have the largest effect on educational achievement. The strongest effects are found for Factor 1 *Elite areas*. This estimate implies that the odds ratio for having a university education at age 30 increases by 80% if, at age 15, you lived in an area with a score for Factor 1 that was one standard deviation above the mean. This large effect of growing up in an area with a high proportion of individuals with university education, high disposable income, and few non-employed fits with the idea that individuals' life choices are influenced by the choices of their peers and by norms that are present in their residential context.

The effect of Factor 2 *Low employment in adjacent areas* is about half as strong as the effect of Factor 1. Moreover, the effect of growing up with low income groups in adjacent areas is to increase the likelihood of getting a university degree by age 30. This is a result of great interest since it goes somewhat against received theory. Other estimates that go in the same direction (but are much weaker) are obtained for Factor 8 *Low employment medium* scale and Factor 9 *Marginal medium* scale. Different explanations can be put forward for these results.

One possibility is that individual's educational ambitions are influenced not only by educational norms but also by relative affluence. If people in adjacent areas have low income this might have a positive effect on your ambitions. And conversely, if people in adjacent areas have high income this could have a negative effect on your self-esteem and ambition.

An alternative explanation is that educational norms are reinforced by social contrast (Jonsson and Mood, 2008). This would mean that students from a non-elite neighborhood would tend to have a more negative view of academic studies if they had an adjacent neighborhood that was elite. And conversely, students in an elite neighborhood would regard the choice of a non-academic career more negatively if they had an adjacent neighborhood that was low income.

A third possibility is that the positive effect on having a university education at age 30 from high values for Factor 2 is not the result of effects on aspiration but instead the results of differences in opportunity structure. In 1995, when our study cohort was 15 years of age, unemployment rates were still high in the aftermath of the early 1990s economic crisis in Sweden. This situation may have stimulated students in regions of high unemployment to consider academic studies as a more secure path to employment than a non-academic career. On the other hand, students living in regions with low unemployment and high labor demand may have been able to secure employment without the need for costly academic studies. The opportunity structure explanation is supported by the fact that Factor 2 is associated with high levels of non-employment, not in students' close neighborhood but mainly in neighborhoods of up to 25 600 people. In contrast, the effect of a low level of employment in the close neighborhood is negative (but weak), as shown by the estimate for Factor 7 *Low employment small-scale.*

Factor 3 *Foreign-born*, Factor 4 *Marginal Nearby*, and Factor 5 *Marginal intermediate* all have parameter estimates that are negative, with a strong effect for Factor 3 in particular. These three factors are all associated with a high proportion of foreign-born residents and a high proportion of households receiving a social allowance. Factor 4 and Factor 5 in addition are associated with a high proportion of single mothers and a low proportion of single-family housing. Factor 3 is associated with high loadings across all neighborhood scales, Factor 4 has high loadings only for large scale neighborhoods, and Factor 5 mainly for small- and medium sized neighborhoods. One reason for the negative effects of these factors on the probability of having a university education at age 30 could be that a high presence of marginal groups has negative effects on the school achievements (Sykes and Kuyper, 2009).

Table 6 also reports a positive parameter estimate for Factor 6 *Single family housing.* This effect is significant but not strong in comparison to the effects of Factor 1, Factor 2 and Factor 3. A similar effect has been reported earlier by Andersson (2004). Bramley and Karley (2007) have also reported positive effects of home-ownership on educational achievement, and they provide a discussion of possible mechanisms for this positive effect.

Finally, the estimate for Factor 10 *Non-Academic Elite*, which is associated with high income but not with high levels of education of parents, is negative. This corroborates the view that high income *per se* does not imply that you have strong norms concerning the values of education.

INTERACTIONS

In Table 6 we present model 4 where the projected effects for some of the contextual variables have been allowed to depend on the gender and parental education of the students. The analysis shows that the strength of the contextual effects varies according to gender and parental education.

The strongest effect of Factor 1 *Elite areas* is found for men with university-educated parents. The effect is weaker for women with university-educated parents. This is a group that, irrespective of context, has a high propensity to achieve a university degree. But the effect is even weaker for men with parents lacking a university degree. This group, thus, is less influenced by an elite environment. One interpretation of this pattern is that elite areas can help to tip the balance for groups that are willing to consider the idea of a university education. This fits with the fact that women with parents lacking a university degree also experience a relatively strong effect of growing up in an elite area.

A tipping-the-balance pattern is also true for Factor 3 *Foreign-born*. Here it is again men with university-educated parents that experience the strongest effect of context, here with a clear negative effect on the probability of achieving a university degree. And again it is women with parents lacking a university degree that experience the second strongest negative effect of a high proportion of foreign-born residents in the neighborhood. For men with parents lacking a university degree, local context as measured by Factor 3 is of smaller importance.

However, for men with parents lacking a university degree Factor 2 *Low employment in adjacent areas* plays an important role. Indeed, the effect of Factor 2 is much stronger for this group than for any other group. This can be seen as favoring the opportunity structure argument for the positive effect of low local employment levels on the probability of getting a university education. The idea would be that the risk of becoming unemployed after school could help young men to overcome barriers to higher education that are linked to their gender and to parental education.

A MULTILEVEL APPROACH

To further analyze the finding of larger contextual effects we tested the same data in a multilevel model. The multilevel approach is common in neighborhood effect literature because it offers a way of analyzing data in hierarchical structures, for example, individuals in neighborhoods, in municipalities, in counties etc. The results can thereafter be interpreted as variance explained at different geographical levels. In this particular analysis the individuals in the 1980s cohort constitute the individual level and the SAMS areas constitute the second, contextual level (7 704 areas). Because the individualized neighborhoods are flexible in size they could not be used as a hierarchical level in the model. Instead, mean values from EquiPop over SAMS areas were used.

In an empty model, no explanatory variables included, the unexplained variance of educational achievements for the 1980s cohort was 5.8% at the contextual level. The rest of the variance in educational achievement was attributed to the individual level. The level of variance of around 5% is found in other Swedish studies using multilevel approaches (Andersson and Subramanian, 2006; Bergsten, 2010), and in a study of the Oslo region a larger contextual level variance of 15% was found (Brattbakk and Wessel, 2013). Furthermore, studies in other contexts, such as the United States, show higher contextual level proportions of variance for different outcomes. Thus, it is commonly believed that the welfare state regimes produce more equal societies with lower contextual effects (Sampson, 2012).

When we included individual level variables to explain university education in 2010 the contextual level variance was reduced to 2 percent. This remaining unexplained variance at the contextual level was then to be tested with both SAMS area variables and the individualized neighborhoods/factors (as means) to try to reduce the unexplained variance. Not only the log likelihood test above, but this test also showed individualized neighborhoods to be a better measure of context; it could explain more variance than the SAMS areas. Of the remaining unexplained variance at the contextual level the individualized (EquiPop) measure captured 35% whereas the SAMS areas captured 8%. As stated above we consider the individualized and scalable measure from EquiPop efficient in showing what neighborhood effects are expected to be.

TABLE 7. AREA DESCRIPTION, EFFECT ON PROPORTION OBTAINING A UNIVERSITY EDUCATION.

Proportion higher education	Factor 1 Elite areas	Factor 3 Foreign-born	Factor 6 Single family housing
10th percentile mean	45.6%	63.7%	57.3%
mean	59.4%	59.4%	59.4%
90th percentile mean	72.3%	54.6%	61.2%

Because of the seemingly low remaining variance at the contextual level it is worth describing actual consequences in terms of the difference in the numbers of individuals that achieved a university education in 2010; see Table 7. The difference can be seen between individuals living in the lowest 10^{th} percentile of Elite area factor loadings, where 45.6% were obtaining university education. This compared to Elite areas with the highest factor loadings, (90^{th} percentile), where 72.3% had obtained a university education at 30 years of age. The difference of 26 percentage points should not be neglected as a contextual effect.

Factor 3, including foreign-born and to some extent parents with social allowances, has a negative association with university education. As a consequence, in areas with low factor 3 loadings (lowest 10^{th} percentile), 63.7% obtained a university education. Adolescents living in areas highly loaded with Factor 3 had a 9% lower probability of becoming university-educated.

As for the factor 6 describing loadings of single family housing, the difference between the least loaded 10th percentile's proportions compared to the highest 90th percentile was smaller.

CONCLUDING DISCUSSION

In this paper we have used Swedish register data to analyze contextual effects on educational achievement for a cohort born in 1980. For this cohort, neighborhood exposure was measured in 1995 (at age 15) and educational achievement was assessed in 2010 (at age 30). Therefore, the design in this study is similar to the one used in Andersson (2001, 2004) and Andersson and Subramanian (2006). An important innovation in this study, however, is that context is not measured using aggregate values for statistical areas. Instead, we have used statistics computed for individualized neighborhoods that have been expanded to include between 50 and 25 600 nearest neighbors. With this method—which departs significantly from the standard approach—we have obtained results that in many ways improve those obtained in earlier studies.

Our first finding is that the strength of the estimated contextual effects increases when statistics based on individualized neighborhoods are used to measure context. Compared to traditional, area-based measures the effect is about three times stronger. These stronger effects are also tested with a multilevel approach.

Second, the stronger overall effect allows us to get significant estimates for several contextual indicators when they are used simultaneously in the same model. To avoid problems of multicollinearity, earlier studies of contextual effect on educational achievement have often included only one contextual variable per model. However, using individualized neighborhoods of varying size makes it possible to capture context at different scale levels: variation in the composition of the 50 nearest neighbors, variation in the composition of the 100 nearest neighbors, etc. This increases the amount of contextual variation that is used to estimate contextual effects, and with increased variance in the explanatory variables the problem of multicollinearity can be reduced. Hence, we have been able to show that high levels of education, low levels of marginality, and a dominance of single family housing in the neighborhood all have separate, positive effects on educational achievement.

Third, the use of individualized neighborhoods has allowed us to explore how contextual effects are linked to scale. Most important here is the unexpected finding that low employment levels among the 1000+ nearest neighbors can have a positive effect on educational achievement.

Fourth, stronger overall contextual effects have allowed the estimation of interaction effects. Here our results indicate that the effects of a specific neighborhood context can be of great importance for one group but less important for a different group. As we see it, this finding provides a strong rationale for a new generation of neighborhood effect studies that focus less on diffuse overall neighborhood effects and more on how specific circumstances influence different groups.

Taken together, we would claim that the findings presented above suggest that a revised methodology that takes advantage of the possibilities offered by the use of individualized neighborhoods would not only provide neighborhood effect studies with a new lease of life, but would also help to make neighborhood effect studies a more central concern for social science research in general.

We acknowledge that the application of the individualized-neighborhood methodology can be difficult in circumstances where researchers do not have access to geo-coded individual level data. However, even if the computation of measures based on individualized neighborhoods requires data that is sensitive from an integrity point of view, this is not the case with the resulting aggregate measures. Thus, an important advantage with measures based on individualized neighborhoods is that they can provide very detailed geographical information about the variation in a neighborhood context, and this information need not be sensitive since it is based on population aggregates.

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