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Neighborhood variation in early adult educational outcomes: The case of Norway

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Abstract

Individuals originating in different neighborhoods fare differently in later life. Part of this is because families sort non-randomly over the urban landscape; different types of families live in systematically different neighborhoods. Another part of the explanation is that children in different neighborhoods are exposed to different urban opportunity structures. The opportunity structure can exert its influence through social interactive, environmental and institutional factors. Using a multi-level framework applied to a Norwegian register-based data set with complete coverage of 1986-1992 cohorts with siblings, we decompose the variation in high school completion and in enrollment in higher education at age 22 into variances at the levels of family and neighborhood occupied at age seven. The variations in both outcome variables among young adults raised in different neighborhoods are substantively important. The gap in expected high school completion rates between children raised in the upper and lower quartiles of the neighborhood distribution is eleven percentage-points; the equivalent gap in being enrolled in higher education is 16 percentage points. We also find substantial heterogeneity in this neighborhood variation; for example, boys are more vulnerable to neighborhood variations, while children residing with both parents at the age of seven are less vulnerable. We argue that the large variation across neighborhoods in educational outcomes of young adults should be of concern for policymakers. It can both imply a suboptimal utilization of human resources and it can feed into inequalities later on in the life course and harm social cohesion thereby.

Keywords urban neighborhoods, neighborhood-of-origin, educational outcomes, Norway, variance decomposition

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1. Introduction

In the seminal book on 'Chicago and the enduring neighborhood effect', *Robert Sampson* notes that "the implication many public intellectuals and scholarly pundits have taken away is that places – especially as instantiated in neighborhoods and community – are dead, impotent, declining, chaotic, irrelevant or some combination thereof" (*Sampson* 2012: 5). *Sampson* argues against this position and claims (in line with *Wilson* 1987 and *Friedrichs* 1998), that neighborhood conditions experienced by children and youngsters can have strong and sometimes devastating impacts on outcomes manifested throughout their life course.

In this (short) paper, we investigate the degree to which the neighborhood experienced during childhood and adolescence matters for educational outcomes during early adulthood. After a brief summary of important theoretical perspectives and selected empirical findings from the neighborhood effects literature, we present an empirical analysis of variations in two educational outcomes for seven cohorts of Norwegian young adults. Our analysis decomposes the variance in educational outcomes into differences in outcomes between neighborhoods, between siblings and individual-specific idiosyncratic variations. We accomplish this within a multilevel variance decomposition frame (*Raaum* et al. 2006; *Bredtmann* and *Smith* 2018), using registry based data with complete population coverage (*Røed* and *Raaum* 2003). Albeit we report results testing other age cuts, our main estimations utilize information on location of children at the age of seven. The empirical estimations are done on a sample consisting of individuals residing in urban parts of Norway. Hence, the most sparsely populated parts of the country, where the concept of a neighborhood does not make much sense, is not part of our analyses.

Obviously, children from different neighborhoods will differ in educational and other outcomes simply because families do not sort themselves randomly across the hierarchy of urban neighborhoods. By decomposing the variance in outcomes into between-neighborhoods variation, between-families variation and an individual-specific idiosyncratic component, we are able to identify the distinct contribution made by neighborhoods – controlling for the non-random spatial sorting of families. In order to identify, and consequently control for, the between-families variation, we utilize the fact that our database contains a family identifier.

More specifically, our analysis of how much different childhood neighborhoods contribute to different educational outcomes in early adulthood employs two measures: a) having completed high school and b) being enrolled in higher education by the age of 22. We undertake variance decompositions of these two outcomes using a data set covering the entire Norwegian population in the cohorts born in the period from 1986 to 1992. It utilizes information on location (census tract) taken from the central population register and information on education taken from the central educational registers. Using population registers with complete coverage provides three important advantages for our analysis. First, we avoid problems of deliberate misreporting that may plague interview-based surveys. Second, we avoid selection bias in responses[1] (*Shroder* 2002). Third, we have a number of observations sufficient to identify effects at small geographical scales (i.e., census tracts with mean population of 823).

2. Theory and evidence regarding neighborhood effects on young adult outcomes

There is a growing consensus in Western Europe and North America that there is an important spatial component to the foundation of social inequality (*Musterd* 2005; *Chetty* et al. 2014; *Galster* and *Sharkey* 2017). Since the coining of the term 'metropolitan opportunity structure' over 20 years ago (*Galster* and *Killen* 1995: 7; *Galster* 2017: 941), one of the most widely debated issues in academic and policymaking circles is the degree to which spatial context exerts a substantial, independent influence on the future life courses of children. Some have argued that the influence of geography on growing social inequalities is trivial and that it is instead social inequalities that primarily influence residential locational patterns (*Cheshire* 2012), whereas others see it as foundational (*Galster* and *Sharkey* 2017). The argument is typically couched in terms of methodological debates about appropriateness of different causal identification strategies and the strength of the empirical evidence (*Sampson* et al. 2002; *Durlauf* 2004; *Galster* 2008; *Ross* 2011; *van Ham* et al. 2012).

The neighborhood in which one is raised could affect a variety of young adult outcomes through several (not mutually exclusive) plausible mechanisms. These include forces within social interactive, environmental, and institutional domains (*Jencks* and *Mayer* 1990;

Brooks-Gunn 1997; *Leventhal* and *Brooks-Gunn* 2000; *Wessel* 2009; *Galster* 2012). Because these mechanisms are well known, we describe them only briefly. In the social-interactive domain, youth may develop distinctive values, behaviors and expectations about school, health habits, illegal activities and work as a result of interactions with neighborhood peers and role models. Adolescents may obtain differential amounts of information about skill enhancing and employment opportunities, depending on the degree to which they rely on local social networks and the resources these networks can access. In the environmental domain, variations in the intensity of pollution from a variety of sources and exposures to violence can lead to durable differences in youths' physical and mental health that, in turn, affect their development of human capital (*Pearce* et al. 2010; *Gamper-Rabindran* and *Timmins* 2011). In the institutional domain, prospective employers may evaluate young adult job applicants raised in certain locales based on the reputation of the places (a version of 'statistical discrimination'), especially if they have limited prior employment history (*Andersson* and *Musterd* 2005). Public and private institutions controlling important services and facilities in neighborhoods may vary in their quantity and quality, thereby differentially affecting youths' opportunities to develop human capital and secure labor market success as young adults.

Whatever the underlying causal process(es) involved, estimating the unbiased magnitude of such effects is confounded by numerous methodological challenges (for an extensive discussion, see *Galster* 2008). Perhaps the most contentious aspect in this realm of scholarship, however, is the issue of geographic selection bias (*Manski* 1993, 2000; *Duncan* et al. 1997; *Dietz* 2002; *Angrist* 2014). The central issue is that individuals being studied (or their parents) likely have unmeasured motivations, behaviors, and skills related to their own (and/or their children's) socioeconomic prospects and move from and to certain types of places as a consequence of these unobserved characteristics. Any observed relationship between geographic conditions and outcomes for adults or their offspring may therefore be biased because of this systematic spatial selection process. Skeptics may rightly argue that what is being measured is simply another impact of (unmeasured) individual or parental attributes, not the impact of the space in which the individual resides.

Several methodological approaches have convincingly met the challenge of geographic selection effects, including random assignment experiments, quasi-random natural experiments, instrumental variables, fixed-effects, differencing, sibling comparisons, inverse probability of treatment weighting and propensity score matching (for a recent review of these methods, see, for example, *Galster* and *Sharkey* (2017). A majority of the studies employing these techniques conclude that a youth's neighborhood does effect employment and educational outcomes.

Galster et al. (2007) analyze individual longitudinal data from the U.S. Panel Study of Income Dynamics matched with census tract data, and use instrumental variables to estimate cumulative neighborhood effects experienced during childhood on various outcomes when individuals are between 25 and 31 years of age. They find that cumulative neighborhood poverty effects had strong impacts on high school attainment and earnings. *Galster* et al. (2015) quantify how young adult employment and educational outcomes for low-income African Americans and Latinos relate to their adolescent neighborhood conditions, using a natural experiment involving public housing assignments in Denver. Their control function logistic analyses[2] found that higher percentages of foreign-born neighbors predicted higher odds of no post-secondary education and neither working nor attending school. Neighborhood occupational prestige predicted lower odds of young adults, receiving public assistance and neither primarily working nor attending school.

A study of long-term outcomes of children of public tenants in Toronto found no differences in expected earnings, when being about 30 years of age, between children allocated to different segments of the neighborhood hierarchy (*Oreopoulos* 2003). This study utilizes the fact that the allocation mechanism of public housing closely resembled random assignment. Dissenting evidence also comes from analysis of data generated by the U.S. Moving to Opportunity demonstration, based on a random assignment of low-income public housing residents to low-poverty neighborhoods. Investigations using Moving To Opportunity (MTO) data revealed some positive impacts on the experimental group's mental and physical health, safety, and self-assessed well-being, but failed to find substantial short- or long-term context effects on young adult educational or labor market outcomes (*Orr* et al. 2003; *Ludwig* et al. 2012).

The results from the MTO-studies mentioned above have been challenged by, for instance, *Chetty* et al.

(2016). They analyzed the subset of MTO experimental children who moved to low-poverty neighborhoods before they were age 13 and observed that they subsequently exhibited as young adults, significantly higher earnings, better chances of attending college and lower rates of single parenthood than either experimental group children who moved after age 13 or children from the other MTO treatment groups. By contrast, effects on those who moved during ages 13 to 18 were mainly nil or even negative. These results for young adults have recently been confirmed by *Galster* and *Santiago* (2017), using instrumental variable analyses of data from their natural experiment in Denver.

Exposure to upper class neighbors of adolescents in Oslo and subsequent educational outcomes are studied by *Toft* and *Ljunggren* (2016). They find that both completing higher education and completing what they classify as an elite field of study (a higher degree in engineering, economics, business administration and law) correlates significantly with the share of upper class neighbors during adolescence. *Kauppinen* (2007) studies the correlation between high school completion by the age of 20 and characteristics of neighborhoods in Helsinki. His study does not reveal any significant relationships between neighborhood composition (e.g., share of high-earners, unemployed and owner-occupiers) and high school completion, although some effects on the choice between theoretical and vocational oriented secondary schooling are found.

In sum, the salient empirical literature offering plausible causal estimates of neighborhood effects generally finds several aspects of childhood residential context that strongly predict educational and other economic outcomes experienced as young adults, although there are a few dissenting studies. What none of these studies do, however, is attempt to assess the degree to which actual variations in neighborhood contexts shape what happens to a nation's children. Put differently, even if neighborhood effects are powerful, how much inequality in social outcomes can be explained by observed variations in neighborhoods? It is this gap in the literature that our paper addresses.

3. Data

Our study utilizes register information of all individuals born from 1986 to 1992 in Norway who are alive and have not emigrated before the age of 22. The data are compiled from different public registers (e.g., tax registers, population registers, registers of welfare transfers, educational registers) by Statistics Norway, and are extensively utilized for research purposes. Moreover, they are regarded to be of very high quality (*Røed* and *Raaum* 2003). The sizes of the seven cohorts range from almost 49,000 in 1986 to a bit more than 58,000 in 1991, leaving us with a total of 381,431 observations. Our analyses will utilize information on those who have at least one sibling born during the same period so we can measure within-family differences in sibling outcomes. Note that we do not only utilize information on sibling pairs in families containing more than two siblings born during the period; we use information on all of them. In the set of cohorts studied, we have 210,672 individuals born from 1986 to 1992 who have siblings born during the same period. Moreover, we will undertake separate analyses of such sibling cohorts on subsets of girls who have sisters (55,237 observations) and boys who have brothers (62,853 observations).

We pragmatically defined neighborhoods as Norwegian census tracts. In the national sample, we have a bit more than 13,500 census tracts.[3] There is large variation in populations; the individuals residing in tracts with an average population 823, with upper and lower quartiles at 345 and 1100 inhabitants respectively. The average child from the 1986-1992 cohorts resided at the age of seven in a census tract with 98 children from the same cohort (upper and lower quartiles 35 and 128). Restricting the sample of children to only those who have a sibling in the same cohort, the average is 36 (UQ=71 and LQ=19).[4]

The purpose of this paper is to investigate the correlation between childhood neighborhood exposure and two different educational outcomes in early adulthood. We have chosen to study outcomes at the age of 22, and how they correlate between individuals residing in the same neighborhood at the age of seven. In part, we made these specific choices in order to maximize the size of the sample studied.

We investigate two young adult educational outcomes, both measured at age 22: having completed high school and being enrolled in higher (post-high school) education. The normal age of high school completion in Norway ranges from 17 to 19 years. We gather information on educational position and attainment from the central register of educational institutions.

Descriptive statistics for these outcomes in our analysis sample are presented in *Table 1*.

Table 1 Outcome variables, percent by cohort. Source: data set compiled from public registers (e.g. population register, register of educational achievements and tax registers) by Statistics Norway

	Completed high school by age 22		Enrolled in higher education at age 22	
Cohort	Male	Female	Male	Female
1986	63.9	74.4	31.2	50.4
1987	64.1	73.7	31.7	51.5
1988	65.2	73.6	33.5	52.4
1989	66.2	74.3	34.2	54.1
1990	66.2	74.2	36.2	55.1
1991	66.3	74.7	38.3	56.1
1992	66.8	75.3	37.6	58.0

We note that educational attainment rates grow over time across birth cohorts and that in every cohort boys have lower attainments than girls.

We undertake the primary analyses in the paper using the sample consisting of all individuals born during the 1986-1992 period, who have at least one sibling born during the same period and who resided in an urban region of Norway at the age of seven, and are still residing in Norway when 22.[5] These restrictions reduce the sample size to 169,736 observations. In addition, we will briefly refer to some results from estimations of the core models undertaken on subsets of the sample.

4. Empirical analysis: model specification

To reiterate, our aim is to investigate how large a share of the variability in educational outcomes is due to between-neighborhood and between-family variation. We accomplish this in a variance decomposition frame (*Raaum* et al. 2006; *Bredtmann* and *Smith* 2018). A variance decomposition approach is a suitable tool for identifying how different levels contribute to the overall variation of a dependent outcome variable. Technically, the variance decomposition approach is equivalent to estimation of a multilevel random intercept model without any covariates (*Rabe-Hesketh* and *Skrondal* 2008). Hence, we estimate the model given by equation (1).

(1) $y_{ifj} = \mu + u_j + w_f + \varepsilon_i$

where:

y_{ifj} is the outcome of interest, of individual *i* residing in neighborhood *j* and originating in family *f*;

μ is the population mean;

u_j and w_f are residual components shared at respectively the neighborhood *j* and family (f) level;

ε_i is an individual-level residual;

$u_j \sim N(0, \sigma_u^2)$;

$w_f \sim N(0, \sigma_w^2)$.

Assuming the residual components to be independently normally distributed, the total variance of the outcome variable (σ_y^2) can be written:

2) $\sigma_y^2 = \sigma_u^2 + \sigma_w^2 + \sigma_\varepsilon^2$

where σ^2 stands for the variance. The variance components of equation (2) can be estimated using a restricted maximum likelihood (REML) procedure.

An often-used measure of the contribution of shared characteristics at, for example, the family level to the total variability of an outcome is:

$\rho_z = \frac{\sigma_z^2}{\sigma_y^2}$, where z=u, w.

We would argue that albeit ρ is a valuable measure of the relative importance of different subsets of correlates of the outcome variables of interest, it does not tell the whole story of the importance of a subset (e.g., the neighborhood) of explanatory variables. Following *Glaeser* et al. (2016), one can interpret equation (1) as a random intercept model and predict the intercept of a specific neighborhood (or family) using the procedure of *Bates* and *Pinheiro* (1998). In this way, we capture the magnitude of differences between neighborhoods. It is, for example, perfectly possible that the variation in some outcome of interest is dominated by individual variations. In this case, estimated ρ-values will be very low. Still, the magnitude of the systematic differences between neighborhoods and family could be of great interest. The parameter σ_u can be interpreted as an approximation to the expected difference between two randomly drawn individuals residing in different neighborhoods at the age of seven; as such, it is obviously highly interesting.

The empirical analyses begin by estimating models that ignore the between-families component[6]. This gives an estimate of the between-neighborhoods variation not controlled for within-families similarities of outcomes. This measure we can denote, $\sigma_u(u,0)$. Our prime interest lies in the magnitude of the variation between neighborhoods, after controlling for family similarities – this we denote $\sigma_u(u,w)$. The decrease in expected neighborhood differences when the restriction σ_w^2=0 is abandoned is, however, of interest. This is kind of Δ-approach that resembles the approach in, for example, *Bredtmann* and *Smith* (2018).

3) $$\Delta = \frac{\sigma_u(u,0) - \sigma_u(u,w)}{\sigma_u(u,0)}$$

Hence, our interpretations of estimations focus on the measures $\sigma_u(u,w)$ and Δ.

5. Empirical results

We estimated equation (1) described above using the aforementioned data. *Table 2* reports outcomes with (only) neighborhood random intercepts. Note that the tables report standard deviations at the different levels rather than variances, as the standard deviations have an intuitive immediate interpretation. In the baseline models, reported in *Tables 2* and *3*, the estimates are obtained from a sample consisting of all observations of individuals born between 1986 and 1992 and residing in an urban location at the age of seven, who have at least one sibling born in the same period. Our prime interest lies in similarities of outcomes of siblings who resided in the same neighborhood at age seven (i.e., the between-neighborhood variation) and how that is affected by controlling for the fact the part of the similarities of outcomes is due to the fact that they not only shared the same neighborhood but also the same family. First, we present results from a model that contain only a random intercept capturing characteristics shared at the neighborhood level, then, second, we include (in *Table 3*) random intercepts capturing characteristics shared at the family level.

The main estimations reported decompose the variance in expected high school completion rates and enrollment in higher education by the age of 22, according to neighborhood of residence and family situation at the age of seven. One may note that there is virtually no difference between these results and those obtained when utilizing information of the situation at the ages ten and 13 instead of at seven. In part, this is probably due to the strong correlation between the contexts experienced at these ages.

Table 2 Educational Outcomes, neighborhood-level random intercepts. All individuals born between 1986 and1992 with a sibling born during the same period. Source: data set compiled from public registers (e.g. population register, register of educational achievements and tax registers) by Statistics Norway

	Completed high-school by age 22		Enrolled in higher education at age 22	
	Coeff	Se	Coeff	Se
Constant	0.722	0.002	0.461	0.002
sd family σ_w	N/A		N/A	
sd tract $\sigma_u(u,0)$	0.093	0.002	0.131	0.002
sd residual	0.437	0.001	0.483	0.001
N=	169,736		169,736	
LL	-102,562.5		-120,447.8	
Rho-family*100	N/A		N/A	
Rho-tract*100	4.3		6.9	

Using the conventional rho-measure, we see that between-neighborhood variance constitutes only a tiny fraction of the total variance in the young adult outcomes considered here, with rho-values ranging from 4.3 to 6.9 %. An important driver of this is that many different factors contribute and that idiosyncratic, individual-specific random variations are large. The magnitude of the expected difference between individuals in different neighborhoods can still be considerable, however, both in a statistical and a substantive sense. Consider, for example, the probability of completing high school by age 22. The expected value across neighborhoods is equal to μ=0.722, as $E[u_j]$ by assumption is equal to zero.

The standard deviation across neighborhoods u_j is estimated to be 0.093. As u_j is assumed to be normally distributed, the upper quartile in the distribution of expected completion rates are 0.67 standard deviations above the mean, while the lower quartile is 0.67 standard deviations below the mean. Hence, 25 % are expected to have a probability above (0.722+0.67*0.093=) 0.784, while 25 % are expected to have a completion probability below 0.660[7]. This gap of *at least* 12.4 percentage points in high school completion rates across neighborhoods in which half of our sample children were raised is not a negligible variation. Similar arguments could also be made for the propensity to be enrolled in higher education at the age of 22.

The raw between-neighborhood variations described above could be interpreted as an upper bound of the between-neighborhoods variability of the early adulthood outcomes considered (*Raaum* et al. 2006). The estimations in *Table 3* show how the variation between neighborhoods is affected when we take account of similarities between siblings within the same family. Siblings that are relatively close in age often share neighborhoods, but they share much more than this – financial resources, genetic heritage and home environment and atmosphere. In short, they share parents. As expected, controlling between-neighborhoods variation in young adult educational outcomes for family similarities tightens the upper bound, as shown in *Table 3.*

Table 3 *Educational Outcomes, neighborhood and family-level random intercepts. All individuals born 1986-1992 with a sibling born during the same period. Source: data set compiled from public registers (e.g. population register, register of educational achievements and tax registers) by Statistics Norway*

	Completed high-school by age 22		Enrolled in higher education at age 22	
	Coeff	Se	Coeff	Se
Constant	0.721	0.002	0.462	0.002
sd family σ_w	0.225	0.002	0.258	0.002
sd tract $\sigma_u(u,w)$	0.083	0.002	0.119	0.002
sd residual	0.376	0.001	0.409	0.001
N=	169,736		169,736	
LL	-100,432.5		-117,802.3	
Rho-family*100	25.5		26.8	
Rho-tract*100	3.5		5.7	
Δ=	0.11		0.09	

Comparing the results reported in *Tables 2* and *3*, one immediately notices that the magnitude of the between-families variation (as measured by the standard deviation at the family level) in educational outcomes of young adults is (between two- and three-times) larger than the between-neighborhoods variation (standard deviation tract). The Δ-scores reported in *Table 3* is a direct measure of how controlling for sibling similarities reduces the expected between-neighborhood variation. They demonstrate that the variation in educational outcomes between neighborhoods-of-origin is reduced by around 10 % when taking out the part that is due to family similarities.

Turning to the rho-measures, *Table 3* shows that the total variance in young adult educational outcomes (see equation 2) can be decomposed into roughly one-fourth between-family differences and one-twentieth between-neighborhood differences, the remainder being attributed to between-individual purposes. Nevertheless, between-neighborhood variations are significant in a statistical sense. Moreover, they are significant in a substantive sense, as we amplify below.

As mentioned above, youngsters who follow the 'main track' through adolescence and early adulthood, complete high school during the age-span of 17-19. The fact that 27.8 % have not completed high school by age 22 reveals that stepping out of the main track is not that deviant. Our empirical analyses can be interpreted as tests of whether there is a spatial pattern in such deviations from the main track. The highly significant standard deviation at the neighborhood level ($p < 0.001$) confirms that there exists a neighborhood-based difference in high school completion.

The estimated standard deviation between neighborhoods of origin (i.e., 0.083) is also significant in substantive terms, considering its interpretation as the expected difference between expected young adults originating in different tracts. The lower quartile in the neighborhood distribution of expected high school completion rates is 0.667, while the upper quartile is 0.778, an attainment gap of 11.1 percentage points. The difference in expected completion rates between the first and ninth decile in the neighborhood distribution is 21.3 percentage points. These differences are substantial, and should be a concern both for educational and social policymakers.

The road into higher education is another important aspect of the educational outcomes in early adulthood. Even though we do not discuss the results concerning the propensity to be enrolled in higher education due to space constraints, they are reported in the *Tables 2* and *3*. It should, however, be noted that there are clear qualitative similarities between the discussed results for high school completion and for the propensity to be enrolled in higher education.

6. Neighborhood variations: heterogeneity

The main results of our empirical analyses reported above should be interpreted as averages over young adults residing in urban areas in Norway, and as such, they are interesting. These average standard deviations may, however, mask important differences in expected differences between neighborhoods in terms of educational outcomes. In order to illuminate differences between different groups of young adults, we have therefore estimated the empirical model that decomposes variation in high school completion rates on a number of subsamples. For reasons of brevity, we report the results of these estimations in the form of figures[8].

In the *Figures 1* and *2*, we illustrate the difference between the upper and lower quartile in the distribution of expected high school completion across neighborhoods. This difference is calculated as $(2 * 0.67 * \sigma_u)$, as 0.67 is the absolute value of the upper and lower quartile of the standardized normal distribution.

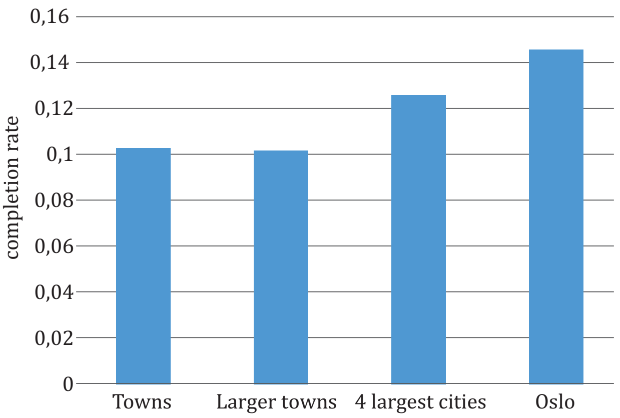

Fig. 1 Expected differences between upper and lower quartile in the distribution of high school completion of neighborhoods – in different locations. Source: data set compiled from public registers (e.g. population register, register of educational achievements and tax registers) by Statistics Norway

The estimations based on samples split according to type of region, as illustrated in *Figure 1*, show a pronounced pattern with between-neighborhood variation being larger the larger the urban region is. A tentative (and admittedly speculative) interpretation is that the larger cities in general and Oslo in particular have a more diverse menu of neighborhoods – simply because they are larger, over which the population is self-sorted. This yields more internal homogeneity and stronger self-enforcing effects within neighborhoods. This, in turn, raises the between-neighborhoods variation. Note that the differences (except between towns and larger towns) are significant as the estimated standard deviations have non-overlapping confidence intervals.

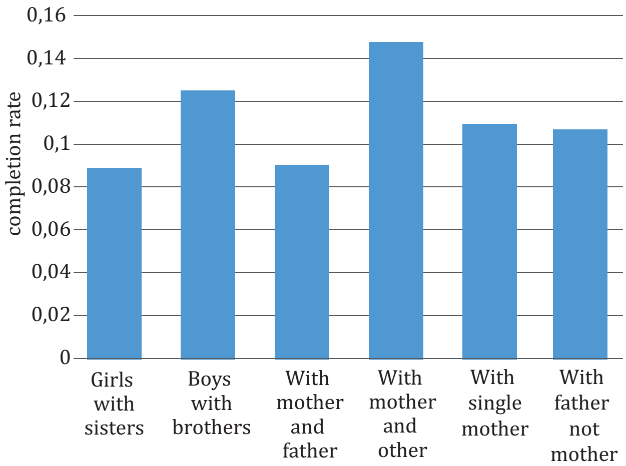

Fig. 2 Expected differences between upper and lower quartile in the distribution of high school completion of neighborhoods – according to family configurations. Source: data set compiled from public registers (e.g. population register, register of educational achievements and tax registers) by Statistics Norway

Figure 2 illustrates differences in variability between neighborhoods for different family configurations. We observe that the between-neighborhood variation for boys with brothers is 40 % higher than it is for girls with sisters. In short, this means that in terms of high school completion boys are more vulnerable to a less-educationally supportive environment outside of the family than are girls.

The strength of variations between neighborhoods also differs quite strongly across family configurations at the age of seven. Expected high school completion by age 22 of children who resided with both parents at age seven exhibits far lower between-neighborhood variability than that of children in other family configurations. For example, the between-neighborhoods variability is 62 % higher for children who at age seven co-resided with the mother and a non-father spouse, compared to those who co-resided with mother and father. It is tempting to hypothesize that neighborhood influence substitutes for family influence for children in families with weaker within-family ties. As a majority of children resides with their mothers at age of seven, we have treated those who live with father and another adult and those resided with single fathers at the age of seven into one aggregate category: with father and other.

There is an important lesson to learn from this brief demonstration of differences in between-neighborhood variation in expected high school completion across family configurations and location. When it comes to the influence of neighborhood-of-origin on average effects across groups, they are exactly that: average effects. For policy purposes, it is important to identify who is affected, where and how. The same applies for research efforts to increase the understanding of how young adults are affected by the neighborhoods, in which they grew up.

7. Concluding remarks

Urban Norway exhibits large differences in the educational outcomes of young adults raised in different neighborhoods. We have studied this using a variance decomposition approach. Our empirical findings demonstrate that, though between-family variations account for five times more than those between neighborhoods, a nontrivial part of these variations prevail even if we control for similarities for siblings raised in the same neighborhood. The gap in expected high school completion rates by age 22 between children raised in the upper and lower quartiles of the neighborhood distribution is eleven percentage-points. The equivalent gap in the probability of being enrolled in higher education at age 22 is an even larger 16 percentage points. These average measures of the variations in young adult educational outcomes across neighborhoods are an important finding. Even more important is the demonstration that the magnitude of the (small-scale) geographical variation varies between groups of youngsters. The availability of large-scale register information gives us a sufficient number of observations that enable us to disaggregate into these smaller groups.

Our study does not enable us to claim that we have identified causal neighborhood effects, but it demonstrates some important patterns of differences in young adult educational outcomes that should be of concern. It is pertinent to point towards *Sampson*'s arguments against the strong focus on controlling for selection when estimating of neighborhood effects. Selection is in itself a component of an enduring neighborhood effect (*Sampson* 2012).

At the societal level, there are at least two reasons for being concerned by the substantial between-neighborhood differences in young adult educational outcomes we document. Firstly, if some neighborhoods contribute negatively towards early adulthood educational outcomes, it could be seen as a suboptimal utilization of human resources and abilities – harming both society and individuals. Second, inequalities in early adulthood educational outcomes would probably feed into even stronger inequalities later in the life course of a cohort. This again may harm social cohesion. Consequently, we would argue that policy efforts to decrease the variations in educational outcomes should be considered. It is beyond the scope of this article to discuss the design of such policy interventions. We can just speculate that a set of optimal interventions consists of a combination of general area-based initiatives and efforts targeted directly towards schools in vulnerable neighborhoods.

Notes

[1] For example, a disorganized, marginalized lifestyle in early adulthood will probably harm both higher educational outcomes and the propensity to participate in a survey.

[2] This is a version of an instrumental variables approach.

[3] Note that Norwegian census tracts are about one-fifth the population of the similarly labelled delineation in the U.S.

[4] Note that we have also tried out a kind of clusters-of-tracts as a neighborhood definition. Each cluster-of-tracts consists of 2-7 census tracts. Using this definition gave us a bit (but not much) lower estimates of the standard deviations (SDs) in the later variance decompositions, and a bit higher standard errors of the SDs. This forms the basis of our pragmatic choice of using tracts as our preferred definition of a neighborhood.

[5] We add this constraint so that we have more consistency in the geographic scale and population of our census tracts. Note that we do not restrict the sample to sibling pairs who live in the same neighborhood when they are age seven, though in practice most do so given limited geographic mobility in Norway.

[6] Technically, we do this by imposing the restriction =0 on equation (1) when estimating the model.

[7] This argument is a bit simplified as it ignores the uncertainty around the estimated standard deviations. The sample size renders the error we do by this negligible.

[8] Full estimation results available on request.

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