For whom neighborhoods matter: Heterogeneous effects of socioeconomic neighborhood composition on child achievement

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Abstract

The role of neighborhoods in shaping child and adolescent development is well-documented in empirical research. However, the extent to which neighborhood conditions differentially affect individuals based on their background and individual characteristics remains less explored. This paper investigates the heterogeneous effects of neighborhood socioeconomic composition by combining Norwegian administrative data with genetic data from the Norwegian Mother, Father, and Child Cohort Study (MoBa). Employing the Neighborhood Choice Model to address selection bias, we find that exposure to neighborhood disadvantage during a child's first ten years impacts 5th-grade standardized test scores. Furthermore, we find that the impact of neighborhoods varies considerably by socioeconomic background, gender, and children's load for genetic variants correlated with educational attainment. Notably, boys, children with a lower polygenic index for educational attainment, and those from families with lower incomes and parental education levels face the strongest neighborhood effects. Conversely, children with a higher polygenic index for education are unaffected by neighborhood disadvantage, as are children with affluent parents. These findings highlight the importance of studying heterogeneous neighborhood effects.

Keywords: Neighborhood effects; heterogeneity; gene-environment interaction; socioeconomic background; gender; the Norwegian Mother, Father and Child Cohort Study

Introduction

There is consistent evidence that the neighborhood children grow up in has a causal effect on school achievement and other life chances (e.g., Burdick-Will et al., 2011; Chetty & Hendren, 2018; Chyn & Katz, 2021; 2019; Wodtke, Harding, & Elwert, 2011). Moreover, while much of the neighborhood literature has focused on exposure in adolescence, there is increasing evidence that exposure during the first decade of life also plays a significant role (Donnelly et al., 2017; Leventhal, 2018). For example, after reanalyzing the Moving to Opportunity data, Chetty et al. (2016) found that moving during childhood to a neighborhood with less poverty had positive effects on future economic outcomes, while moving during adolescence had none or even negative effects. Similarly, using neighborhood moves caused by housing demolition, Chyn (2018) found long-term effects when this happened early in children's lives. However, while these and other experimental and quasi-experimental studies have provided strong support for causality, they have come at the expense of more nuanced perspectives on heterogeneity in neighborhood effects (Sharkey & Faber, 2014a).

Few studies examine whether neighborhoods affect children's development differently despite strong reasons for expecting such heterogeneity. Scholars from various disciplines, such as sociology, psychology, economics, and quantitative genetics, have all argued that neighborhoods affect different individuals in different ways as a function of their individual and family characteristics (Belsky et al., 2018; Chyn & Katz, 2021; Galster, 2012; Harding, Gennetian, Winship, Sanbonmatsu, & Kling, 2011; Leventhal, Dupéré, & A. Shuey, 2015; Levy, Owens, & Sampson, 2019; Sharkey & Faber, 2014b). Hence, these scholars point to one of the paths forward for studying the effects of neighborhoods: to understand *for whom* neighborhoods matter.

While research on heterogeneity in sociology and economics has only recently gained traction (Levy, 2022), there is at least some convergence across disciplines in conceptions on how to define the *for whom* question, that is, what is the child- and family characteristics with which neighborhood effects should be expected to vary. Gender and family socioeconomic resources are key candidates. Moreover, individual biological and psychological vulnerability and resources, like genetics, have also been hypothesized to differentiate how children are affected by neighborhood socioeconomic conditions (e.g., Leventhal et al., 2015; Sharkey & Faber, 2014b), known as 'gene-environment interaction' in psychology and behavioral genetics (Plomin, DeFries, & Loehlin, 1977).

In this paper, we take a novel approach to studying heterogeneity in neighborhood effects by integrating population-wide data from national registries with genetic data from a large health survey. Moreover, we use a state-of-the-art approach to tackle the endemic selection into neighborhoods by incorporating the Neighborhood Choice model, recently developed by van Ham, Boschman, and Vogel (2018), as well as studying the effects of randomly occurring genetic variation within families. Specifically, we examine whether the impact of neighborhood socioeconomics on children's 5th-grade test scores in reading and math depends on gender, family socioeconomics, and within-family genetics. Our registry data include information on each child's family income, parental education, migrant background, and test scores, as well as aggregate information on a wide range of socioeconomic (SES) characteristics of their immediate neighborhoods. In the subset of analyses including genetics, we have coupled the population data with genetic data from the Norwegian Mother, Father, and Child Cohort Study (MoBa) (70,000 parent-offspring trios), using the Educational Attainment Polygenic Index (EA4-PGI), which measures the individual child's and their parents' load for genetic variants correlated with educational attainment.

We find an overall effect of neighborhood SES on children's test scores, with a magnitude in the range of other studies (one SD difference in neighborhood SES is, on average, associated with about 6% of an SD higher test scores in our preferred model). Moreover, our main finding is considerable heterogeneity in these effects: boys are twice as affected by neighborhood SES as are girls, and children with lower SES backgrounds are more affected than children of higher SES backgrounds. Additionally, the neighborhood effects are stronger for children with a lower load for genetic variants correlated with educational attainment.

Heterogeneous Effects of Neighborhoods: Theory and Evidence

Individual development is often considered to be embedded in the wider ecology of neighborhoods, where individual characteristics and biological predispositions interact with developmental contexts (Bronfenbrenner, 1979; Harding et al., 2011; Leventhal & Brooks-Gunn, 2000; Leventhal et al., 2015). From this perspective, the child's developmental outcomes should be considered as a function of individual vulnerabilities and strengths within the characteristics of the neighborhood they live in. Concerning the effects of neighborhood socioeconomics, this is expected to interact with both risk and protective factors in the family and the individual (Leventhal & Brooks-Gunn, 2000). More specifically, Harding et al. (2011) argue that families and individuals differ in their susceptibility to risks in the neighborhood and their ability to benefit from opportunities. As a supplementary perspective, developmental psychologists have also discussed how developmental risk and resilience in the family and for the individual may contribute to heterogeneity in neighborhood effects (Leventhal & Brooks-Gunn, 2000; Leventhal et al., 2015; Leventhal, 2018).

Heterogenous Effects Across Families

Families may have different resources—financially or human capital-wise—to protect their children from negative influences or to take advantage of opportunities in their neighborhoods. For example, compound disadvantage theories (e.g., Jencks & Mayer, 1990a) suggest that a lack of family resources makes children more receptive to negative neighborhood influences because the family lacks the capacity to insulate their children from exposure to neighborhood risks. For instance, wealthier families have the resources to seek out more supportive environments (e.g., leisure activities) for their children outside of the immediate neighborhood, which could reduce the negative impact of growing up in disadvantaged areas for this group (see Wodtke, Elwert, & Harding, 2016 for an updated review). In contrast, a lack of family resources may prevent children from being able to take advantage of developmental opportunities in their neighborhoods, particularly if they are more advantaged (Galster, 2012; Jencks & Mayer, 1990b; Wodtke et al., 2016).

Another perspective of SES differences builds upon relative deprivation theory. Social contrast perspectives argue that students compare themselves to the relevant reference group, which in this case is their neighbors (Crosnoe, 2009; Marsh, 1987). Thus, children of low socioeconomic backgrounds who grow up in affluent areas may experience feelings of inferiority, shame, and dissatisfaction, which may negatively impact their development and well-being, thereby counteract some of the positive effects of the affluent neighborhoods, such as high-quality schools (DeAngelis, 2021; Nieuwenhuis et al., 2017).

Although some regard socioeconomic background as a univariate concept, it is more common to consider it multidimensional (Bukodi & Goldthorpe, 2013; Mastekaasa & Birkelund, 2022; Thaning, 2021).[1] Moreover, different socioeconomic dimensions may moderate the neighborhood effects. For example, Duncan and Magnuson (2003) have argued that income and education may affect outcomes through distinct mechanisms. Parental income may affect developmental outcomes through the capacity to invest in activities and educational opportunities both within and outside the neighborhood, as well as parental stress and parenting styles (e.g., Yoshikawa, Aber, Bergman, & Beardslee, 2012). The mechanisms through which parental education—seen as a measure of human capital—affects developmental outcomes may be through the home learning environment, educational aspirations, and conversational styles (Magnuson, 2007). These mechanisms may also include parents' capacity to maneuver within the neighborhood's constraints and opportunities to facilitate their child's development and well-being, as well as their local network and (to some extent) hence the child's peers (Harding et al., 2011; Levy, 2022).

A few studies have examined whether the effects of neighborhood socioeconomic conditions vary as a function of parental income and education. In nationwide US data, Wodtke et al. (2016) found that neighborhood disadvantage during adolescence had a stronger impact on

[1] The extent to which family income and parental education should be treated as exchangeable resources in the family varies across sociopolitical contexts. The correlation between parental income and education is about 0.4 in Norway, which has a comparably compressed wage structure and low inequality (Sandsør, Zachrisson, Dearing, & Karoly, 2021). In contrast, in more unequal countries, like the United States, the correlation is about 0.7 (Reardon, 2012).

high school graduation for adolescents from lower-income families, and more so than exposure during childhood. Similarly, Levy et al. (2019) found neighborhood disadvantage in Chicago to be strongly associated with lower attainment of a bachelor's degree, but only for blacks and Latinos, with no effect for whites. In Norway, Borgen and Zachrisson (2023) found that 8th grade standardized tests of children from less educated and affluent families are more affected by neighborhood disadvantage than their more privileged peers. These studies support a compound disadvantage theory.

Heterogenous Effects Across Children

A basic tenet in developmental psychology is that children's individual differences shape development within the wider ecological context (Overton & Molenaar, 2015). Gender has been one key marker of individual differences in neighborhood research. The neighborhood context constitutes a source of socialization, with the socialization processes depending on gender (Harding, 2009). Because boys are expected to receive less parental monitoring, they are more exposed to influences from outside of the family. Thus, boys should be more sensitive to neighborhood influences than girls (Leventhal et al., 2015). Specifically addressing educational achievement, Leventhal et al. (2009) review nonexperimental studies and conclude that achievement for boys is more affected by neighborhood characteristics than for girls.

However, experimental and quasi-experimental studies find the opposite pattern. Analyses of the Moving To Opportunity (MTO) experiment showed positive effects on educational outcomes for girls but not for boys (Kling, Liebman, & Katz, 2007). A subsequent investigation explained this through girls' better ability to adapt to neighborhood norms and navigate the new neighborhood (Clampet-Lundquist, Edin, Kling, & Duncan, 2011). Supporting the notion that girls benefit more than boys from moving away from highly disadvantaged neighborhoods, Chyn (2018) mainly found positive effects on future incomes among girls. However, these findings may not be generalizable to the wider context of neighborhood influences, as they stem from children moving from extremely disadvantaged neighborhoods to (at least somewhat) more affluent ones (Chyn & Katz, 2021). In sum, the current literature is inconsistent with regard to gender differences in neighborhood effects.

Classical neighborhood research rarely theoretisize nor empirically studies whether neighborhood effects vary based on individual susceptibility or genetic background (Sharkey & Faber, 2014a). However, social sciences studies covering various topics are increasingly incorporating genetic data (Mills & Tropf, 2020), and there is a long research tradition examining gene-environment interactions. Gene-environment interactions have traditionally been studied indirectly using twin methods, but more recently using polygenic indices, which measure individual-level propensity to a trait using DNA data (Plomin & Viding, 2022).

Of the various theoretical gene-environment models, the literature often tests the notion that disadvantaged environments, as opposed to more advantaged ones, suppress genetic influences. Most famously, Sandra Scarr argued that genetic factors largely explained developmental outcomes within the normal range of environments, while in extremely disadvantaged environments, genes mattered less (Scarr-Salapatek, 1971). More generally, positive environments are seen as an enhancement that accentuates advantageous genetic predispositions (Shanahan & Hofer, 2005). From the neighborhood perspective, this would imply that neighborhoods matter more for children with high genetic potential for education.

However, other theoretical models lead to contrasting hypotheses, suggesting that neighborhood disadvantage activates negative genetic predispositions. For example, the diathesis-stress model proposes that some individuals have a genetic makeup that increases their risk of adverse outcomes in unfavorable environments. In contrast, others, less genetically vulnerable individuals, are less affected (Boardman et al., 2014). The same predictions can be made based on the compensatory advantage model (Bernardi, 2014). Based on these perspectives, we may expect that children with genetic vulnerabilities for low achievement are most affected by growing up in disadvantaged neighborhoods.

The gene-environment interaction literature has mainly focused on parental socioeconomic status (e.g., Baier & Lang, 2019; Erola, Lehti, Baier, & Karhula, 2021; Ghirardi, Gil-Hernández, Bernardi, van Bergen, & Demange, 2023; Isungset et al., 2021; Ruks, 2022) and, to a somewhat lesser extent, school characteristics (Cheesman et al., 2022a; Cheesman et al., 2022b; Stienstra, Knigge, & Maas, 2024; Trejo et al., 2018). The results vary between contexts, with little evidence from family SES-gene interactions in Europe (Baier et al., 2022; Tucker-Drob & Bates, 2016).

Less is known about how neighborhoods and genetic potential for education interact. One study by Silva, Wolfram, and Tropf (2023) used the National Child Development Study from the United Kingdom to examine neighborhood-by-gene interaction for individuals born in the same week in 1958, which was followed up to the late 1970s. They found that after holding school SES constant, the gap between individuals with high and low scores on the educational attainment PGI was smaller in socioeconomically advantaged neighborhoods than in less advantaged ones.

However, the interaction between genetic predispositions and school SES was in the opposite direction, suggesting that attending a school with high SES enhances genetic differences.

Additionally, one Norwegian study, using partly the same genetic data as ours, showed that the effects of polygenic index for educational attainment varied at the school but not at the neighborhood level (Cheesman et al., 2022a). However, that study used multilevel models to estimate the total effects of social context and looked at neighborhood effects net of any school effects, in a context where children predominantly attend local schools. In contrast, we consider any school effects, including gene-environment interactions, as part of the total neighborhood effect (Wodtke & Parbst, 2017). Moreover, since the previous Norwegian study, the number of genotyped individuals has more than doubled, which reduces the risk of erroneously concluding that there is no gene-environment interaction.

The Norwegian Context

Although wealth inequality is comparably high (Hansen & Toft, 2021; Pfeffer & Waitkus, 2021), Norway is often considered a relatively egalitarian country, with low levels of income inequality, redistributive welfare state institutions, and high rates of intergenerational mobility. Moreover, in relative terms, economic segregation is low in Norway (Musterd, 2005). However, there are tendencies toward increasing segregation patterns (Markussen & Roed, 2018; Wessel, 2016), and a considerable proportion of individuals are continuously exposed to either dense poverty or dense affluent areas, especially in large urban areas (Toft, 2018).

There is considerable variation in neighborhood characteristics in our data (the data section provides details about variable construction). For example, as shown in Figure 1, looking at Norway as a whole, 1% of children live in neighborhoods where 17% of adults are on social welfare, compared to nearly none on welfare in the most advantaged neighborhood. Likewise, among the most disadvantaged communities, nearly 70% have low education, compared to less than 10% in the most advantaged areas.

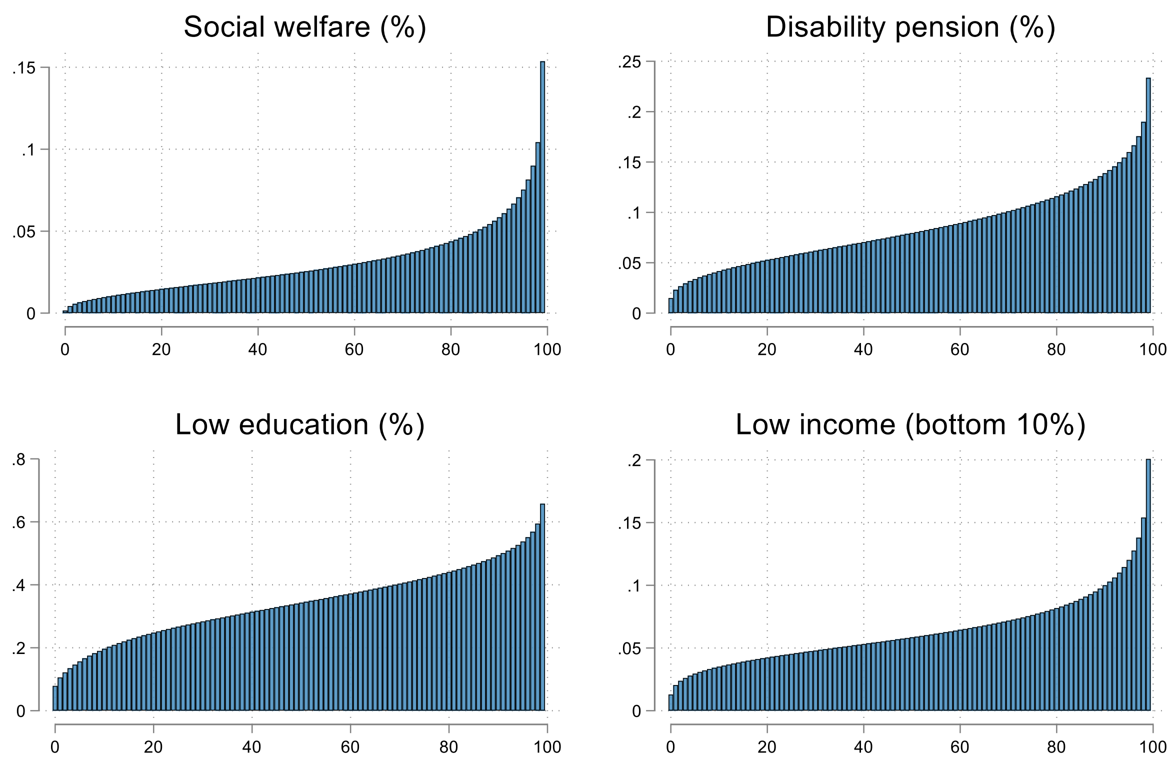

Figure 1: Distribution of neighborhood characteristics in Norwegian data.

Note: Details of variables are provided in the data section. Each variable is divided into 100 equal pieces, and the mean is calculated within each piece. This graph shows 4 of 9 neighborhood characteristics studied; Appendix Figure A3 shows the distribution for all neighborhood variables used in this paper.

Some earlier studies have examined neighborhood effects in Norway.[2] Using sibling fixed effects, Markussen and Roed (2018) found that neighborhood socioeconomic composition has a

[2] Additionally, two studies have examined changes in intraclass correlations over time. Raaum, Salvanes, and Sørensen (2006) found that educational attainment and earnings correlations were reduced for birth cohorts born in the 1940s to cohorts born in the 1960s. Hermansen, Borgen, and Mastekaasa (2020) found that educational

hump-shaped impact on grade point average at age 15-16, suggesting that children growing up in medium-ranked neighborhoods had the best outcomes. Moreover, they found that girls were more affected than boys and that low-income children were unaffected by the neighborhood. However, unlike standardized tests, teacher-assessed grades are influenced by within-school grading on a curve, which may inflate (deflate) grades in areas with many low (high) achieving students (Borgen, Borgen, & Birkelund, 2023; Calsamiglia & Loviglio, 2019). Norwegian studies examining standardized test scores have not found a hump-shaped pattern. Rather, they find a negative effect on attending disadvantaged neighborhoods, with stronger neighborhood effects for boys and children from less educated and affluent families (Borgen & Zachrisson, 2023) and lower neighborhood effects for children of non-western immigrant groups than natives (Borgen, Borgen, & Zachrisson, 2024).

Other studies have focused on Oslo, the capital of Norway, where neighborhood segregation is most pronounced (Hernæs, Markussen, & Røed, 2020), using more traditional covariate adjustment strategies. Brattbakk and Wessel (2013) found a small influence of neighborhood deprivation during adolescence on later education, income, and employment. Concerning affluent neighborhoods, Toft and Ljunggren (2016) found that living in upper-class neighborhoods during adolescence was associated with a higher likelihood of attending higher education and gaining upper-class membership, especially for working-class youth.

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attainment and earnings correlations among former neighbors born during the 1960s, 1970s, and 1980s were stably small, with most of the variance in these outcomes being within contexts.

Data and Variables

We use Norwegian register data covering individuals born in Norway between 1997 and 2008 (approx. 650,000 children),[3] which are matched with genetic data on parents and children from the Norwegian Mother, Father, and Child Cohort Study (MoBa) (approx. 62,000 children). Neighborhood units are defined based on Statistic Norway's detailed 'Basic Statistical Unit' classification, which are stable geographical units designed to resemble genuine neighborhoods and are relatively homogeneous concerning location and type of housing. There are about 14,700 neighborhood units in Norway, with about 350 individuals in each unit.

We measure the socioeconomic composition in these neighborhood units using all individuals born between 30 and 60, including non-parents, separately for each year. First, we calculate the neighborhood characteristics using the following indicators: percent on social welfare, percent on a disability pension, percent receiving housing allowance, percent higher educated, percent school dropout (non-completion of upper secondary education), percent among top 10% income, percent among bottom 10% income, average earnings rank. Second, we calculate the children's average neighborhood characteristics when aged 1-10. Third, we use principal component analysis with these SES indicators to produce our socioeconomic neighborhood disadvantage variable (mean=0 and standard deviation=1). As expected, the socioeconomic neighborhood indicators are correlated (Appendix Table A1). Moreover, using the separate indicators in place of the principal component score produces similar estimates, as does taking a simple average of the indicators (Appendix Figure A1).

[3] Foreign-born students are excluded because we measure neighborhood exposure between ages 1 and 10.

We use the average of standardized national 5th-grade tests in reading (Norwegian) and mathematics as the primary outcome variable, which are compulsory tests designed to capture the full range of subject skills among 5th-graders. Test development is commissioned by the Directorate of Education and Training and carried out by subject experts at universities in Norway along with psychometric experts in the Directorate. About 96% of all students in Norway take the standardized test; students with special needs and those following introductory language courses may be exempt.

Genetic variables are from the Norwegian Mother, Father, and Child Cohort (MoBa) Study (Magnus et al., 2006). MoBa is a population-based pregnancy cohort study conducted by the Norwegian Institute of Public Health. Participants were recruited from all over Norway from 1999-2008. The women consented to participation in 41% of the pregnancies. The cohort includes approximately 114.500 children, 95.200 mothers, and 75.200 fathers. The establishment of MoBa and initial data collection was based on a license from the Norwegian Data Protection Agency and approval from The Regional Committees for Medical and Health Research Ethics. The MoBa cohort is currently regulated by the Norwegian Health Registry Act. The current study was approved by The Regional Committees for Medical and Health Research Ethics (project # 2017/2205).

All women giving birth in Norway from 1999 to 2008 in hospitals and birth units with more than 100 births annually were invited to participate in MoBa, and we have access to data from children born between 2002 and 2008. For the present study, MoBa was linked (through person identification numbers) with Norwegian administrative records provided by Statistics Norway. We have access to genetic data for about 16% of the full birth cohorts, ranging from 10% among the

2002 cohort to 19% in the 2006 cohort (Appendix Figure A4). Appendix Table A4 shows the sample characteristics of children included in MoBa compared to those born in Norway. This appendix table shows that families with lower income and education levels, and those residing in socioeconomically deprived areas, are underrepresented in MoBa. However, the bivariate associations between independent and outcome variables are similar in the MoBa sample and the comparable full population (Appendix Table A5). Thus, although there is a slight overrepresentation of middle-class families in the MoBa, the similarity of associations suggests that selection into the MoBa sample does not bias associations.

Genetic analyses were conducted on a subsample of parent-offspring trios with complete data for genome-wide genotyping. Online Appendix B describes our quality control of the MoBa genetics data. We generated EA4-PGI for all 207,283 parents and children in MoBa who passed the quality control, based on genome-wide association summary statistics excluding 23andMe and MoBa samples. We used the PRSice software to calculate scores using all SNPs (i.e., p-value threshold of 1), with clumping parameters kb=500, p=1, r2=.25. We computed mid-parental PGI by taking the average maternal and paternal PGI. PGI for children from independent families and mid-parental PGI (hereafter 'parental PGI') was then centered to have mean zero and standard deviation one. In all gene-environment analyses, we included parental PGI as controls, such that the effects of offspring PGI are within-family direct genetic effects (further described below).

Register-based control variables include a dummy for being girl (=1), dummies for year of birth, a dummy for having an immigrant background (at least one foreign-born parent), quadratic functions of parental earnings rank (at child age six, separate for father and mother), dummies for parents receiving welfare benefits (age six, separate for father and mother), housing benefits (age six, separate for father and mother), unemployment benefits (age six, separate for father and mother), and disability pension (age six, separate for father and mother), and dummies for educational level (9 dummies, separate for father and mother).

Methods

Unobserved confounding has been a concern in the neighborhood literature for decades (Mayer & Jencks, 1989). The main threat has been that families sort into affluent neighborhoods based on characteristics that also positively influence children's learning (Chyn & Katz, 2021). We use the recently developed two-step Neighborhood Choice model to solve this challenge to causal inference (Schachner & Sampson, 2020; van Ham et al., 2018) under an assumption of selection on observables (Morgan & Winship, 2015, pp. 79-81). This modeling approach first creates correction terms that measure families' propensity to sort into particular neighborhoods and then controls for these correction terms in a linear regression model. The following two sections explain these two steps.

Neighborhood Choice Model

The neighborhood choice model is based on the idea that a family with certain (observable) characteristics will choose to live in a neighborhood with certain (observable) characteristics (van Ham et al., 2018). By modeling this selection into neighborhoods, it can subsequently be used to rule out selection bias in the regression model.

We estimate neighborhood correction terms separately for all Norwegian municipalities using a conditional logit model. We have records of all possible census tracts parents may move to each year within each municipality. Based on the mother's residential moves, we find the year of the family's last neighborhood move. Thus, we know which families that change census tracts during our observation period, as well as all available census tracts (within the municipality) to which they can potentially move to. We then estimate the likelihood P that family i will select neighborhood j based on the interaction between family characteristics ($\boldsymbol{X}$) and the characteristics of the jth neighborhood (N_j) in a within-family model. Family characteristics we include are parents' average age, parents' average number of kids, parents' average years of education, parents' average income, at least one parent born abroad, parents receive social welfare, parents receive disability pension, parents receive housing allowance, and parents receive unemployment benefits.

$$P_{ij} = \frac{\exp\left(\beta N_j \boldsymbol{X}_i\right)}{\sum_{k=1}^{j} \exp\left(\beta N_k \boldsymbol{X}_{\boldsymbol{i}}\right)}$$

With this model, we can predict the probability that family i selects any of the k neighborhoods based on the family's socioeconomic background. Following van Ham et al. (2018), we transform these predicted probabilities into inverse Mills ratios before using principal component analysis (PCA) to reduce the predicted probabilities into a fixed set of orthogonally rotated correction terms.

Both computational and substantial considerations guide our choice to estimate the neighborhood choice model separately by the municipality. With approximately 13,000 neighborhoods and 440,000 families, it is computationally unfeasible to estimate selection models for the entire country, as this would mean estimating a conditional logit model on a sample of 5.7 billion observations. From a more substantive standpoint, we also expect that the relevant choice set considered by parents is primarily within the municipality, especially in large urban municipalities, where the neighborhood sorting is strongest.

The number of within-municipality choice sets differs between municipalities, and so do the corresponding types of neighborhoods that households may sort into. As a result, the number of correction terms is typically larger in urban municipalities with considerable variation in neighborhood characteristics than in more sparsely populated areas. To make sure we use all available information in the correction terms, we replace the remaining correction terms with random noise for municipalities and, as explained below, interact correction terms with municipality fixed effects.

Neighborhood Effects Model

In the second step, the correction terms are used in the neighborhood effect model to account for the household's propensity to reside in a certain type of neighborhood. Specifically, we estimate the neighborhood effects by regressing test scores y on the neighborhood composite (N) and the control variables. The control variables include municipality fixed effects (α), interactions between municipality fixed effects and the neighborhood correction terms ($\alpha * PCA$), and some additional individual-level covariates (year of birth, birth month, gender, and in some models, child and parental EA4-PGI):

$$y_{ij} = \beta_0 + \beta_1 N_{ij} + \beta_2 x_{ij} + \beta_3 PCA_{ij} * \alpha + \alpha + \varepsilon_{ij}$$

, where i and j index individual and cohort.

The interactions between the correction terms and the municipality fixed effects constitute an important part of this model. Since we model the neighborhood choice within the separate municipalities, the values of the correction terms cannot be directly compared between municipalities. Including municipality fixed effects and allowing the coefficients of the correction terms to vary by municipality solves this challenge.

Treatment Effect Heterogeneity Models

We examine heterogeneous neighborhood effects using interaction variables. We include neighborhood interactions between neighborhood disadvantage and parental education, parental earnings rank, gender, and child EA4-PGI:

$$y_{ij} = \beta_0 + \beta_1 N_i + \beta_2 x_{ij} + \beta_3 PCA * \alpha + \beta_4 N_i M_i + \beta_5 M_i + \alpha + \varepsilon_{ij}$$

, where M_i is shorthand for the separate moderators. This model allows us to check whether, for example, children of low-educated parents are more strongly influenced by neighborhood characteristics than children of high-educated parents. When estimating the interaction with EA4-PGI, we control for parental EA4-PGI. This within-family PGI model controls for the non-random selection of neighborhoods by parents (Cheesman et al., 2022a).

Table 1: Descriptive statistics.

	N	Mean	SD	Min	Max	Correlation
Neighborhood disadvantage	651593	-0.034	0.968	-4.743	9.507	1.000
National tests 5th	651593	0.021	0.994	-3.978	2.602	-0.203
Birth year	651593	2002.535	3.472	1997.000	2008.000	-0.118
Birth month	651593	6.379	3.373	1.000	12.000	0.001
Girl	651593	0.494	0.500	0.000	1.000	0.002
Parental years of education	651593	13.813	2.470	7.000	21.000	-0.375
Parental earnings	651593	51.500	21.720	0.000	99.000	-0.415
Parent disability pension	651593	0.031	0.173	0.000	1.000	0.090
Parent unemployed	651593	0.105	0.307	0.000	1.000	0.089
Parent housing allowance	651593	0.062	0.240	0.000	1.000	0.166
Parent social welfare	651593	0.065	0.247	0.000	1.000	0.173
Children of native-born parents	651593	0.798	0.401	0.000	1.000	-0.092
Children of foreign-born parents	651593	0.202	0.401	0.000	1.000	0.092
Child EA PGI	65752	-0.001	0.996	-4.176	3.997	-0.163
Parent EA PGI	62040	-0.003	0.996	-4.831	5.464	-0.194

Note: Correlations=Bivariate correlations between neighborhood and variable.

Results

Average Neighborhood Effects

The neighborhood socioeconomic composition is strongly associated with students' test scores; a one standard deviation increase in the neighborhood disadvantage composite is associated with a decrease in national test scores by 21% of a standard deviation (column 1 in Table 2). To contextualize the size of this association, let us compare achievement gaps between the most advantaged and least advantaged neighborhoods with the corresponding gap between wealthy and low-income families. Figure 2 demonstrates a difference of about one standard deviation in test scores between the most and least affluent neighborhoods (1.06 standard deviations), which is close to the achievement gap among children of the richest and poorest parents (about 1.2 standard deviations).

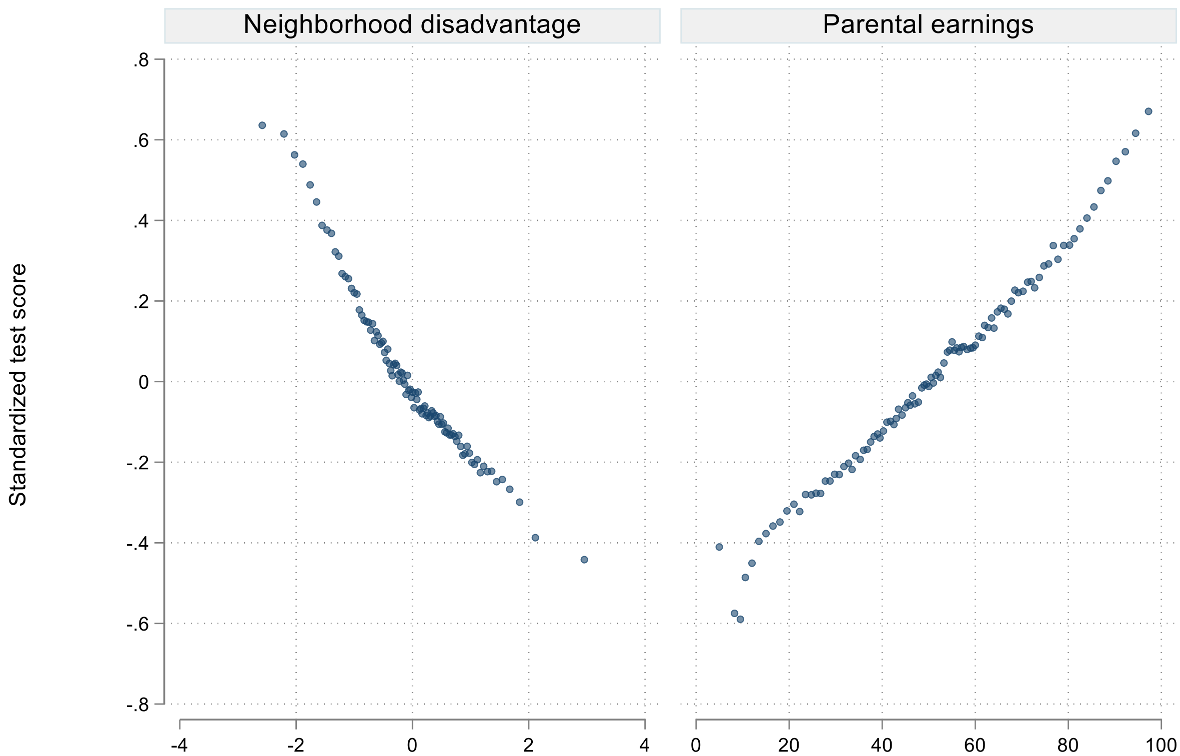

Figure 2: Bivariate associations between neighborhood disadvantage and standardized test scores (left) and parental earnings (right).

Although the neighborhood children grow up in is strongly associated with achievement outcomes in childhood, not surprisingly, a large part of the achievement differences between neighborhoods are driven by sorting. Still, after accounting for sorting via the neighborhood choice model, the neighborhood's socioeconomic composition has a sizeable influence on test scores: a one standard deviation increase in the neighborhood disadvantage composite reduces reading scores by about 5.5% of a standard deviation (column 2 in Table 2).[4] These results mean that compared to growing up in the most advantaged areas, growing up in the most

[4] As shown by Appendix Figure A2, more flexible function forms suggest that the impact of neighborhoods is fairly linear. Moreover, the appendix figure demonstrates that after accounting for sorting, children growing up in the 1% least advantaged neighborhood score about 25% of a standard deviation lower on standardized national tests than children growing up in the 1% most affluent neighborhood.

disadvantaged neighborhoods leads to about 22% of a standard deviation lower achievement (i.e., comparing -2SD with +2SD). Translated into percentile points, this effect size involves moving a student who scores at the median to the 58th percentile.[5]

Table 2: Estimated neighborhood effect on national test scores.

	(1)	(2)	(3)	(4)	(5)	(6)
Neighborhood disadvantage	-0.212***	-0.0547***	-0.0678***	-0.0552***	-0.0722***	-0.0222**
	(0.00326)	(0.00259)	(0.00298)	(0.00377)	(0.00439)	(0.00747)
x Girl			0.0264***			
			(0.00266)			
x Parental education				0.00264***		
				(0.000742)		
x Parental earnings					0.000687***	
					(0.0000728)	
x EA4-PGI						0.00983*
						(0.00461)
Observations	540138	540138	540138	540071	539066	50652
Selection model	No	Yes	Yes	Yes	Yes	Yes

Note: Standard errors clustered on neighborhood in parentheses. Parental education is centered at 10 years. Model (1) shows the bivariate association between neighborhood disadvantage and test scores, while models (2)-(6) show estimated neighborhood effects using the Neighborhood Selection Model. In models (3)-(6), interactions with gender, parental education, parental earnings, and EA4-PGI is included. These models also controls for the main effects of the variable going into the interaction. Further, model (6) includes controls for parental EA4-PGI.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Heterogeneous Neighborhood Effects

The neighborhood effects differ considerably by individual and family background characteristics, as shown in columns 3-6 in Table 2, with children with lower achievement levels most affected by growing up in a disadvantaged area. First, boys are considerably more affected by the neighborhood than girls; neighborhood SES affects boys' test scores by 6.8% of a standard deviation, compared to 4.1% among girls (column 3).

Second, the test scores of children of disadvantaged parents, as measured by parental education and earnings, are more affected by neighborhood than those of advantaged parents

[5] Calculated using the rule of thumb suggested by von Hippel (2024): SD effect $* 37$.

(columns 4-5). The estimated neighborhood effect at different levels of parental education and earnings is presented in Figure 3. Among children of parents who have completed compulsory schools (9 years of education for the parental cohort), a one standard deviation increase in neighborhood disadvantage reduces test scores by 5.8%, compared to 3.4% among parents with a master's degree (18 years of education). Neighborhood effects heterogeneity is even more pronounced by parental earnings; comparing children of parents at the top and bottom of the earnings distribution, there is a difference in neighborhood effects of 7.2% and 0.4%.

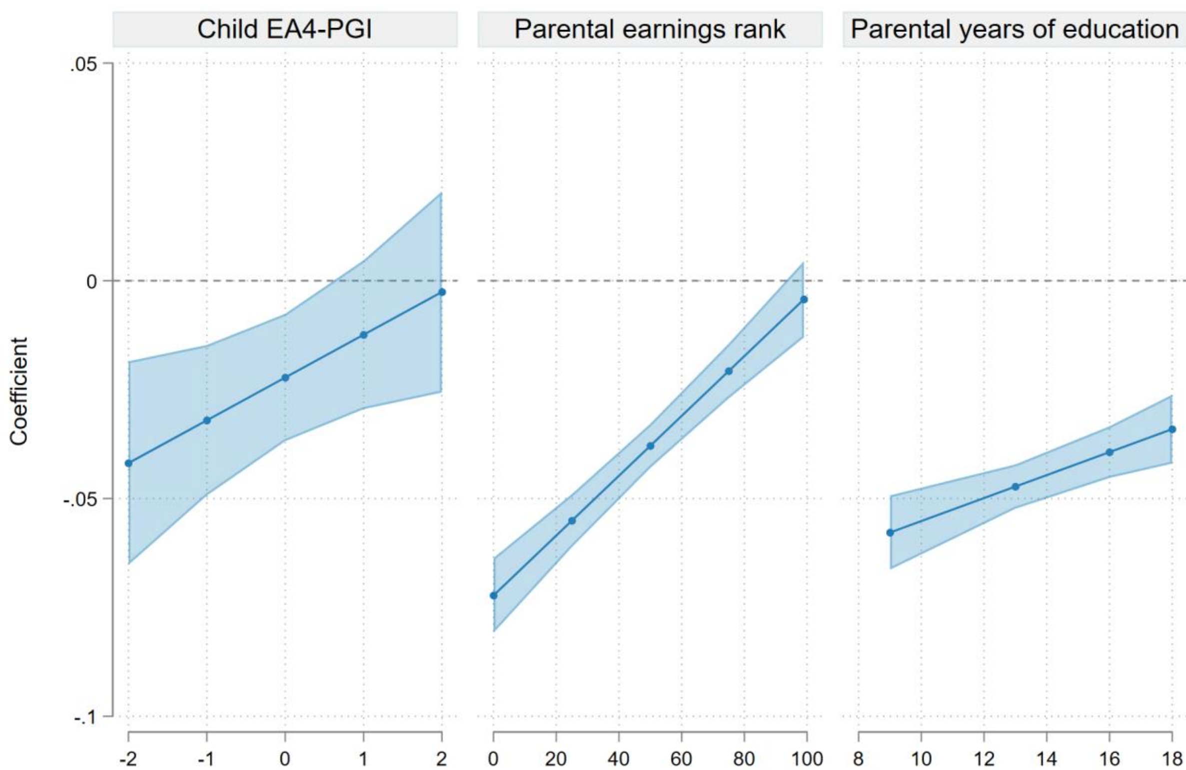

Figure 3: Estimated neighborhood effects at different levels of child genetics, parental earnings rank, and parental years of education.

Note: Coefficients are based on the results in Table 2.

Finally, children's polygenic index for educational attainment, as measured by EA4-PGI, significantly moderates the neighborhood effect (column 6). The results indicate a gene-environment interaction where children with the highest load for genetic variants correlated with educational attainment are unaffected by neighborhood disadvantage.

Robustness

The neighborhood effects are estimated using the neighborhood choice model (Schachner & Sampson, 2020; van Ham et al., 2018). We test the robustness of the results by including genetic controls and using a covariate adjustment strategy. Table 3 shows estimated neighborhood effects using a covariate adjustment strategy, with the full register sample in columns 1 and 2, and the reduced neighborhood choice sample in column 3. The covariate adjustment strategy results in a lower neighborhood effect; a one standard deviation increase in neighborhood disadvantage reduces test scores by 4.7% of a standard deviation in the covariate adjustment model, compared to 5.5% in the neighborhood choice model (compare columns 2 in Table 2 and 3). The results in column 3 show that the neighborhood effects are nearly identical in the full register sample and the sample included in the neighborhood choice model.

Table 3: Estimated neighborhood effects using a covariate adjustment strategy.

	(1)	**(2)**	**(3)**
Neighborhood disadvantage	-0.208***	-0.0465***	-0.0454***
	(0.00305)	(0.00233)	(0.00247)
Observations	651593	651593	537594
Covariate adjustment	No	Yes	Yes

Note: Standard errors in parentheses. Control variables include gender, year of birth, immigrant background, earnings rank, parents receiving welfare benefits, housing benefits, unemployment benefits, and disability pension, and dummies for parental educational level. Estimates in columns (1) and (2) are from the full register data, while the estimate from column (3) is from the sample included in the selection model.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

We also test the robustness of the results by including genetic controls. Because they capture only a small portion of the genetic effects, polygenic indices are better suited to study gene-environment interactions than serving as control variables. Still, there are clear genetic sorting patterns in neighborhoods in Norway, as shown by the bivariate correlation in Table 1 and graphically in Appendix Figure A5. Moreover, although child and parental PGI only explain a quarter of the twin heritability in education (which is $\sim$40%), it is nevertheless a strong predictor of test scores compared to other background characteristics. For example, explaining 10% of the variation in test scores, child and parental PGI explains only slightly less than parental education (12.7%), and more than parental earnings rank (7%) (i.e., R^2 in Table A3).

Thus, if genetic confounding exists, we expect the PGI controls to reduce the estimated neighborhood effects. In Table 4, columns 2 and 4 replicate the selection and covariate adjustment model in the MoBa genetics sample. The adjusted neighborhood effects are lower when estimated on the subsample where genetic controls are available (cf. columns 2 in Tables 2 and 3), suggesting some selection into the genetic sample. Additionally, including genetic control variables reduces the estimated neighborhood effects further, suggesting that unobserved genetic confounding could slightly upwardly bias the main neighborhood effects. However, the estimates are still statistically significant, and the smaller sample size with the genetic data introduces some uncertainty; the 95% confidence intervals with and without the genetic controls overlap.

Table 4: Estimated neighborhood effects controlling for parental and child EA4-PGI.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Neighborhood disadvantage	-0.189***	-0.0349***	-0.0271***	-0.0362***	-0.0306***
	(0.00522)	(0.00725)	(0.00701)	(0.00556)	(0.00542)
Child EA4-PGI			0.229***		0.219***
			(0.00542)		(0.00459)
Parent EA4-PGI			0.0160***		-0.0009
			(0.00564)		(0.00478)
Observations	62210	55580	55580	62040	62040
Covariate adjustment	No	No	No	Yes	Yes
Selection model	No	Yes	Yes	No	No
PGI controls	No	No	Yes	No	Yes

Note: Standard errors in parentheses. Only individuals observed in the MoBa genetics are included. Model (1) shows the bivariate association between neighborhood disadvantage and test scores in the MoBa sample, while models (2) and (3) show estimated neighborhood effects using the Neighborhood Selection Model and models (4) and (5) estimated using covariate adjustment model. Covariate adjustment controls are explained in the table note of Table 3. PGI controls in column (3) and (5) include parental and child EA4-PGI.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Discussion

There is limited research on neighborhood effects on early school outcomes and even less research on for whom neighborhoods matter. Adapting the Neighborhood Choice Model of van Ham et al. (2018) to the entire country of Norway, we find that exposure to neighborhood disadvantage during a child's ten first years impacts test scores: compared to growing up in the most affluent areas, the children in the most disadvantaged neighborhoods get about 22% lower test scores in fifth grade. Moreover, we find that boys are more affected by neighborhood disadvantage than girls and that socioeconomically disadvantaged groups are more affected than advantaged groups. Additionally, our findings suggest that children with lower polygenic index for educational attainment are more affected by their neighborhood surroundings than other children.

By finding that neighborhood influences test scores, our study fits with extensive literature that finds that growing up in disadvantaged areas affects student outcomes (Leventhal, 2018;

Sharkey & Faber, 2014a). To contextualize our findings, let us compare the neighborhood effect to the influence of parental earnings and education. Indeed, the family environment is more influential than the more distal neighborhoods. Additionally, the family variables operate partly through neighborhood choice, which means that parental education and earnings capture the effects of both neighborhood and family environment. Nevertheless, the size of the estimated neighborhood effects is 15-20% of the parental earnings and education coefficients; a one standard deviation increase in parental earnings and education is associated with an increase in test scores by 26.4% and 35.6% of a standard deviation (Appendix Table A3), compared to 5.5% for neighborhood disadvantage score.[6] Thus, neighborhoods have a meaningful influence on children's test scores.

While previous studies have provided strong evidence of causality, less is known about how neighborhood effects vary by family background, gender, and individual traits (Levy, 2022; Sharkey & Faber, 2014a). In our results, children of low socioeconomic backgrounds are most negatively affected by growing up in disadvantaged neighborhoods. This finding fits with US research showing more influential neighborhood effects on later-life outcomes for disadvantaged groups (Levy et al., 2019; Wodtke et al., 2016).

It is challenging to conclude why parental socioeconomic background moderates neighborhood effects. However, one clue may be found in the fact that neighborhood effects vary more with parental earnings than parental education. Parental education and income are correlated (Sandsør et al., 2021) and are likely to influence the consequences of growing up in

[6] The relative importance of neighborhoods are calculated by dividing the neighborhood coefficient on the parental SES coefficient. For example, for parental earnings: $.0547/_{.264} = .2072$.

disadvantaged neighborhoods for many of the same reasons: parents' capacity to maneuver within the neighborhood's constraints and opportunities to facilitate their child's development and well-being, home learning environment, and conversational styles. However, parental earnings are a better predictor of parents' capacity to invest in activities and educational opportunities within and outside of the neighborhood, and a better predictor of parental stress.

There has been mixed evidence on whether boys are more negatively affected by neighborhood disadvantage than girls: while moving to opportunity types of studies have found stronger effects for girls than boys (Chyn, 2018; Kling et al., 2007), nonexperimental studies typically found the opposite (Leventhal et al., 2009). Our findings support the latter, suggesting that neighborhood disadvantage affects boys considerably more than girls.

Moreover, it is improbable that these neighborhood-by-gender interaction effects are biased. Although parents sort into various neighborhoods based on partly hard-to-observe personal characteristics and resources, the child's gender is independent of these sorting processes; girls and boys are randomly distributed across neighborhoods (in the developmental period we investigate). This randomness essentially eliminates the concern that girls (boys) with specific characteristics are more likely to live in certain neighborhoods, allowing us to estimate the difference in neighborhood effects by gender credibly. (For neighborhood-by-gender interactions to be biased, boy parents must systematically move into different neighborhoods than girl parents based on the treatment effect.) Thus, as has been hypothesized in several studies, the gendered processes involved when children and youth move away from highly disadvantaged communities to more affluent ones may, in some ways, differ from the processes involved when growing up in disadvantaged areas (Chyn & Katz, 2021; Clampet-Lundquist et al., 2011).

Turning to genetic dispositions, we find that children's genetic propensity toward education significantly moderates the effect of growing up in disadvantaged neighborhoods, with the strongest effects among children genetically likely to struggle in school. This finding contradicts the predictions of the Scarr-Rowe hypothesis (Scarr-Salapatek, 1971), where advantaged neighborhoods are assumed to provide the most stimulating environment, allowing children with a high genetic potential for education to express their advantages fully. Instead, our findings support the predictions of the diathesis-stress model, which proposes that genetically vulnerable children are at an increased risk of adverse outcomes in unfavorable environments, while less genetically vulnerable children are less affected (Boardman et al., 2014).

Finding that neighborhood effects vary by genetics is hardly surprising, given the compelling arguments for gene-environment interactions. Yet, the empirical literature, which has focused mainly on parental socioeconomic status, has been less consistent, especially in Europe (Baier et al., 2022; Tucker-Drob & Bates, 2016). A few studies have examined gene-by-school interactions using polygenic indices (Cheesman et al., 2022a; Cheesman et al., 2022b; Trejo et al., 2018), but less is known about how neighborhoods and genetic potential for education interact. One exception is an earlier Norwegian study, which, contrary to our study, found that genetic liability for education did not vary at the neighborhood level (Cheesman, 2022). However, our results may differ from that study because it investigated neighborhood effects net of any school effects, and because it had access to a considerably smaller sample of genotyped individuals.[7]

The case for the causal interpretation of our genetic neighborhood interactions is solid, although slightly more complicated than for the gender interactions. We use a within-family PGI design where the neighborhood-by-PGI interaction is estimated conditional on parents' PGI. In the within-family PGI design, the child PGI reflects the random segregation of alleles at conception. Therefore, the child's PGI is uncorrelated with the social environment the parents select (Cheesman et al., 2022b), and we can credibly estimate the gene-environment correlation using this within-family PGI design. However, measurement errors in the polygenic index are likely to attenuate the size of the gene-environment interaction (Pingault et al., 2022).

To conclude, using the Neighborhood Choice Model of van Ham et al. (2018), we find that exposure to neighborhood disadvantage during a child's ten first years has a meaningful impact on 5th-grade standardized test scores. Moreover, neighborhood effects vary considerably by socioeconomic background, gender, and polygenic index for education, highlighting the importance of studying heterogeneous neighborhood effects. This negative effect of neighborhood disadvantage potentially compounds with individual risk (lower load for genetic variants correlated with educational attainment) and family risk (lower family income and parental education levels) for underachievement at school, and potentially most strongly so for boys. Hence, our findings suggest that policies designed to improve opportunities and life chances

[7] Moreover, our results are consistent with recent neighborhood studies from other fields. Supporting the diathesis-stress model, polygenic gene-environment studies have found that neighborhoods with more trash and vandalism trigger genetic risk for type 2 diabetes (Robinette, Boardman, & Crimmins, 2019), and found some support for socioeconomically advantaged neighborhoods (which increase the risk for substance abuse) accentuates the genetic risk for alcohol use.

for these children should also incorporate interventions at the neighborhood level, to reduce neighborhood disadvantage or compensate for the detrimental effect of it.

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Supplementary Online Appendix

For whom neighborhoods matter: Heterogeneous effects of socioeconomic neighborhood composition on child achievement

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Content of supplementary online appendix:

Online Appendix A: Supplementary tables and figures
Online Appendix B: MoBa genetics quality control

Appendix A: Supplementary Tables and Figures

Table A1: Correlation between neighborhood characteristics

	1	2	3	4	5	6	7	8	9
1. Neighborhood disadvantage	1								
2. Social welfare (%)	0.638	1							
3. Housing allowance (%)	0.594	0.801	1						
4. Disability pension (%)	0.803	0.438	0.508	1					
5. Earnings rank	-0.970	-0.528	-0.487	-0.746	1				
6. Higher education (%)	-0.747	-0.191	-0.0942	-0.545	0.740	1			
7. Low education (%)	0.788	0.324	0.194	0.588	-0.740	-0.883	1		
8. High income (top 10%)	-0.829	-0.322	-0.284	-0.583	0.868	0.744	-0.677	1	
9. Low income (bottom 10%)	0.664	0.749	0.723	0.501	-0.558	-0.201	0.366	-0.266	1

Table A2: Distribution of neighborhood characteristics.

	10th	25th	50th	75th	90th
Neighborhood disadvantage	-1.296	-0.638	-0.007	0.597	1.141
Social welfare (%)	0.010	0.016	0.025	0.039	0.057
Housing allowance (%)	0.007	0.013	0.022	0.037	0.057
Disability pension (%)	0.041	0.057	0.079	0.107	0.137
Earnings rank	43.223	46.613	50.663	55.016	59.530
Higher education (%)	0.183	0.239	0.317	0.424	0.554
Low education (%)	0.193	0.265	0.342	0.420	0.490
High income (top 10%)	0.036	0.055	0.086	0.132	0.195
Low income (bottom 10%)	0.035	0.045	0.058	0.076	0.099

Note: Cells shows the percentile of the variables' distribution.

Table A3: Differences in achievement by individual and background characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)
Parental years of education	0.354***					
	(0.00115)					
Parental earnings rank		0.264***				
		(0.00118)				
Girl			-0.00294			
			(0.00245)			
Child EA PGI				0.306***		0.254***
				(0.00360)		(0.00488)
Parent EA PGI					0.244***	0.0781***
					(0.00377)	(0.00488)
Constant	0.0173***	0.0161***	0.0165***	0.234***	0.237***	0.237***
	(0.00115)	(0.00118)	(0.00172)	(0.00359)	(0.00376)	(0.00368)
N	659114	657523	661331	65930	62210	62210
R-square	0.127	0.0704	0.0000022	0.0986	0.0630	0.102

Note: Standard errors in parentheses. Parental years of education, parental earnings rank, and child and parent PGI is standardized to have a mean of 0 and standard deviation of 1.
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table A4: Descriptive statistics in full register sample and MoBa genetics sample.

	N	Mean	SD	Min	Max
Panel A: Register sample					
Neighborhood disadvantage	661329	-0.031	0.972	-4.743	9.507
National tests 5th	661331	0.015	0.996	-3.978	2.602
Birth year	661331	2002.520	3.469	1997.000	2008.000
Birth month	661331	6.381	3.374	1.000	12.000
Girl	661331	0.494	0.500	0.000	1.000
Parental years of education	659114	13.810	2.483	7.000	21.000
Parental earnings	657523	51.261	21.848	0.000	99.000
Parent disability pension	657523	0.031	0.173	0.000	1.000
Parent unemployed	657523	0.105	0.307	0.000	1.000
Parent housing allowance	657523	0.063	0.243	0.000	1.000
Parent social welfare	657523	0.067	0.250	0.000	1.000
Children of native-born parents	661315	0.789	0.408	0.000	1.000
Children of foreign-born parents	661315	0.211	0.408	0.000	1.000
Panel B: MoBa genetics sample					
Neighborhood disadvantage	62210	-0.302	0.936	-4.743	4.454
National tests 5th	62210	0.237	0.970	-3.251	2.602
Birth year	62210	2005.211	1.862	2002.000	2008.000
Birth month	62210	6.334	3.341	1.000	12.000
Girl	62210	0.495	0.500	0.000	1.000
Parental years of education	62209	14.842	2.129	8.000	21.000
Parental earnings	62095	58.796	19.596	0.000	99.000
Parent disability pension	62095	0.015	0.123	0.000	1.000
Parent unemployed	62095	0.069	0.254	0.000	1.000
Parent housing allowance	62095	0.018	0.134	0.000	1.000
Parent social welfare	62095	0.018	0.134	0.000	1.000
Children of native-born parents	62210	0.911	0.285	0.000	1.000
Children of foreign-born parents	62210	0.089	0.285	0.000	1.000

Table A5: Bivariate associations between independent variables and standardized test scores in full register sample and MoBa genetics sample.

Variable	**Register**	**MoBa**
Neighborhood disadvantage	-.211***	-.189***
	(.00123)	(.00409)
Birth month	-.0372***	-.0362***
	(.00036)	(.00115)
Girl	-.00294	-.00941
	(.00245)	(.00777)
Parental years of education	.143***	.153***
	(.000462)	(.00172)
Parental earnings	.0121***	.0109***
	(.0000542)	(.000194)
Parent disability pension	-.358***	-.377***
	(.00707)	(.0316)
Parent unemployed	-.209***	-.208***
	(.004)	(.0153)
Parent housing allowance	-.53***	-.591***
	(.00502)	(.029)
Parent social welfare	-.595***	-.649***
	(.00486)	(.0288)
Children of native-born parents	.166***	-.134***
	(.00299)	(.0136)
Children of foreign-born parents	-.166***	.134***
	(.00299)	(.0136)

Note: Coefficients are obtained by regressing test scores on the independent variables in separate models.

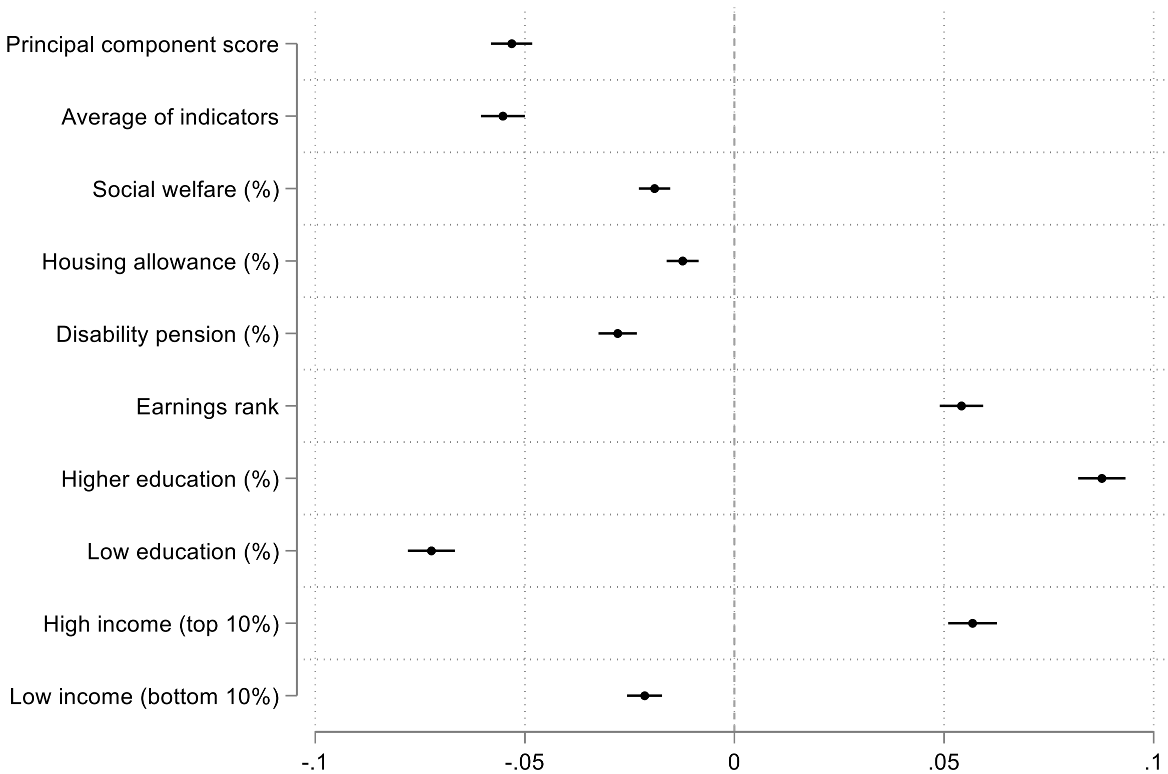

Figure A1: Effects of different indicators

Note: Principal component score is the neighborhood disadvantage variable used in the main analyses, while the average of indicators is a simple average of the neighborhood indicators. All variables are standardized to have a mean of 0 and a standard deviation of 1.

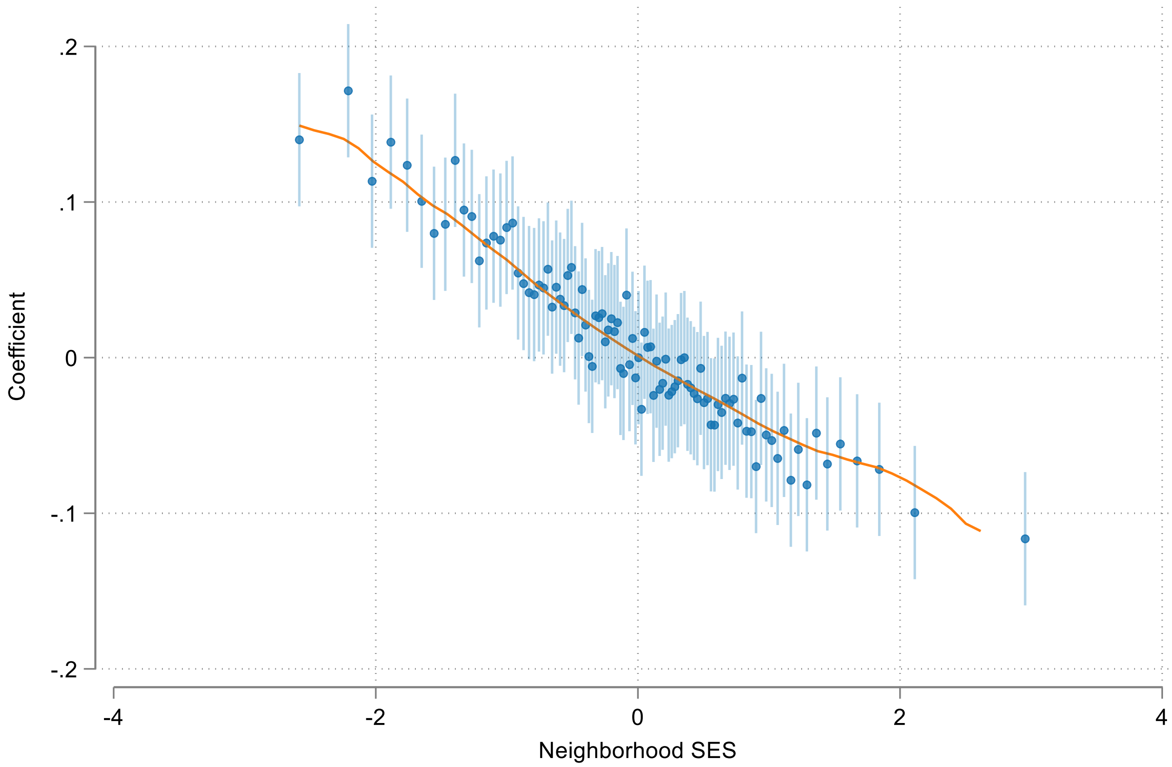

Figure A2: Non-linear effects of neighborhood disadvantage.

Note: The neighborhood variable is divided into 100 equal-sized groups and test scores are regressed on this categorical variable using the selection model (the median neighborhood is reference category). The circles show coefficients (relative to the median neighborhood) and the bars show 95% confidence intervals. The solid line is estimated using a local polynomial smooth of the estimated coefficients on the binned neighborhood variable.

Figure A3: Distribution of neighborhood characteristics

Note: Each variable is divided into 100 equal pieces, and the mean is calculated within each piece.

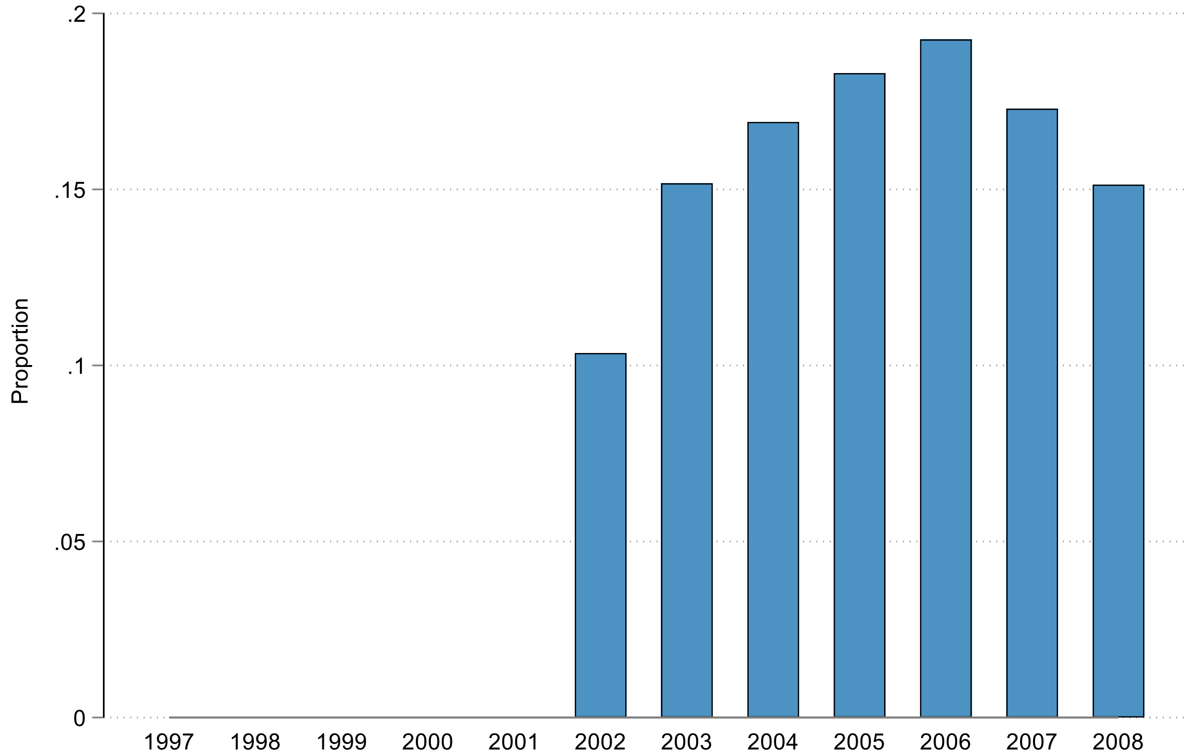

Figure A4: Proportion of full birth cohorts observed in the MoBa genetics data.

Note: Bars show the proportion in the full birth cohorts that we observe both child and parental EA4-PGI in the MoBa genetics data.

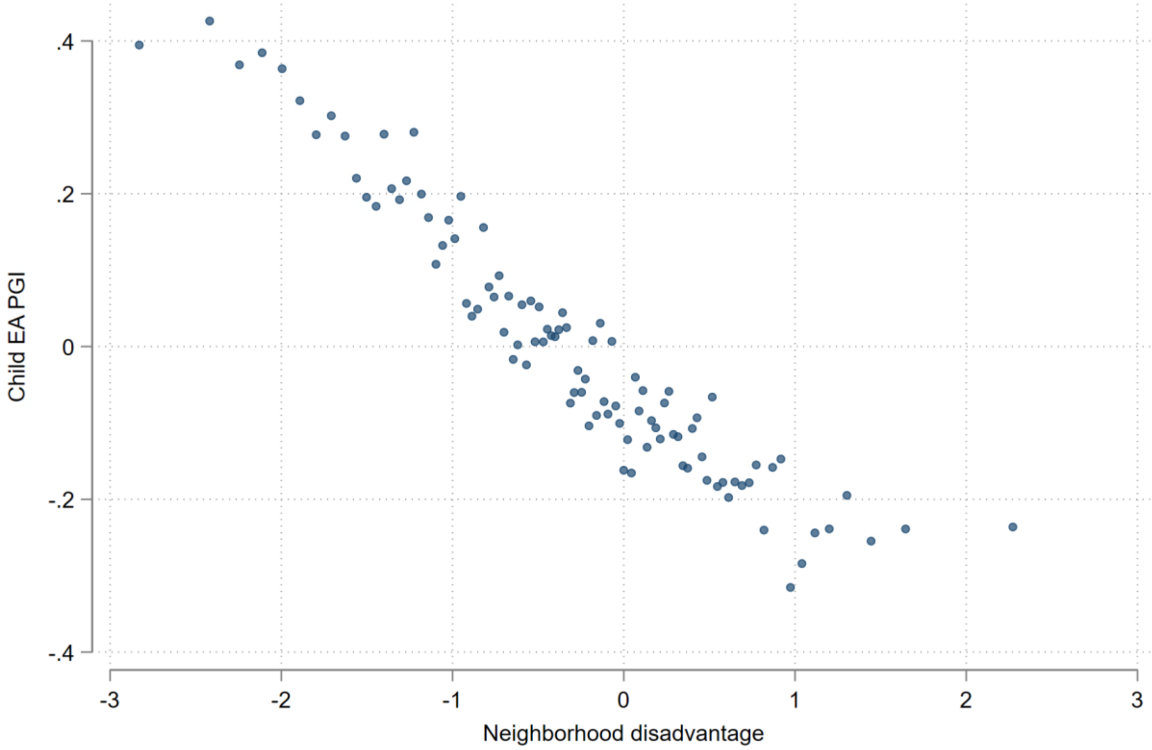

Figure A5: Bivariate association between neighborhood disadvantage and child genetics.

Note: Neighborhood disadvantage is divided in 100 equal bins and then the average of child EA PGI is calculated in each bin.

Appendix B: MoBa Genetics Quality Control

The current MoBa genomic dataset comprises imputed genetic data for 207,283 individuals, derived from nine batches of participants, who comprise four study cohorts. Within each batch, parent and offspring genetic data were quality controlled separately. Pre-imputation quality control criteria have been described in previous publications. We conducted post-imputation quality control, retaining SNPs meeting the following criteria: imputation quality score ≥ 0.8 in all batches, non-duplicated (by position or name), call rate >98%, minor allele frequency >1%, Hardy-Weinberg equilibrium p<0.001, not associated with genotyping batch at the genome-wide level, and not causing a mendelian error. We removed individuals with the following criteria: heterozygosity outliers (F-het +/- 0.2), call rate <98%, reported sex mismatching SNP-based sex, duplicates (identified using PLINK's–genome command as having pihat>=0.98, and distinguished from monozygotic twins through linkage to unique IDs in the population register, plus age, sex, and kinship information within MoBa), individuals with excessive numbers of close relatives (cryptic relatedness) and mendelian errors. To minimize environmental confounding, we identified a sub-sample of individuals with European ancestries via principal component analysis using the 1000 Genomes reference; thresholds for exclusion of outliers were based on visual inspection of a plot of principal components 1 and 2. The final numbers of individuals and SNPs passing quality control were 93,582 and 6,797,215, respectively. Principal components of genetic ancestry were computed for all participants using PLINK's –within and –pca-clusters commands, based on an LD-pruned version of the final quality-controlled genotype data.