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A comparison of family and neighborhood effects on grades, test scores, educational attainment and income—evidence from Sweden

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Abstract This paper compares sibling and neighborhood correlations in school performance, educational attainment and income as a way to learn whether the neighborhood where a child grows up in might explain parts of the sibling similarities found in previous sibling correlation studies. The data are based on a cohort of nearly 13,000 individuals born in 1953 and their siblings, all of whom grew up in the Stockholm area. The results show that neighborhood correlations are in general very small and in particular they are much smaller than the sibling correlations. Living in the same neighborhood does not seem to add much to the sibling similarities.

Keywords Neighborhoods · Siblings · Family background

JEL Classification J13 · R23

1 Introduction

There is a general interest in society to understand the importance of family and community background. In particular, the focus of many economists' research efforts during the last 15 years has been to explore the role of an individual's background in explaining future achievement, such as school grades, level of education and income.

One approach in this literature is to use sibling correlations as summary measures of the importance of family and community background. From a simple decomposition of long-run income into a family and an individual component, it follows that a sibling correlation tells us what fraction of overall inequality is attributable to the family and community component shared by siblings. For example, the brother correlation in long-run income in the Nordic countries is about 0.25 [3] and in the

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US, it is as high as 0.50 [30]. Björklund et al. [4] estimate sibling correlations in school grades using Swedish data. They find that about half of the variation in school grades can be attributed to family and other background factors.

Out of this we can conclude that in general, background factors seem to matter a great deal. But what do we know about the background factors that make siblings similar in terms of future achievement? Exactly what is it about background that matters? Previous results in the intergenerational literature can help explain parts of the sibling correlation. A sibling correlation can be decomposed into the squared intergenerational elasticity and a second term that captures factors uncorrelated with parental income. The income elasticity in Sweden is estimated at around 0.25 for fathers and sons and squaring this estimate will account for only about 0.06 of the 0.25 brother correlation.[1] So, only a quarter of the brother correlation can be attributed to father's income. If parental income is not of major importance, exactly what is?

One hypothesis is that because most siblings grow up in the same neighborhood, this could explain parts of the sibling similarity. Solon et al. [40] suggest using neighbor correlations to study the influence of the environment a child grows up in. Just like sibling correlations reflect siblings' shared background factors, correlations between neighboring children show how much of the variation in an outcome variable can be attributed to neighborhoods. Neighborhood conditions may influence future achievement in many respects. For example, a safe physical environment along with solid financial resources in the community may promote a child's development and these are factors that can vary between neighborhoods. How important is the neighborhood compared to the family background? This is a question of great concern, both to parents and policymakers and this is also the topic of this paper.

In a first step, this paper estimates correlations in education and income among siblings and neighboring children for nearly 13,000 individuals and their siblings, all of whom grew up in the Stockholm area. The results show that both brother and sister correlations in years of education are slightly above 0.40 and the correlations in income are almost 0.27 and 0.17 respectively, which is in line with results in previous studies.[2] In comparison, the neighbor correlations in education are much smaller: 0.02 for males and 0.01 for females when family background characteristics are accounted for.[3] For income, the neighbor correlations are close to zero for both males and females.

The school environment is potentially an important part of an over-all neighborhood effect and in a next step, this paper presents correlations in income and education among sixth grade schoolmates and classmates. A good school environment facilitates learning, but also affects social interaction during the school day. Each class room provides a small and intimate sphere where children spend a lot of their time. Classmates face the same teacher everyday and interact with the same friends. Therefore, peer effects are likely to be larger among classmates than among schoolmates. Comparing groups within a given school that differ randomly in peer composition, Hoxby [23] finds that peer effects do exist. For instance, her results

[1] See Björklund and Jäntti [2] for estimates of Swedish intergenerational income results.

[2] See Björklund et al. [3, 5, 6].

[3] In line with previous research, the neighborhood correlations are adjusted for parental income and education.

suggest that having a more female peer group raises both male and female scores in reading and math. For Sweden, Sund [42] estimates peer effects in the class room on student's high school grades using time, school, teacher and individual fixed effects. He finds that a one standard deviation increase in the peer grade point average leads to a 0.08 standard deviation increase in high school grades. In this paper, correlations in income and education among sixth grade schoolmates and classmates are found to be similar to or slightly higher than the neighborhood correlations mentioned above.

Finally, this paper investigates the possibility that the environment could have a larger impact on short-term outcomes than on long-term outcomes. In order to study the potential short-term impact of neighborhoods, correlations in grade point averages and test-scores from the sixth grade in compulsory school are estimated. Sibling data on grades and test scores are unavailable, but previous papers estimate sibling correlations of 0.50 in school grades and slightly above 0.60 in test scores.[4] The results show that neighbor, schoolmate and classmate correlations in grade point averages are small and similar to the above results. The correlation in test score results among classmates stands out from the rest, indicating a classroom effect, especially for boys. But the general result in this paper is that family background is much more important than neighbourhoods. Living in the same neighborhood does not seem to add much to the sibling similarity.

The paper is organized as follows: The next section begins with a background discussion and reviews previous research. Section 3 describes how the correlations are estimated and Section 4 presents the data and offers some insight into the main variables used in the analysis. Section 5 presents results and the paper ends with a concluding discussion in Section 6.

2 Background and previous research

Social scientists suggest three main channels through which neighborhoods are thought to affect residents, namely epidemic models, collective socialization models and institutional models.[5] Epidemic models focus on peer influences and predict that young people are highly influenced by the behavior of schoolmates and friends in the neighborhood. Several previous studies report positive peer effects on school achievement [35, 42, 43]. Proponents of collective socialization models argue that adults (other than parents) who live in the community are important and serve as role models for children and teenagers. Similarly, Cutler and Glaeser [12] find that some of the effects of segregation on economic performance can be attributed to less contact with well-educated adults. Finally, the institutional models suggest that adults working in institutions within the community, such as teachers and social workers, influence the performance of the children. Closely related to this is the "membership theory" of inequality [15, 16]. Membership theory tries to understand the mechanisms behind socioeconomic outcomes and its main idea is that certain kinds of memberships or groupings such as gender, ethnic groups and residential neighborhoods may influence individual performance. Similarly, Akerlof

[4] See Björklund et al. [4], Mazumder [30].

[5] These models are briefly summarized here, see Jencks and Mayer [25] for more information.

and Kranton [1] discuss the impact of identity or a person's sense of self on economic outcomes. Specifically, they show how to incorporate identity into an economic model of behavior.

Trying to measure effects of neighborhoods on individual outcomes entails several empirical problems. Most important is the non-random sorting of households into neighborhoods of different quality. The sorting is obviously affected by the households' resources and people are likely to move into areas they believe are good for their offspring. Hence, it is crucial to address the problem that neighborhood effects are correlated with the family background of the individuals. Further, which neighborhood characteristics are relevant to study and how are they ideally measured?

The neighborhood literature has tried to address some of these problems, leaving others behind. A great deal of research both within sociology and other disciplines has been carried out in this field, for example Brooks-Gunn et al. [7] and Crane [11] for the US and McCulloch and Joshi [31] for the UK.[6] The typical procedure in this literature is to link individuals' socioeconomic outcomes to data on local neighborhood characteristics and apply regression techniques to estimate neighborhood effects.[7] One drawback of this approach is the arbitrariness connected with the choice of neighborhood variables to be included and another is that some neighborhood variables may be hard to measure. Ginther et al. [19] find that estimates of neighborhood effects on children's outcomes vary considerably between different studies. Page and Solon [32] also underline that although regression-based neighborhood studies often control for a considerable number of variables, the amount of variation that can be explained in these studies has failed to reach the magnitudes of the sibling correlations.[8]

To overcome some of these problems, Solon et al. [40] use correlations in education and earnings of siblings and neighboring children in order to measure the impact of similar environments in the US. This method avoids problems connected to choosing neighborhood variables and how they should be measured. They estimate sibling correlations in educational attainment slightly above 0.50, while the correlation among neighboring children is 0.10, when family background characteristics are accounted for.[9] In a following study, Page and Solon [32] estimate a brother correlation in earnings exceeding 0.3, while the correlation among neighboring boys is estimated at 0.16. Duncan et al. [13] estimate correlations in test scores and delinquency among siblings, peers, neighbors and schoolmates and find that family-based correlations are much greater. In sum, the main finding in the US studies is that the impact of neighborhoods is small compared with family background.

A few years later, Raaum et al. [34] provide estimates on sibling and neighborhood correlations in Norway. Their study enables a comparison of results between countries with different institutional settings; in particular, they are different in terms of income inequality. The US is at the top of international income inequality rankings

[6] See Duncan and Raudenbush [14], Solon et al. [40] for a review of the US literature and Gibbons [18] for a review of the British literature.

[7] Examples of neighborhood characteristics used in these studies are 'fraction of families that are low-income earners in the neighborhood', 'fraction black' and 'fraction males outside the labor force'.

[8] They also remind us that Corcoran et al. [9] were probably the first to mention this.

[9] Family background characteristics are single year as well as a 3-year average of parental income.

among developed countries, while the Nordic countries are at the bottom.[10] In the Norwegian data, sibling correlations in years of educational attainment are estimated at 0.40–0.50, depending on cohort and gender; younger cohorts and women have higher correlations. The correlation among neighboring children in Norway is only about 0.01 for both men and women. The results for earnings show sibling correlations between 0.15 and 0.20 while the neighbor correlation is about 0.02. Raaum et al. [33] also estimate the composite effect of primary schools and neighborhoods on adult educational attainment in Norway. They find negligible effects of factors shared by children who graduated from the same school at the age of 15–16. Finally, there are some related results for Sweden in Brännström [8]. He finds a 0.02 neighborhood correlation for single-year income measures, using the same data as in this paper.[11] As the focus is on neighborhoods only, sibling correlations are not estimated in that study.

In contrast to the descriptive studies mentioned above, there are also experimental neighborhood studies that try to establish causal inference. One example is "Moving to opportunity", (MTO) a national demonstration program implemented by the US Department of Housing and urban development between 1994 and 1999. The MTO demonstration had an experimental design that offered housing vouchers to families in public housing through a randomized lottery. This enabled one group of families to move into low-poverty neighborhoods, while a control group received no assistance. Among many others, the MTO studies include Ludwig et al. [27], who find positive effects on reading and math test scores among children in families that were offered vouchers in one of the five MTO sites. In a later study, Sanbonmatsu et al. [36] find no significant effects on reading and math scores when looking across all five sites. One limitation in this kind of study is that potential neighborhood effects from moving a small number of people into better neighborhoods may differ from those that would appear if the experiment was turned into a large scale policy intervention [17].

3 The statistical model and estimation[12]

Suppose that an outcome y_{cfs} such as long-run income, for sibling s, in family f, in neighborhood c can be expressed as:

$$y_{cfs} = \alpha' X_{cf} + \beta' Z_c + \varepsilon_{cfs}. \tag{1}$$

Here X_{cf} is a vector of family characteristics that might affect long-run income with associate coefficients α, Z_c is a vector of neighborhood characteristics with coefficients β, and the error term, ε_{cfs}, represents individual factors that are unrelated to family and neighborhood background.[13]

[10]See for example Horrace et al. [22] for rankings based on the Gini coefficient, the Theil index and the variance of log income index using data from the Luxembourg Income Study (LIS).

[11]Using single year income measures rather than long-run income, is likely to produce a downward bias.

[12]This illustration draws on Solon et al. [40].

[13]In the literature, the term cluster is often used to refer to neighborhoods. In this paper, the neighborhoods are large and the term cluster seems incorrect. Nevertheless, the notation c for cluster is used instead of n for neighborhood as n is easily confused with sample size.

The family and neighborhood characteristics, $\alpha' X_{cf}$ and $\beta' Z_c$, are expected to be positively correlated with each other as well-to-do families tend to choose advantaged neighborhoods. The estimation problem that occurs is that X_{cf} and Z_c cannot be observed perfectly, and the variables that can be observed are not measured perfectly. Therefore, simply estimating Eq. 1 will not give reliable estimates. Instead, it is possible to estimate an upper bound on the proportion of variation in long-run income that is due to neighborhood influences. The population variance of y_{cfs} is:

$$\mathrm{var}\left(y_{cfs}\right) = \mathrm{var}\left(\alpha' X_{cf}\right) + Var\left(\beta' Z_c\right) + 2\mathrm{cov}\left(\alpha' X_{cf}, \beta' Z_c\right) + \mathrm{var}\left(\varepsilon_{cfs}\right). \quad (2)$$

The covariance in y_{cfs} between neighboring children s and s′ from families f and f′ is:

$$\mathrm{cov}\left(y_{cfs,cf's'}\right) = \mathrm{var}\left(\beta' Z_c\right) + \mathrm{cov}\left(\alpha' X_{cf}, \alpha' X_{cf'}\right) + 2\mathrm{cov}\left(\alpha' X_{cf}, \beta' Z_c\right). \quad (3)$$

The first term is the variance in neighborhood characteristics and it can be thought of as the "pure" neighborhood effect. The second term, $\mathrm{cov}(\alpha' X_{cf}, \alpha' X_{cf'})$, is the covariance in y_{cfs} between children from different families who live in the same neighborhood. It is expected to be positive because similar families tend to sort into the same neighborhoods. The third term, $2\mathrm{cov}(\alpha' X_{cf}, \beta' Z_c)$, is the covariance in y_{cfs}, between family and neighborhood characteristics. It is also assumed to be positive due to sorting of well-to-do families into advantaged neighborhoods. Interpreting the neighbor covariance in terms of neighborhood effects will ascribe all of the second and third terms to neighborhoods even though parts of them are due to family effects and to sorting.

One way to handle this problem is to include some observed family background characteristics in the estimation of neighborhood correlations. In the previous literature, parental education and income are included to adjust for family background. To the extent that family background is captured by these variables, the problem with the second term is reduced. The result is a tighter upper bound on the neighborhood effect. But as the observed family background variables are probably measured with some error and some unobserved family background characteristics are still omitted, and also because of the presence of the third term in Eq. 3, the neighborhood covariance can still only be interpreted as an upper bound on the influence of neighborhoods.[14]

Siblings share both family background and neighborhood. The covariance between the outcomes of two siblings s and s′ in family f is:

$$\mathrm{cov}(y_{cfs}, y_{cfs'}) = \mathrm{var}(\alpha' X_{cf}) + \mathrm{var}(\beta' Z_c) + 2\mathrm{cov}(\alpha' X_{cf}, \beta' Z_c). \quad (4)$$

The strategy for estimating sibling, neighbor, schoolmate or classmate correlations is similar in its basic structure. The estimation of neighbor correlation in income proceeds as follows:[15]

[14] A related problem is that of simultaneity, which recognizes that neighbor and family environments can be assumed to affect each other. This is the so-called reflection problem (see Manski [28]).

[15] Note that correlation coefficients are not estimated directly, instead variance components are estimated and are used to calculate the correlation. Also note that this paper uses long-run income directly. Another approach would be to use annual income and include a time index, in order to take autoregressive processes into account, see for example Björklund et al. [3]. This method choice is not likely to affect the results here where the main focus is to compare sibling and neighborhood correlations.

Let the logarithm of long-run income for the *i:th* individual in neighborhood *c*, y_{ci}, be:

$$y_{ci} = \beta' A_{ci} + \varepsilon_{ci}, \tag{5}$$

where the vector A_{ci} includes age dummies intended to capture lifecycle effects. The error term, ε_{ci} is decomposed into two orthogonal parts:

$$\varepsilon_{ci} = a_c + u_{ci}. \tag{6}$$

The first one, a_c, is a permanent component common to all individuals in a neighborhood and the second one, u_{ci}, is an individual specific component. The variance of age-adjusted income is then:

$$\sigma^2_\varepsilon = \sigma^2_a + \sigma^2_u, \tag{7}$$

where σ^2_a captures the variation in income that is due to differences between neighborhoods and σ^2_u captures the variation in income that is due to differences within neighborhoods. The neighbor correlation is the share of the between-neighborhood variation of the overall variance:

$$\varphi = \sigma^2_a / \left(\sigma^2_a + \sigma^2_a\right). \tag{8}$$

Following Mazumder [30], this paper estimates the variance components that are needed to calculate the neighborhood correlation using restricted maximum likelihood (REML), as implemented in the *xtmixed* command in STATA.[16] A drawback of using REML is that the error components a and b must be assumed to be normally distributed. For variables such log income and grade point averages, this may be unproblematic, but for variables such as education, the normality assumption may be more troublesome. The *xtmixed* command provides standard errors of the variance components, but the standard errors of the correlations are calculated with the Delta method using the *nlcom* command in STATA.

4 The data

The data come from The Stockholm Birth Cohort (SBC), which was created in 2004/2005 by means of a probability matching of two longitudinal datasets.[17] The first

[16]Solon et al. [38] and Björklund [3] use ANOVA formulas that are modified to handle unbalanced data, which is needed because of varying family sizes. But, as Mazumder [30] points out, most of the benefits to using ANOVA are foregone when working with unbalanced data. Mazumder [29] quotes Searle et al. [37]: “It is our considered opinion that for unbalanced data each of ML and REML are to be preferred over any ANOVA method.” Further, Mazumder [30] finds that the results based on REML and ANOVA are similar, which is also true for this paper.

[17]See Stenberg and Vågerö [41] for a full description of the data and the matching procedure. The creation and maintenance of the Stockholm Birth Cohort Data Base is a collaboration between CHESS and SOFI, financed by the Swedish Research Council. Sten-Åke Stenberg at SOFI prepared the original Metropolitan Data Base, Denny Vågerö at CHESS the follow-up data for 1980–2002 and Reidar Österman at CHESS organised the probability matching of the two data sets. The match rate in the probability matching was 96% and the unmatched individuals are likely to have emigrated.

is *The Stockholm Metropolitan Study 1953–1985* (SMS), which consists of all children born in 1953 who were living in the Stockholm metropolitan area on November 1, 1963.[18] This study contains a rich set of variables concerning individual, family, social and neighborhood characteristics. The second is *The Swedish Work and Mortality Database* (WMD) which consists of income, work and unemployment data for all individuals living in Sweden in 1980 or 1990 who were born before 1985.

Data from the WMD for the years 1990–2001 were matched to data from the SMS. These data include information on education and income, two of the main outcome variables in this study. Information on each individual's highest educational degree is collected for 2000, at which time the individuals were likely to have completed their formal education.[19] The income variable is annual labor income and comes originally from registers based on employers' statutory reports to the tax authorities. Annual labor income includes sickness benefits, parental allowances and income from self-employment and farming activity, but excludes capital income, pensions, unemployment benefits and social assistance. Long-run income is calculated as the log of average labour income over the years 1990–2001, using only those income years that exceed SEK 10,000 in 2001 prices (approximately USD 1,400). Sensitivity tests are applied to check if the results are affected by different income definitions (see Appendix Tables 6 and 7).

The *Stockholm Birth Cohort* dataset also includes income data from the WMD for all siblings of the original SMS cohort members. Siblings were identified using Statistic Sweden's *Multi-Generational Register*. Cohort members and siblings are identified through their mother, which means that the data include biological siblings as well as half-siblings on the mother's side, and a small number of adopted children. Unfortunately, half-siblings and adopted children cannot be distinguished from full biological siblings in this particular data set. When calculating sibling correlations, only data for closely spaced siblings are used, since siblings that are close in age probably experience more similar childhood environments than siblings with large age differences. The age of older and younger siblings is centered on the SMS cohort members' age (who were all born in 1953). The youngest siblings were born in 1956 and the oldest were born in 1950. Thus, the maximum possible age difference between any pair of siblings is 7 years.[20]

[18] The Stockholm area was defined as the City of Stockholm and the surrounding municipalities that met the following criteria in 1960: (1) had an agglomerated population of more than 50%, (2) with less than one third of the population working in agriculture, and (3) where more than 15% of the economically active population commuted to central Stockholm. See Jansson [24] for further details.

[19] The information on level of education is transformed into years of education as follows: 7 years for short compulsory school, 9 years for long compulsory school, 11 years for short upper-secondary school, 12 years for long upper-secondary school, 14 years for short university, 15.5 years for long university and 19 years for doctoral degree.

[20] Since we have income data for the years 1990–2001, our age limits imply that we observe income for ages 34–51. According to Lindquist and Böhlmark [26], this means that the measure of long-run income is appropriate for the women in the sample, but that it is probably too high for the men. For men, it would be preferable to have it centered around (or, at least, closer to) the age of 34. See also Haider and Solon [21] for US results on estimates of lifetime income.

Besides the data mentioned above, which are sourced from official census and/or register data, this paper makes use of survey data from *The School Study* which took place in 1966 when the individuals were 13 years old. During one school day, pupils at practically all schools in the area filled out two questionnaires with a non-response rate of 9%, explained by pupils being absent on that particular school day. To study short-term achievements, data on grade point averages from local school registers and test scores from *The School Study* are used. The test score data include one verbal comprehension test, one spatial ability test and one integer sequences test. The maximum score of each test is 40 points, and the test score variable used in the analysis simply adds the results of these tests, which gives a maximum score of 120 points. The data on school grades were collected at a time when grades were measured on a scale of 1–5 and relative to the performance of other students. The population grade distribution was assumed to be normal, which generates a national average for each cohort of 3.0.[21] Finally, parental income and education are used to control for family background. Father's and the mother's total income in 1963 is taken from the official tax register.[22] Parental education taken from Statistics Sweden's census data is coded into just three categories: (1) grade school, (2) high school and (3) college.

4.1 The use of a Stockholm sample

Although a metropolitan area such as Stockholm with suburbs is of great policy interest in its own, both nationally and internationally, a concern is whether the results can be generalized to all of Sweden. First of all, we can note that at the time the neighborhood data were collected, about one fourth of the Swedish population lived in the Stockholm area. So, even though the paper provides a big-city perspective, a non-negligible part of the population is covered. But to examine the potential differences in results for Stockholm and the rest of the country, I have extracted a nationally representative sample from Statistics Sweden of men born in the 1950s and made it comparable in terms of income definitions, number of income years etc.[23] While there is no information on neighborhoods in the nationally representative sample, there are data on parishes that can be used to estimate correlations in income. While larger than neighbourhoods, parishes are still numerous: there are 74 parishes in the Stockholm area. The results for Stockholm show that the between-parish variance (i.e. the parish correlation) of the male cohort member's labor income is 0.8% of the total variance, which is close to the 0.5% found for all of Sweden.

[21] From 1996, grades are set according to specific goals in the curriculum and not related to the performance of other students. Further, in the 1960s, grades in the compulsory school were given already in sixth grade.

[22] The logarithm of each parent's income is used. Information for some 12% of the parent sample is lacking for 1963. For these 12%, the average income of the rest of the parent's sample is used together with a dummy variable that equals 1 if the income is missing and 0 otherwise. The estimates are not sensitive to this procedure compared to dropping observations with zero income.

[23] In order to increase the sample size, I used an age window of 8 years around the 1953 birth cohort.

I have also calculated standard deviations in long-run income separately for the full population and for those who lived in the Stockholm area in 1970. My findings are that in the national sample, the 12-year income average is 248,497 SEK (standard deviation 135,301 SEK) compared to 282,497 SEK (standard deviation 170,103 SEK) in the Stockholm area. So, the Stockholm sample has somewhat higher mean and variance in income than the representative sample but in my view, these differences are not very large. The coefficient of variation is 54.4% nationally and 60.2% in the Stockholm sample.

Moreover, Björklund et al. [3] show that brother correlations in income based on nationally representative and comparable samples (in terms of income definition, choice of income restriction, birth years of the cohorts etc.) are very similar to the brother correlation in income presented in this paper. In addition, Björklund et al. [4] estimate trends in sibling correlations in school grades separately for the big-city area and the rest of the country. Although less precisely estimated, their finding is that the sibling correlation estimated for big-city areas does not differ much from that of the rest of the country. Neither did the big-city areas have a trend in sibling correlation that differed from the rest of the country.

Finally, due to the fact that Norway and Sweden have very similar institutional settings, large differences in neighbourhood correlations between the two countries would be cause for alarm. However, the findings in Raaum et al. [34] based on representative Norwegian samples are very similar to those reported in this study. Taken together, these observations support that the results in this paper using a Stockholm sample might be generalized to apply to the entire population.

4.2 Neighborhood definition

Initially, the neighborhood classification was done by Statistics Sweden and individuals were connected to the geographical areas using Statistics Swedens' census registers. The intention was to make the neighborhoods as homogeneous as possible. The classification was also based on the age and general economic standard of the buildings.[24]

What constitutes a good neighborhood measure? As discussed in the previous literature, one can start by asking just how "neighborly" the neighborhoods are. Small neighborhoods are likely to capture more of potential social interactions between the people living there. On the other hand, one can imagine people being influenced by their neighborhood even without direct social contact. For instance, living in a high status area might influence the inhabitants even if they do not spend time with their neighbors. In 1970, the average number of individuals living in a neighborhood in the city was 1,629 and in the metropolitan area (city and suburbs) it was 1,907, which is about 15% of the size of an average Stockholm parish. In comparison, the average number of individuals in the neighborhoods observed in

[24] An example of a neighborhood is 'Observatorielunden', limited by Drottninggatan, Odengatan, Sveavägen and Kungstensgatan.

the sample is 21. In Norway, the average tract population is 464 [34] while Solon et al. [40] and Page and Solon [32] use very small neighborhoods, each including only a handful of households.

To get a better view of the neighborhood homogeneity of the data, one would like to compare the within-neighborhood variance to the between-neighborhood variance of some informative variable, for example the income of the cohort members' fathers. This exercise will illustrate the extent to which Stockholm with suburbs were socially stratified at this point in time. Among the fathers in the sample, the between-group variance of labor income is 18% and the within-group variance is 82%. So, the overall variance in income is to a larger extent due to within-group variance, indicating fairly low neighborhood homogeneity. Finally, this section ends with a few

Table 1 Sample means

Variable	Mean	Standard deviation	Sample size
1953 cohort			12,893
Men			6,585
Age in 2001	48.0	0	6,585
Education (years)	12.3	2.52	6,274
Average income (2001 SEK), 1990–2001	279,8	182,6	6,585
Log of average income (2001 SEK), 1990–2001	12.4	0.57	6,476
Grade point average, sixth grade	3.14	0.69	6,120
Test scores, sixth grade	62,3	27,1	6,585
Women			6,308
Age in 2001	48.0	0	6,308
Education (years)	12,6	2.28	6,118
Average income (2001 SEK), 1990–2001	191,9	86,4	6,308
Log of average income (2001 SEK), 1990–2001	12.1	0.47	6,308
Grade point average, sixth grade	3.34	0.68	5,983
Test scores, sixth grade	61,3	25,6	6,308
Full sample (1953 cohort + siblings)			19,924
Families			12,893
Singletons			1,655
Men			10,167
Age in 2001	47,9	1.45	10,167
Education (years)	12.2	2.52	9,864
Average income (2001 SEK), 1990–2001	269.9	153.1	10,167
Average log income (2001 SEK), 1990–2001	12.4	0.50	10,167
Grade point average, sixth grade	n.a.	n.a.	n.a.
Test scores, sixth grade	n.a.	n.a.	n.a.
Women			9,757
Age in 2001	47,9	3,38	9,757
Education (years)	12,36	2.31	9.558
Average income (2001 SEK), 1990–2001	188,8	86,8	9,757
Average log income (2001 SEK), 1990–2001	12.00	0.51	9,757
Grade point average, sixth grade	n.a.	n.a.	n.a.
Test scores, sixth grade	n.a.	n.a.	n.a.

Income data × SEK 1,000. All samples include individuals whose average income over the years 1990–2001 exceeded 10,000 in 2001 SEK

Table 2 Summary statistics of the parent's sample

Variable	Mean	Standard deviation	Sample size
Father's income 1963	286.2	197.3	16,937
Mother's income 1963	62.8	56.8	10,007
Log father's income 1963	10.13	0.50	16,937
Log mother's income 1963	8.50	0.67	10,007
Father's education	1.29	0.69	19,022
Mother's education	1.04	0.41	19,022

Income data × SEK 1,000

words about the information on neighborhood status over time. One shortcoming in previous neighborhood studies is that there is only information on neighborhood status at one point in time.[25] Knowing where people live in 1 year alone might be a poor proxy for long-term neighborhood effects if people move around a lot. This paper uses information on neighborhood status in 1963, 1967 and 1971, when the cohort was 10, 14 and 18 years old.[26] In this way, the importance of long-term neighborhood data is checked by stepwise requiring individuals to have lived longer in the same neighborhood.

4.3 Schools and classes

The compulsory school system in Sweden is rather uniform with a common curriculum, in contrast to the upper secondary level which is more diversified. There are also class teachers up until the sixth grade who are likely to provide more homogenous teaching than at the higher levels. The compulsory school system is organized around municipal schools and students residing close to the school have priority to admittance.[27]

Table 1 presents summary statistics of the metropolitan and sibling samples that are used in the estimation. The sample sizes differ due to varying amounts of missing observations in the outcome variables. It can also be noted that women have spent a slightly longer time in education, have lower incomes, slightly higher grade point averages and marginally lower test score results. Table 2 presents summary statistics for the parent sample. Parents in this generation have on average 7 years of education, earn little less than their sons and more than their daughters. Table 3 displays the number of neighborhoods (629) and schools (201) in the sample and on average, there is a school in every third neighborhood.

[25] Solon et al. [40] address this problem by comparing neighborhood quality among movers. They find some support for the hypothesis that people usually move to similar neighborhoods.

[26] What happens between those years is unknown, so it is possible that families who are in the data in all of the years may have moved out and back within the period.

[27] This was the only regulation during the 1960s when the data were collected. Since 1992, all students are free to apply to a school of their and their parents' choice and the municipalities are required to provide a study slot as long as there are no space limitations. But in practice, residing close to school (the residence principle, *närhetsprincipen*) is still the main principle for admittance.

Table 3 Summary statistics of neighborhoods (nbd), schools and classes for the 1953 cohort

Variable	Sample size	Number of nbds/ schools/ classes	Average number of cohort members
Observed in nbd in 1963	12,893	629	21
Same nbd in 1963 and 1967	11,128	620	18
Same nbd in 1963, 1967 and 1971	9,139	615	15
School	12,893	201	64
Class	12,893	621	21

5 Results

The main purpose of the empirical analysis is to learn if neighborhood characteristics shared by siblings account for substantial parts of the sibling correlations, as estimated in the previous literature. Below, I compare sibling and neighbor correlations for a number of different outcome variables.

5.1 Long-term outcome variables

Table 4 presents estimates of sibling and neighbor correlations in years of education and income. The estimated brother and sister correlations in education shown in column 1 are slightly above 0.40. These estimates are similar to the Norwegian estimates in [34], but smaller than the 0.50 estimate for US in [39]. The estimated neighborhood correlations in education (columns 2–4) are much lower than for siblings, around 0.08 for males and 0.05 for females. These "raw correlations" have not been adjusted for any family background characteristics and still only account for 15–20% of the sibling correlation. Rows 2–4 show estimates adjusted for the impact of family background, as discussed in Section 3. It appears that correlated family background accounts for much of the neighborhood variation as most adjusted estimates decrease to around 0.02 for males and even lower for females.[28] These results are slightly higher than the 0.01 estimate in the Norwegian study, but lower than the US 0.10 estimate.[29] When the family background variables are added one at a time, correlated parental education appears to matter more than income.

Living in a neighborhood for a short period of time could be a poor proxy for long-term neighborhood effects. As the data include information on neighborhood for several years, it is possible to compare the results for those observed in the same neighborhood in several years. In column 3 and 4, the individuals are required to have lived in the same neighborhood for two and three periods. The correlations increase with residence, but only marginally so. It should also be noted that these

[28] In Solon et al. [40], the estimated coefficients of the family background characteristics are purged from potential neighborhood effects by applying least squares to the regression of y_{cfs} on a vector of neighborhood dummy variables together with the family background characteristics. Application of the same procedure did not change the results in this paper.

[29] The US results vary between different weighting schemes and whether a 1-year or a 3-year average of parental income is controlled for. The results span from 0.06 to 0.12 (see Solon et al. [40]).

Table 4 Correlations in education and adult income among siblings, neighbors, school and classmates

	Siblings	Neighbors (1963)	Neighbors (1963, 1967)	Neighbors (1963, 1967, 1971)	Schoolmates (sixth grade)	Classmates (sixth grade)
Education in 2000						
Males	0.411 (0.019)	0.079 (0.012)	0.082 (0.013)	0.084 (0.014)	0.070 (0.011)	0.113 (0.012)
Adj. for parental education (PE)	–	0.027 (0.007)	0.026 (0.008)	0.027 (0.008)	0.026 (0.006)	0.058 (0.010)
Adj. for parental income (PI)	–	0.037 (0.008)	0.034 (0.009)	0.035 (0.009)	0.034 (0.007)	0.073 (0.011)
Adj. for PE and PI	–	0.022 (0.006)	0.021 (0.007)	0.022 (0.008)	0.022 (0.006)	0.053 (0.010)
Females	0.432 (0.019)	0.051 (0.010)	0.052 (0.010)	0.060 (0.012)	0.068 (0.010)	0.081 (0.010)
Adj. for PE	–	0.012 (0.005)	0.011 (0.005)	0.018 (0.007)	0.027 (0.006)	0.034 (0.008)
Adj. for PI	–	0.020 (0.006)	0.021 (0.007)	0.026 (0.010)	0.037 (0.009)	0.047 (0.009)
Adj. for PE and PI	–	0.009 (0.004)	0.009 (0.005)	0.014 (0.007)	0.024 (0.006)	0.029 (0.008)
Average income 1990–2001						
Males	0.267 (0.022)	0.024 (0.006)	0.024 (0.007)	0.020 (0.007)	0.022 (0.006)	0.028 (0.007)
Adj. for PE	–	0.009 (0.004)	0.008 (0.005)	0.005 (0.005)	0.012 (0.004)	0.018 (0.006)
Adj. for PI	–	0.011 (0.005)	0.009 (0.004)	0.007 (0.005)	0.014 (0.004)	0.021 (0.006)
Adj. for PE and PI	–	0.008 (0.004)	0.006 (0.005)	0.004 (0.004)	0.012 (0.004)	0.019 (0.006)
Females	0.168 (0.021)	0.0003 (0.002)	0.001 (0.001)	0.003 (0.003)	0.006 (0.003)	0.007 (0.004)
Adj. for PE	–	0.001 (0.002)	0.001 (0.001)	0.002 (0.002)	0.005 (0.004)	0.007 (0.004)
Adj. for PI	–	0.002 (0.002)	0.001 (0.001)	0.002 (0.002)	0.005 (0.003)	0.006 (0.004)
Adj. for PE and PI	–	0.001 (0.002)	0.001 (0.001)	0.002 (0.002)	0.005 (0.003)	0.007 (0.004)

Standard errors are in parentheses. Logarithm of average income, calculated over the years when the income exceeded 10,000 in 2001 SEK (about $1,500). The standard errors of the correlations are calculated with the Delta method (nlcom command in STATA) differences could be due to the underlying (smaller) samples used to estimate the correlations in columns 3 and 4.

The second part of Table 4 presents results for income. The brother and sister correlations are 0.267 and 0.168, similar to those found in Björklund et al. [3, 5]. The male "raw" neighbor correlation in income is low, only about 0.02, and after controlling for family background, it is close to zero. For females, even the unadjusted income correlation is statistically indistinguishable from zero.

Appendix Tables 6 and 7 present sensitivity tests to check if the results are sensitive to how income is defined. In Table 1, the income averages are calculated using only those income years that exceed SEK 342 in 2001 prices (approximately USD 50). The sibling correlations drop slightly for brothers and more substantively for sisters (from 0.168 to 0.103). Similarly, the neighborhood correlations are also reduced. As before, the family background adjusted estimates are practically equal to zero. Appendix Table 7 shows results where the average income is calculated over all income years, including years with zero income. The correlations are very much the same as in Appendix Table 6, except that the brother correlation is reduced again. All in all, the general conclusion that neighbor correlations in income are close to zero seems robust to the treatment of low incomes.

The last two columns in Table 4 show correlations in education and income among sixth grade schoolmates and classmates. The unadjusted correlations among schoolmates and classmates are 0.070 and 0.113 for males and slightly lower for females. After adjusting for family background, the male school correlation drops to 0.022, while the male class correlation stays at 0.053. For females, the impact of the classroom is smaller, with an adjusted estimate of 0.029. In sum, the classroom environment seems to be more important for future educational attainment than the overall school environment and the neighborhood, which have a similar impact. The unadjusted income correlations are about as low as for neighborhoods, while the adjusted estimates are slightly higher, but are still very low.

So, with a main finding of very low school mate and class mate correlations, it may be useful to say something about what we know of the role of teachers. As discussed in Grönqvist and Vlachos [20], a substantial amount of research relating "teacher fixed effects" to student outcomes has not been able to identify observable teacher characteristics that matter for student achievement. The main finding in Grönqvist and Vlachos [20] is that there is no significant effect of a teacher's position in the population-wide ability distribution on the average achievement of the students. However, high performing students are found to benefit from high-skilled teachers, while low-performing students actually are disadvantaged by being matched to such a teacher. As compared to the present paper, these results are in line with a very small general or average school and classroom correlation in student achievement, while it could still be the case that teachers matter for certain groups of students.

5.2 Short-term outcome variables

Table 5 shows correlations in grade point averages and test scores in the sixth grade among neighbors, school and classmates. Sibling data on grades and test scores are not available in these data, but previous papers estimate sibling correlations in school grades at about 0.50 in Sweden. In the US, the sibling correlation in test scores

Table 5 Correlations in grade point averages and test scores among neighbors, school and classmates

	Neighbors (1963)	Sixth grade schoolmates	Sixth grade classmates
Grade point average, sixth grade			
Males	0.046 (0.009)	0.045 (0.009)	0.070 (0.010)
Adj. for parental education (PE)	0.016 (0.006)	0.030 (0.006)	0.052 (0.009)
Adj. for parental income (PI)	0.023 (0.007)	0.032 (0.007)	0.055 (0.009)
Adj. for PE and PI	0.017 (0.006)	0.031 (0.007)	0.053 (0.009)
Females	0.028 (0.007)	0.040 (0.008)	0.053 (0.008)
Adj. for PE	0.009 (0.004)	0.028 (0.006)	0.041 (0.006)
Adjusted for PI	0.010 (0.005)	0.030 (0.007)	0.043 (0.008)
Adj. for PE and PI	0.008 (0.004)	0.029 (0.006)	0.042 (0.008)
Test scores, sixth grade			
Males	0.048 (0.009)	0.073 (0.011)	0.171 (0.015)
Adj. for PE	0.021 (0.006)	0.055 (0.009)	0.139 (0.014)
Adj. for PI	0.027 (0.007)	0.060 (0.009)	0.148 (0.015)
Adj. for PE and PI	0.019 (0.006)	0.054 (0.009)	0.136 (0.014)
Females	0.041 (0.008)	0.066 (0.010)	0.104 (0.013)
Adj. for PE	0.019 (0.007)	0.046 (0.008)	0.079 (0.011)
Adj. for PI	0.022 (0.006)	0.050 (0.009)	0.081 (0.011)
Adj. for PE and PI	0.016 (0.005)	0.044 (0.008)	0.076 (0.011)

Standard errors are in parentheses. Logarithm of average income, calculated over the years when the income exceeded 10,000 in 2001 SEK The standard errors of the correlations are calculated with the Delta method using the nlcom command in STATA

is slightly higher than 0.60.[30] The highest family background adjusted estimate is the 0.053 classmate correlation for males, an estimate that is very similar to the educational attainment estimate in Table 4.

Finally, the schoolmate correlation in test score results is of the same magnitude as previous estimates, but the unadjusted classmate correlation in test scores is much higher at 0.171 for males, and 0.104 for females. After adjusting for family background, the estimates drop to 0.136 and 0.076, respectively. So, this paper finds a family background adjusted test score correlation among Swedish classmates of about one quarter of the US sibling correlation in test scores.

What might explain the finding that the correlation in grade point averages is much lower than the correlation in test scores? Note that grade point averages and test scores are quite different as performance measures. While grade point averages measure capacity within particular subjects on the school curriculum, test scores in these data can be viewed as general IQ tests. Test scores are more objective in the sense that there is always a right answer. There is no room for subjective judgement as is the case in the grading process. Unlike test scores, the teacher's judgement in the grading process can be affected by personal opinions about a student. Further, grades at this time were set according to a relative scale, assuming a normal distribution of students' grades over the population. But occasionally, it has been argued that many teachers instead graded according to a normal distribution within the classroom. The

[30]See Björklund et al. [4] and Mazumder [30].

consequence of this would be that in a class with above average students, the teacher might "run out" of high grades and therefore give some students a lower grade than they would have received otherwise. This would affect the classroom distribution of grades and may partly explain why the correlation in grades is lower. But perhaps the more interesting question is why the classmate correlation in test scores is so high? And why is this correlation (as well as others) higher for males? These are interesting questions to be explored further in future research.

6 Concluding remarks

Sibling correlation studies show that a fairly large share of the variation in, e.g., school grades, education and income, can be attributed to family and other background factors. Even though there is an extensive amount of research on family background, we know relatively little about why siblings are so similar in terms of future outcomes.

This paper compares sibling and neighborhood correlations in school performance, educational attainment and income as a way to learn whether neighborhoods might be one of the background factors that make the achievement of siblings so similar. It also presents school correlations for several outcome variables, both for school mates and class mates. Finally, this paper presents results for school grades and test scores at the sixth grade level as a way to study whether neighborhoods perhaps matter more for short-term than for long-term outcome variables. The results show that while sibling correlations in education exceed 0.40 for both men and women, correlations among unrelated neighbors are estimated at <0.03 after adjusting for correlated family backgrounds. The neighborhood correlations are small in all outcome variables studied here. Among the short-term outcome variables, the correlation in test scores among male classmates stands out from the rest and amounts to about one quarter of the US sibling correlation in test scores. The overall result of this paper is that neighborhood correlations in Sweden are very small and in particular they are much smaller than sibling correlations. Thus, sibling similarities are unlikely to be explained mainly by locational choices. In general, the findings in this paper are in line with what could be expected in Sweden where a persisting aim has been to reduce the importance of individuals' backgrounds. Very small neighborhood correlations are also reported for Norway, where the institutional settings are very similar compared to those in Sweden [34].

Still, it may be going too far to say based on these results that neighborhoods do not matter at all. Neighborhoods may matter more for certain groups in society, or neighborhood influence at very young ages might matter more. It would also be of interest to study the importance of neighborhoods at the time before the comprehensive school reform. The major ingredients of the reform were to increase the length of compulsory education and also to delay tracking. Costas and Palme [10] find that this reform may have led to an increase in intergenerational mobility. Comparing effects of family background and neighborhoods before these changes took place would be an interesting task, but unfortunately, such early neighborhood data are not available.

To sum up, the main finding of this paper suggests that the effects of growing up in the same neighborhood are small compared to the effects of family background. But from a policy perspective, one has to balance the cost of directing policy measures towards neighborhoods inducing smaller neighborhoods effects, against the cost of changing family conditions inducing larger family effects. If family interventions are harder to implement, it could still be worthwhile to consider interventions directed to neighborhoods.

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Appendix

Table 6 Correlations in adult income among siblings and neighbors

	Siblings	Neighbors (1963)
Average log income 1990–2001		
Males	0.240 (0.023)	0.012 (0.004)
Adj. for PE	–	0.004 (0.003)
Adj. for PI	–	0.005 (0.003)
Adj. for PE and PI	–	0.003 (0.003)
Females	0.103 (0.020)	0.001[a]
Adj. for PE	–	0.001[a]
Adj. for PI	–	0.001[a]
Adj. for PE and PI	–	0.000[a]

Average income calculated over the years when the income exceeded SEK 342 (about $50). Standard errors are in parentheses. The standard errors of the correlations are calculated with the Delta method using the nlcom command in STATA

[a]The optimization procedure failed, probably due to lack of variation in data

Table 7 Correlations in adult income among siblings and neighbors

	Siblings	Neighbors (1963)
Average log income 1990–2001		
Males	0.190 (0.022)	0.011 (0.004)
Adjusted for PE	–	0.005 (0.003)
Adjusted for PI	–	0.006 (0.004)
Adjusted for PE and PI	–	0.005 (0.003)
Females	0.105 (0.020)	0.001[a]
Adjusted for PE	–	0.000[a]
Adjusted for PI	–	0.000[a]
Adjusted for PE and PI	–	0.000[a]

Average income calculated over all income years (including years with zero income). Standard errors are in parentheses. The standard errors of the correlations are calculated with the Delta method using the nlcom command in STATA

[a]The optimization procedure failed, probably due to lack of variation in data

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