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The Golden Middle Class Neighborhood
Trends in Residential Segregation and Consequences for Offspring Outcomes

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Abstract

Based on Norwegian administrative registers we provide new empirical evidence on the effects of the childhood neighborhood's socioeconomic status on educational and labor market performance. A neighborhood's status is measured annually by its prime age inhabitants' earnings ranks within larger commuting zones, and the childhood neighborhood status is the average status of the neighborhoods inhabited from birth to age 15. Identification of causal effects relies on within-family comparisons. Our results reveal a hump-shaped relationship between the socioeconomic status of the childhood neighborhood and school results at age 15-16, such that the optimal neighborhood is of medium rank. The top-ranked neighborhoods are as bad as the bottom-ranked. Similar results are obtained for educational and labor market outcomes measured at higher ages.

Keywords: Segregation, neighborhood effects, social mobility, educational outcomes

JEL Codes: C21, I24, R23, Z13

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1 Introduction

The research presented in this paper is motivated by two empirical observations. The first is that residential segregation has risen rapidly over the past decades in both the US and Europe, such that neighborhoods have become more homogenous in terms of family income and/or socioeconomic status (Jagowsky, 1996; Bischoff and Reardon, 2013; Marcińczak et al., 2016; Musterd et al., 2017). The second is that recent empirical evidence shows that neighborhood quality has a large and potentially long-lasting influence on the educational and economic outcomes for children growing up in them (Wodke et al., 2011; Crowder and South, 2011; Chyn, 2016; Chetty et al., 2016; Chetty and Hendren, 2018a; 2018b). Taken together, these observations point toward a future with growing inequality and lower social mobility.

In the present paper, we use administrative data from Norway to examine recent trends in residential segregation and to investigate the impacts of a childhood neighborhood's socioeconomic status on offspring's schooling outcomes by age 15/16 and on educational and labor market outcomes measured at ages 20 and 28-31. We use census tracts to operationalize the concept of neighborhoods. This implies that we focus on very small geographical units in which there is a high probability of face-to-face interaction between the inhabitants. On average, the neighborhoods studied in this paper have as little as 350 residents; hence, the associated "neighborhood effects" capture environmental characteristics at a very low geographical level, incorporating peer effects and role model influences associated with close neighbors. They are relevant for parents making decisions about which neighborhood to live in as well as for policy makers and city planners deciding on the structure of new housing and local development projects. While much of the existing literature has an explicit focus on the impacts of moving away from particularly disadvantaged high-poverty neighborhoods (e.g., Kling et al., 2007; Clampet-Lundquist and Massey, 2008; Ludwig et al., 2008; Chetty et al., 2016; Chyn, 2016), the present paper examines the influence of childhood neighborhoods' socioeconomic status across the complete neighborhood status distribution. In line with recent research emphasizing the temporal dimension of neighborhood effects (Wodke et al., 2011; Crowder and South, 2011; Chetty and Hendren, 2018a; 2018b), we focus on the cumulative neighborhood exposure during childhood as the key explanatory variable.

Our analysis is novel in several respects. First, we identify a neighborhood's socioeconomic status annually from 1993 through 2015 based on the earnings ranks of all its prime age (30-60) inhabitants, where each person's labor earnings are compared to all others who live in the same commuting zone and who are of the same sex and age. This way, we capture neighborhood segregation within larger travel-to-work areas, and we describe each neighborhood in terms of both *average inhabitant rank* (its overall socioeconomic status) and *average rank distance* (the degree of social diversity). By focusing on ranks – rather than earnings levels – we ensure that any measured trends in segregation actually arise from changes in residential patterns or social mobility and not from changes in earnings inequality as such. Moreover, as relative labor market success is stably tied to socioeconomic status, we obtain status and diversity measures that basically have the same interpretation over time and space. In addition, by making the individual ranks age-specific, we avoid disturbances from changes in the demographic composition of neighborhoods.

We first show that while residential segregation in Norway was stable during the 1990s, it has increased monotonously since the turn of the century. As a result, the difference in average inhabitant earnings rank between the top and bottom decile of neighborhoods has increased by 14 percent. Moreover, the shares of the population residing in typically lower or upper class neighborhoods have increased considerably, whereas the shares residing in more diverse middle class neighborhoods have declined.

Next, for all offspring born between 1993 and 1999, we examine how school results – measured by average grade points (GPA) obtained at the end of junior high school at age 15/16 – depends on the socioeconomic status of the neighborhoods inhabited throughout the period from birth to age 15. In this part of the analysis, we use family fixed effects to eliminate biases following from non-random sorting into neighborhoods. Hence, in essence, we compare full siblings who have been exposed to different neighborhood environments during childhood either because they have moved residence and/or because the neighborhood they live in has changed. And since our data provide full coverage of all neighborhoods inhabited before age 16, our approach facilitates identification of critical ages at which neighborhoods have particularly large or small influence. The identifying assumption is that within-family selection effects associated with being exposed to neighborhoods with higher/lower socioeconomic status do not systematically vary with the ages at which these changes occur. While we cannot test the validity of this assumption directly, we assess the consequences of manipulating the sources of identifying variation, both with respect to the ranking of neighborhoods (excluding/including time-variation in individual ranks) and with respect to sources of variation in exposure (excluding/including stayers and movers). Arguably, we can also sign the expected bias resulting from any remaining unaccounted-for confounding shocks. Based on the plausible assumption that events responsible for raising a family's neighborhood class are not systematically associated with events that have negative influences on the offspring's school results, the bias will be positive; i.e., it will tend to overstate the positive influence of living in higher class neighborhoods.

Our results reveal a conspicuous hump-shaped and almost symmetric relationship between childhood neighborhood rank and GPA score. Hence, we confirm previous findings that moving upwards from economically disadvantaged neighborhoods contributes to a considerable improvement in offspring educational outcomes. However, the "best" neighborhood to grow up in – in terms of maximizing junior high school GPA score – is a middle class (medium ranked) neighborhood. To our knowledge, this important non-linearity has not previously been recognized in the literature. Our findings actually suggest that the top ranked neighborhoods are as bad as the bottom ranked neighborhoods. The estimated negative effect of spending childhood in higher-class neighborhoods is statistically significant and highly robust, both with respect to model specification (functional form assumptions), with respect to the inclusion of controls for the school environment in which the GPA score was obtained (such as school-fixed effects and GPA score among same-year schoolmates), and with respect to the sources of identification. It is also robust with respect to outcomes measured at higher ages. In particular, although the outcome data become much thinner as we extend the outcome period, we identify similar humped shaped effects on high-school graduation as well as on a measure of overall education/employment status at age 20.

Finally, while we cannot follow the 1993-1999 birth cohorts for which we have complete information about childhood residency into higher ages, we can look at neighborhood effects for earlier birth cohorts based information on the neighborhoods inhabited during adolescence. In a supplementary analysis, we examine the 1980-87 birth cohorts, with a focus on how adult education and earnings outcomes (measured at age 28-31) are affected by the socioeconomic status of the neighborhoods inhabited during adolescence (age 13-15).

This analysis reveals a remarkably similar pattern of neighborhood effects as those identified for early school results. Again, there is a distinct hump-shaped relationship, such that medium ranked neighborhoods provide the best outcomes. And again, the top-ranked neighborhoods are as bad as the bottom ranked.

Based on the existing literature, we argue that a plausible interpretation of the negative high-class effects is that they represent a relative deprivation mechanism arising from the fact that living in a high-class neighborhood entails a lower relative position in the social hierarchy, ceteris paribus. This interpretation is also supported by our finding that the average socioeconomic status of schoolmates has an additional negative influence on own achievement, with or without controls for their actual GPA score average.

Our results indicate that the childhood neighborhood status has a larger effect on GPA score for girls than for boys, and point estimates suggest that both the preschool age (0-5) and the junior high school age (13-15) are more important than the primary school age (6-12). These latter differences are not statistically significant, however. Point estimates also suggest that neighborhood status is more important for offspring who themselves belong to the middle and upper classes than for lower-class offspring. For the latter group, we actually fail to identify a significant positive effect of moving from a low to a middle class neighborhood, possibly reflecting that the relative deprivation effect kicks in already at medium neighborhood class levels for offspring who themselves belong to the bottom class.

Since residential segregation implies that fewer offspring grow up in middle class neighborhoods and more offspring grow up in lower and upper class neighborhoods, the results presented in this paper imply that the trend toward rising segregation in Norway has also been a force for poorer average educational and labor market performance. However, it has not necessarily been a force for lower mobility and more inequality. According to our results, it is actually offspring from the upper and middle classes that have most to gain from residential diversity.

2 Why neighborhoods matter

Characteristics of the childhood neighborhood may influence adolescent and adult outcomes through a number of channels, related to the physical environment (air and water quality, traffic noise, access to parks and playgrounds), public amenities (quality of schools and childcare facilities), public safety (prevalence of crime and violence), and peer influences (associated with playmates and adolescent/adult role models); see, e.g., Harding et al. (2011) and Sharkey and Faber (2014) for recent discussion and overviews of the literature. The relative importance of these mechanisms depend on contextual factors such as the degree of earnings/wealth inequality, the extent of geographical redistribution, and the provision of publically provided services. For example, in a welfare state like Norway, with moderate earnings inequality and ambitious tax and transfer policies, it is a widely accepted policy goal to equalize the standards of public amenities across neighborhoods. In practice, this often implies that schools and kindergartens in poorer areas command more resources per head than those in richer areas. Hence, in a Norwegian context it is natural to think of neighborhood effects primarily in terms of peer influences, although other channels obviously cannot be ruled out.

In the present paper, the neighborhood's socioeconomic environment is described exclusively in terms of the age-specific earnings rank (within the commuting zone) of the prime-aged adult population. However, the earnings rank of adult residents will clearly be correlated with other peer attributes. In particular, we know from existing evidence that parental earnings rank is highly and positively correlated with educational and economic outcomes in the offspring generation (Chetty et al., 2014, Pekkarinen et al., 2017; Markussen and Røed, 2017); hence, we expect that neighborhoods with high average earnings rank are also characterized by high average levels of human capital, both in the parent and offspring generations. This implies that children growing up in high-class neighborhoods tend to have peers and role models with more human capital than children growing up in low-class-neighborhoods.

There is a large existing literature on neighborhood effects covering a wide range of outcomes, from physical and mental health to criminal behavior to education and adult earnings. Yet, according to a recent comprehensive survey by Oakes et al. (2015), there is little consensus on the nature and direction of the neighborhood peer effects, and the vast majority of contributions fail to deal with the most fundamental identification problems. With respect to peer influences on academic achievement, there is also an extensive literature focusing on the social interaction within classrooms. A typical finding in this literature is that higher-achieving peers have moderate beneficial effects on most pupils, yet with considerable effect heterogeneity; see, e.g., Sacerdote (2011) and Epple and Romano (2011) for recent overviews. Some of the effects identified in classrooms are likely to carry over to neighborhoods. Higher-ranked neighbors tend to be better educated, have higher employment rates and better jobs, and thus to a larger extent than others radiate normative values in support of effort and work. Offspring growing up in these neighborhoods interact with persons who have high human capital and high work morale, and thus presumably constitute good role models for own educational achievements.

Yet, growing up in a higher-class neighborhood also implies a lower relative position in the local distribution of children's status- and/or ability levels, ceteris paribus. A lower relative position may again be associated with less positive attention from peers, parents and teachers, lower self-esteem, and perhaps lower educational ambitions. The finding that higher-achieving peers have negative effects on academic self-concept and academic achievement is prevalent within the psychology literature, where it has been labelled the big-fish-little-pond effect; see, e.g., Marsh (1987) and Marsh and Hau (2003). Similar findings have also recently been reported in the economics literature; see, e.g., Elsner and Isphording (2018) who provide evidence that higher ordinal ability rank within a school cohort reduces risky behaviors and raises expectations regarding own educational achievement. The finding of negative influences of higher-achieving peers has a long tradition within a rich literature discussing what is known as the "relative age effect". This label refers to the age variation typically occurring within grade cohorts in education and sports due to the use of a single cutoff date for enrolment into age-specific groups. Based on the resultant random-assignment-like source of within-group age variation, it has been shown that the oldest members of the groups have been given a lasting advantage, both in education (Bedard and Dhuey, 2006) and in sports (Barnsley et al., 1992; Allen and Barnsley, 1993; Delorme et al., 2010; González-Villora et al. 2015). A typical finding in the latter literature is that persons born soon after the cutoff date have a much higher probability of becoming top athletes than others. For example, Barnsley et al. (1992) show that as much as 47 percent of the players in the international Under-20 world soccer tournament in 1989 were born in the first quarter of the "football year" (August-October), while only 8 percent were born in the last quarter. The existence of a lasting advantage in education is questioned, however, by Black et al. (2011), who find no evidence of a long-term effect of school starting age on education and earnings in Norway.

In our setting, the peer effects of interest encompass neighbors and playmates from birth through primary school, including social arenas in the home environment (such as the local playground), in childcare facilities, and in the classroom. We will be interested in average effects of the neighborhoods' social status, and we will look for differential effects in different phases of childhood/adolescence. Moreover, we will be interested in examining heterogeneity in neighborhood effects with respect to own family class background.

3 Data, definitions, and trends

Our socioeconomic characterization of neighborhoods is based on the residents' earnings ranks within larger commuting zones (travel-to-work-areas). The choice of commuting zones (rather than the whole country) as the foundation for ranking is motivated by our aim of zooming in on residential decisions and their consequences, and not on the more general choices of labor market careers. We first divide Norway into 160 different commuting zones using the classification developed in Gundersen and Jukvam (2013). We then provide a status/class *rank* to all prime age individuals living in each commuting zone. On average, a commuting zone consists of 12,017 prime age individuals, but the variation is large, from less than hundred in the smallest isolated islands to around 570,000 in the largest urban areas. The ranking is done separately for each year from 1993 through 2015 on the basis of observed labor earnings. More specifically, all residents of prime age (30-60) are assigned a *vignitile rank* based on their position in the commuting zone's age- and gender-specific distribution of labor earnings.[1] Hence, each person is for each calendar year attributed a rank number from 1 to 20, describing his/her earnings rank relative to all others of the same age and sex living in the same commuting zone.

[1] We use vigintiles (5-percent groups) rather than percentiles to reduce problems with ties in connection with zero earnings. In some few cases where more than 5 percent have zero earnings, we use a lottery to rank the bottom earners. Our ranking algorithm is set up as follows: For each combination of commuting zone, year, gender, and age, let $k=1,\ldots,K$ be the rank of all persons in a group of size K, where $k=1$ is the lowest, and $k=K$ is the highest rank. Vigintile rank $v=1,\ldots,20$ is then assigned through the formula $v=ceil(20k/K)$. For commuting zones where some age-gender groups have less than 20 people, this implies that ranks will be distributed from the top with distance 20/(number of people). For example, with only five people to rank, they will obtain the ranks 4, 8, 12, 16, 20. Note that since all results presented in this paper are population-weighted, these small commuting zones play a negligible role in the analysis.

We then examine how people with different ranks are distributed across each commuting zone's neighborhoods (census tracts). On average, a commuting zone consists of 79 neighborhoods with an average number of 152 prime age residents each.[2] Again, the variation is large. The smallest commuting zones have just a single neighborhood (implying that they will have no role to play in our empirical analysis), whereas the largest have approximately 2,000 neighborhoods. And the neighborhood size varies from just 10 prime age residents in the smallest to 2,800 in the largest.

Based on earnings rank within commuting zones, we compute for each neighborhood and for each year, the following two metrics:

- <u>Socioeconomic status</u>: Average inhabitant vigintile rank (AIR); i.e., the expected rank of a randomly chosen individual
- <u>Diversity</u>: The average vigintile rank distance (ARD); i.e., the expected rank difference between two randomly chosen individuals

While the former of these will constitute our indicator for each neighborhood's socioeconomic position in our analysis of causal effects, the latter will serve as an indicator for the degree of neighborhood segregation. The larger the expected rank distance, the more diverse is the neighborhood, and the lower is the degree of residential segregation. With zero segregation (random distribution of the population across neighborhoods) it can be shown that the expected values of ARD and AIR are 6.65 and 10.5, respectively.[3]

Figure 1 shows how the population-weighted average neighborhood diversity (ARD) has developed over the past two decades. A first point to note is that the degree of residential segregation is quite low *on average*. The average vigintile rank distance within all Norwegian neighborhoods fluctuates between 6.38 and 6.45, which is not very far from the zero segregation case (random assignment of individuals across neighborhoods) of 6.65. A second point to note is that while residential segregation was slightly diminishing during the 1990s,

[2] Note that our neighborhoods are an order of magnitude smaller than those used by Chetty and Hendren (2018a; 2018b). In their analyses, neighborhoods are represented either by larger commuting zones (with more than 250,000 people) or by counties (with more than 10,000 people). Hence, the neighborhood effects identified in our paper capture social interaction effects at a much lower geographical level.

[3] Note that for each neighborhood *n*, we have that $ARD_n = 2 \times RGINI_n \times AIR_n$, where $RGINI_n$ is the "Rank Gini"; i.e., the Gini-coefficient associated with the distribution of individual ranks (from 1 to 20) within the neighborhood.

it has increased steadily since the turn of the century. The expected rank difference within neighborhoods has declined monotonously in this period. In Appendix A, we take a closer look at the economic forces behind the rise in segregation by regressing the commuting-zone-specific annual ARD metrics on time-varying commuting zone characteristics, such as overall inequality, employment, average education, and the share of immigrants. Our findings suggest that the changes in segregation over the period covered here are explained by rising immigrant shares from developing countries and Eastern Europe.

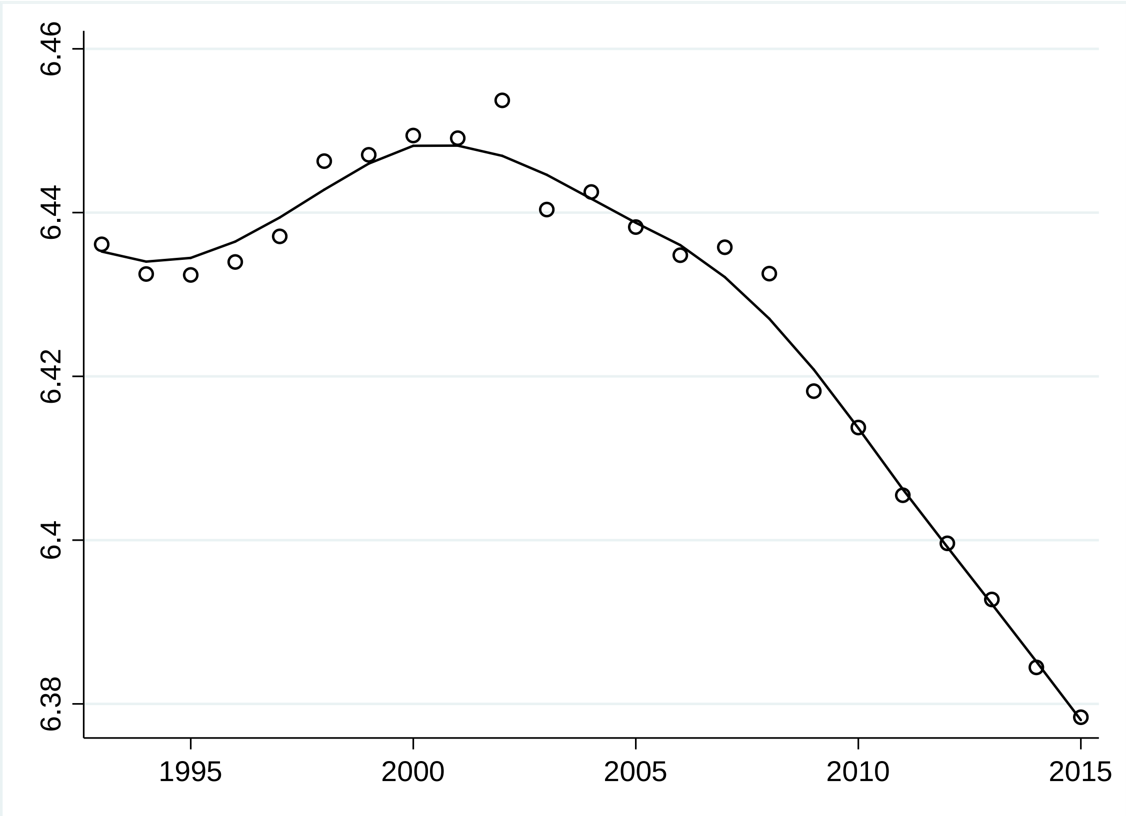

Figure 1. Residential diversity (average ARD) in Norwegian neighborhoods 1993-2015
Note: The figure shows for each year the average vigintile rank distance between two randomly selected individuals within approximately 12,600 different neighborhoods in Norway. The trend line is estimated with a local polynomial (second order) regression.

The rise in overall residential segregation is paralleled by a development toward a more polarized distribution of average inhabitant ranks across neighborhoods; see Figure 2, which shows the average AIR for the top and bottom decile of the population’s neighborhood ranks.[4] While the average rank of the neighborhoods inhabited by the decile with the lowest neighborhood rank has declined considerably over time, the average rank of neighborhoods inhabited by the upper decile has increased. As a result, the average class difference between the top and the bottom deciles has risen from 4.4 to 5.0 vigintiles; i.e., by 14 percent. Moreover, if we define upper and lower class neighborhoods on the basis of absolute rank thresholds, there is a trend toward increasing population shares in extreme neighborhoods. For example, the population share living in neighborhoods with AIR below 8.5 has risen by more than 40 percent (from around 6.0 to 8.5 percent of the population) since year 2000, whereas the share living in neighborhoods with AIR above 12.5 has increased by 30 percent (from 4.8 to 6.2); see Figure 3.

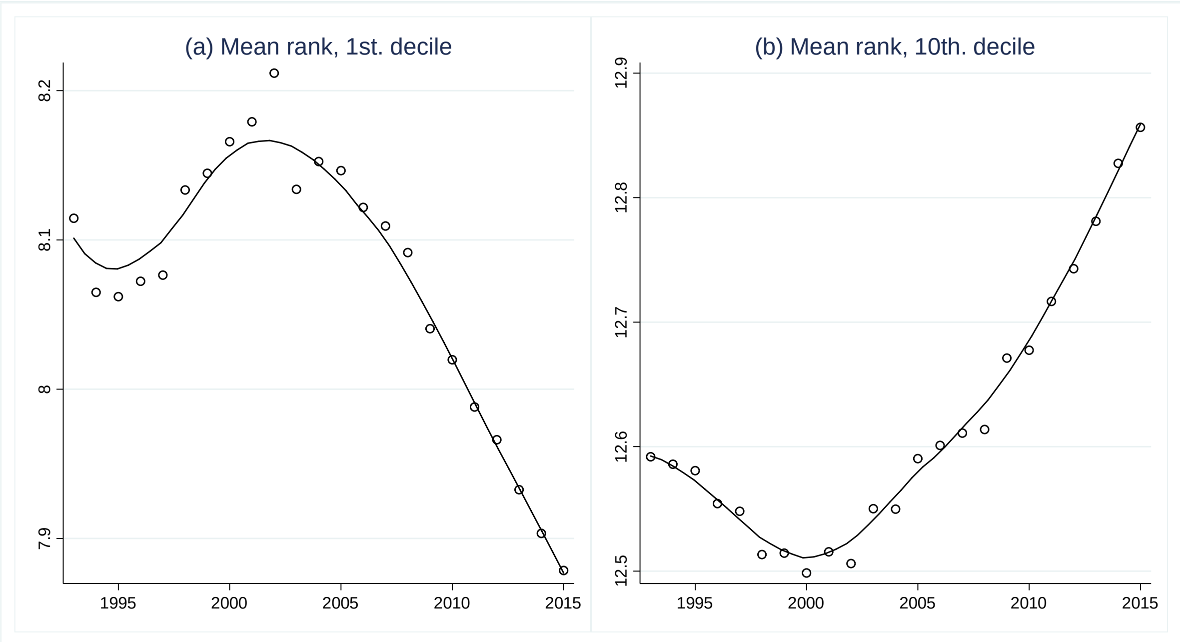

Figure 2. Mean neighborhood rank of the 1st and 10th decile in the neighborhood rank distribution. 1993-2015.

Note: Deciles are calculated at the individual level, such that, for example, the 1st decile shows the average inhabitant vigintile rank of the neighborhoods inhabited by the 10 percent of the population with lowest neighborhood rank. The trend lines are estimated with local polynomial (second order) regressions.

[4] The deciles reported here refer to the neighborhood rank distribution of *individuals,* such that, for example, the number reported for the first decile is the average neighborhood rank assigned to the 10% of the population who lives in the lowest ranked neighborhoods.

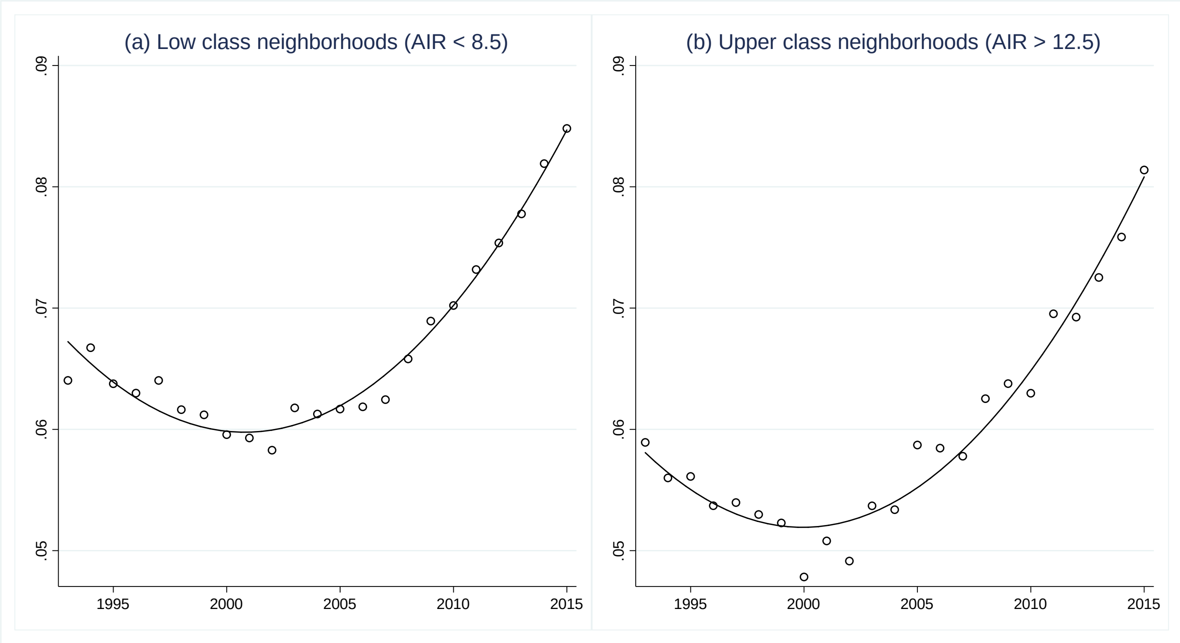

Figure 3. Fractions of adults living in lower and upper class neighborhoods. 1993-2015.
Note: The trend lines are estimated with local polynomial (second order) regressions

These trends also imply that a rising share of offspring grow up in neighborhoods with either very low or very high average inhabitant rank. In the next section, we examine the consequences that this may have for the offspring's educational and labor market performance.

4 Consequences for offspring outcomes

In this section we present a series of regression results where we seek to explain offspring school performance as a function of characteristics of the neighborhoods that each person has lived in from birth to age 15. We follow Crowder and South (2011), Wodtke et al. (2011) and Chetty and Hendren (2018a; 2018b) in that we focus on the impact of accumulated exposure to different local environments during childhood and adolescence, and not on the environment experienced at a particular point in time. In principle, we are interested in the impacts of both the socioeconomic status (AIR) and the diversity (ARD) of childhood neighborhoods. However, these two characteristics are closely linked such that the degree of diversity is systematically larger i middle class neighborhoods than in bottom and top ranked neighborhoods.[5] In practice, it turns out there is too little identifying variation in our data to estimate a separate impact of neighborhood diversity with sufficient precision once we have accounted for neighborhood rank. We therefore focus our analysis on the socioeconomic rank of childhood neighborhoods. In Appendix B we present some illustrative results from models where diversity is explicitly included.

In the present section, the main explanatory variable of interest is the average neighborhood rank exposure. This is computed for each offspring as the weighted average of the neighborhood inhabitant rank (leaving out the offspring's own parents) he/she has been exposed to, such that each age 0,…,15, is attributed a weight of 1/16. The resultant variable AIR_0^{15} thus indicates the average neighborhood inhabitant rank an individual has been exposed to over the complete period from birth to age 15. In some parts of the analysis, we distinguish between different phases of childhood/adolescence and use variables like AIR_0^5, AIR_6^{12} and AIR_{13}^{15}, where each variable represents the average taken over the ages indicated by the sub –and superscripts.

Our primary outcome variable is going to be the grade point average (GPA) from primary school, typically measured at age 15-16. As the key explanatory variable is defined in terms of ranks within commuting zones, we also define the GPA outcome in terms of rank (percentile) in the distribution of GPA scores within the same zones. This also has the advantage that the marginal distribution of the outcome is by construction the same across commuting zones and years.

[5] Note that in the extreme tails of the neighborhood rank distribution, there is by construction little or no diversity, as such diversity will pull the neighborhood away from the extreme. In Appendix B, we provide a description of the relationship between AIR and ARD in our data.

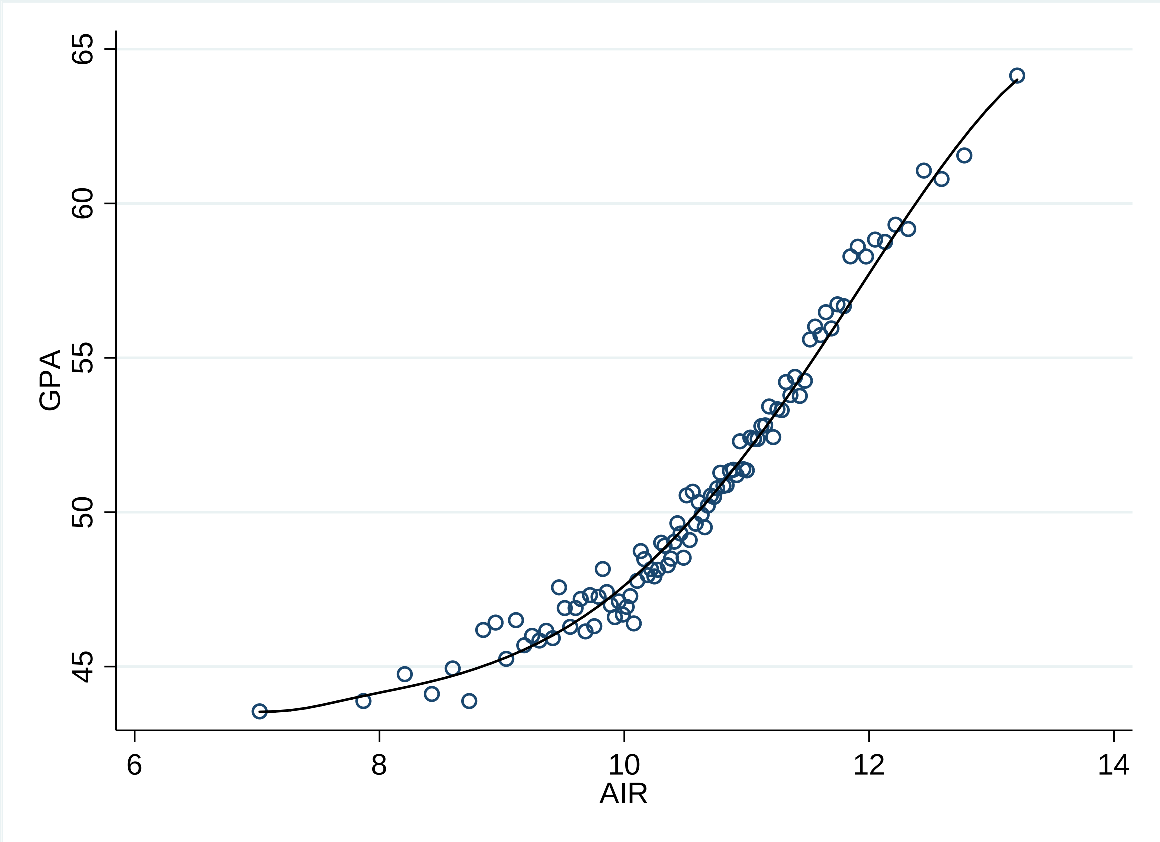

Figure 4. Average inhabitant rank and GPA percentile score within commuting zones. By percentile in the AIR distribution.
Note: GPA score is measured as the percentile rank within commuting zones. The solid line is estimated with local polynomial (second order) regression. Number of observations: 429,919.

In total, we observe childhood neighborhood (AIR_0^{15}) and school performance (GPA percentile) for approximately 430,000 offspring. Figure 4 offers a first descriptive picture of the relationship between AIR and GPA. As expected, there is a strong positive relationship between the two variables: Offspring growing up in higher class neighborhoods do systematically better in school. Given the obvious element of non-random sorting of families into neighborhoods, this does of course not provide any evidence on a causal effect.

4.1 Identification and estimation of causal effects

We now turn to a regression analysis aimed at identifying and estimating the *causal* impacts of the childhood neighborhoods' socioeconomic statuses. As we expect selectivity in the sorting of families into neighborhoods with different ranks, it is essential to control for family characteristics in such a regression. We do that throughout this paper by means of family fixed effects, as originally pioneered in this setting by Aaronson (1998). This has the somewhat unfortunate consequence that identification solely comes from families with at least two children, where both (all) children have experienced the educational outcome of interest and where there at the same time is some variation in the kind of neighborhoods the children have been exposed to. Given our data, with residential information from 1992, this puts some serious limitations on the kind of outcomes we can use. The lower the age at which we measure the outcome, the more observations we will have. Our data allow us to measure junior high school GPA score for all offspring born between 1992 and 2000. Hence, with this outcome, identification comes from families with at least two children born within this time window who have been exposed to varying neighborhood characteristics, either because they have moved or because the neighborhood they live in has changed. This leaves us with 227,202 observations that can be used in our causal analysis. We return to two additional outcomes based on high-school graduation and employment/education at age 20 in Section 4.5 below.

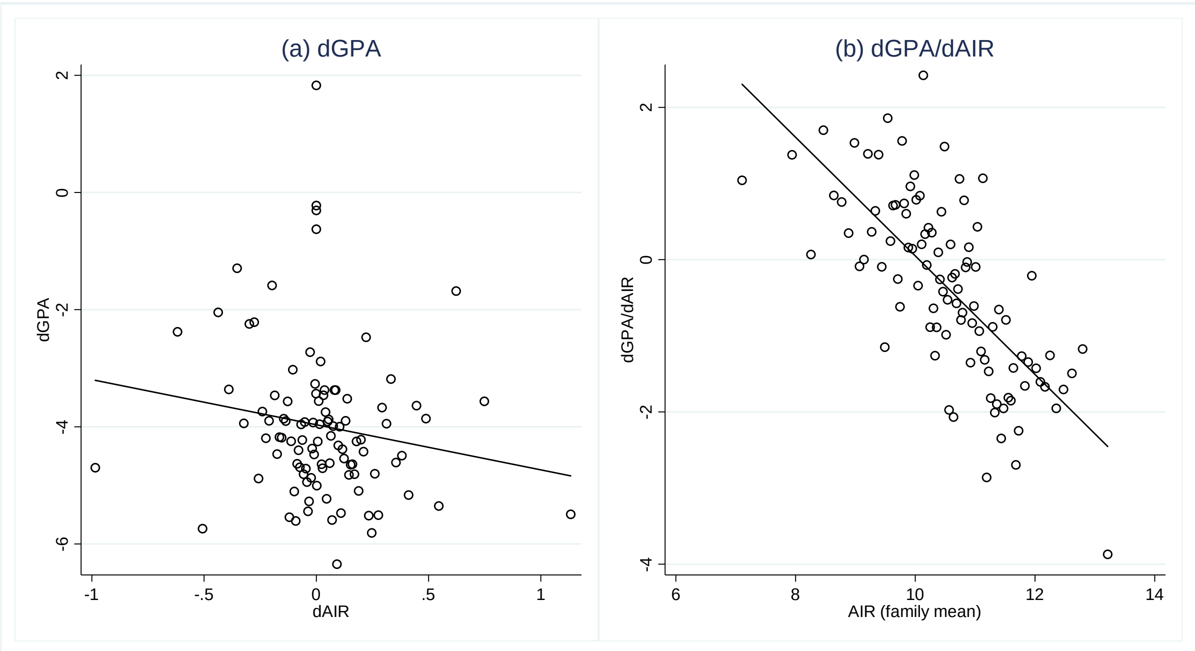

Figure 5. Sibling differences in schooling outcome (GPA) and neighborhood exposure (AIR).
Note: Panel (a) shows the relationship between sibling differences in AIR (youngest minus oldest) and the corresponding differences in GPA score. Each data point represents one percentile in the distribution of sibling differences in AIR. Panel (b) shows the relationship between the family (sibling) average of AIR of and the corresponding difference in their GPA score normalized by the differences in AIR (largest minus smallest) plus 1. We add 1 in the normalization to avoid too large disturbances from the many observations with very small AIR-differences. Each data point in panel (b) represents one percentile in the distribution of AIR family means.
The solid lines are linear regression lines.

Figure 5 gives a descriptive overview of the sibling data used in this section by comparing sibling differences in neighborhood exposure with the corresponding differences in GPA score. In panel (a), the horizontal axis measures the difference in AIR_0^{15} between siblings (youngest minus oldest), and each data point represents a percentile in the distribution of these differences. A first point to note from the distribution across the horizontal axis is that the within-family variation in AIR_0^{15} is small, with almost the whole distribution of sibling-differences lying between -1 and 1. On the vertical axis, we then show the corresponding average differences in GPA percentile score. Although an OLS regression line through these data points becomes slightly negative, the main message coming out of panel (a) is that of a *non-existing* systematic relationship.[6] There is no evidence whatsoever that the size (or the sign of) the difference in neighborhood status is systematically associated with the size (or sign) of the difference in school performance. However, if neighborhood effects are non-linear, such that the impact of sibling-differences in neighborhood exposure depends on location of the change, panel (a) might well conceal a causal relationship. To look at this, we instead sort the observed AIR-differences into percentiles based on the average level of AIR_0^{15} for each involved sibling-pair, and then compute the difference in GPA score divided by the difference in AIR_0^{15}. The result is shown in panel (b); and now a rather clear and illuminating pattern emerges: At low levels of AIR_0^{15}, a positive difference is associated with improved GPA score, whereas at high levels of AIR_0^{15}, the same difference is associated with reduced GPA score. The turning point appears to be in the middle of the neighborhood rank distribution, indicating that the marginal impacts of moving to a higher ranked neighborhood is positive below this point, but negative above. In panel (a), these positive and negative influences essentially cancel out, thus concealing the underlying systematic relationship.

A regression model thus has to take this potential non-linearity into account. In its simplest form, we estimate the following baseline model:

$$GPA_{ij} = \alpha_0 + \delta(AIR_0^{15}) + \gamma_j + \sigma_t + BO + GENDER + \upsilon_i \ , \qquad (1)$$

[6] It is also notable that virtually the whole distribution of GPA score differences lie below zero, but this results from the well-known birth order effect; i.e., the first-born sibling does better in school.

where GPA_{ij} is the GPA score for offspring *i* belonging to family *j*, $\delta(.)$ is some unknown polynomial function, γ_j is a family fixed effect, σ_t is a birth-year fixed effect, and BO and GENDER are terms controlling for sibling birth-order and gender, respectively.[7]

A potential problem with using GPA as the outcome of interest is that teachers' grade point standards to some extent may be adjusted to student composition, such that it is easier to obtain a high GPA score in a school with low overall student performance, ceteris paribus. In addition, there may be systematic differences in teacher or school quality. To account for such problems, we include in some of our regressions controls for school characteristics, by adding in school-fixed effects and time-varying variables describing the traits of same-year schoolmates, including their family background and their average GPA score. We also return to some alternative outcomes in Section 4.5 below that are not subjected to these concerns.

As our identification strategy is entirely based on sibling comparisons, we arguably control appropriately for any systematic sorting into neighborhoods based on stable family characteristics. However, we cannot rule out confounders generated by events that influence both a family's neighborhood quality and their offspring outcomes. There are essentially three sources of identification available in our data: i) families who move to a new neighborhood, ii) families who stay in the same neighborhood, but are exposed to changed neighborhood conditions due to in- and outmigration of others, and iii) families who stay, but are exposed to changed neighborhood status due to economic mobility of existing neighbors. These sources of identification can be thought of as representing different levels of intervention, where the movers have been subjected to a family-level intervention, whereas the stayers have been subjected to a neighborhood intervention; see Sampson (2008) for a discussion of neighborhood effect interpretations in this context.

Each source of identification raises distinct concerns regarding possible confounders. For example, a move to a new neighborhood can be triggered by a wealth shock, a job loss, or a divorce; and such events may have different direct effects on offspring depending on their age. A change in the rank of an existing neighborhood can be triggered by local events

[7] A family is defined as siblings having both the mother and the father in common, without any requirement that the family stays together.

such as a major plant closure of the establishment of new employment opportunities, which again may affect siblings differently. While we use all sources of identification in the main part of our analysis to ensure sufficient power, we therefore also provide a careful analysis of robustness, where we examine our findings' sensitivity with respect to the inclusion/exclusion of each particular identification source. In Section 4.4, we offer a separate analysis of movers and stayers, and in Appendix E we provide, both for the complete sample and for movers and stayers separately, an analysis where we have re-ranked neighborhoods based on fixed individual inhabitant earnings ranks only (defined as the average rank obtained for all available earnings years). These different exercises will show that our main findings are robust with respect to which of these sources that forms the basis for identification.

The robustness of estimated neighborhood effects based on sibling-identification accords well with findings reported in a similar context by Chetty and Hendren (2018a). We also note that as long as unaccounted-for shocks that are favorable to offspring outcomes raise the probability of moving to (or staying in) a higher ranked neighborhood, whereas adverse shocks raise the probability of residing in a lower ranked neighborhood, the omission of such shocks imposes a positive bias on the impact of AIR_0^{15}.

4.2 Average neighborhood effects

As we have no clear a priori knowledge regarding the appropriate functional form relationships between neighborhood rank and GPA score we start out by specifying a number of alternative models. More specifically, we estimate alternative versions of Equation (1), where we represent the effects of AIR_0^{15} thorough polynomial functions varying from degree one to degree five. Our plan is then to select the most parsimonious model that captures the essential features of the data for further exploration and robustness checks. The result of this exercise is displayed in Figure 6 (panel (b)), where we also show the distribution of AIR_0^{15} (panel (a)) for the whole sample of offspring used in this analysis. It is clear that within the range of actual support (note the vertical lines marking the 1^{st} and 99^{th} percentiles of the distribution in panel (b)), the estimated impact of neighborhood rank (AIR_0^{15}) follows a distinct quadratic pattern. All the non-linear models form an almost symmetric concave relationship between neighborhood rank and GPA score, with the highest score obtained by growing up in medium ranked neighborhoods.

Based on the robust finding of a concave functional form relationship in the relevant area of actual neighborhood rank support, we present in Column I of Table 1 the estimated parameters following from a baseline model which is quadratic in AIR_0^{15}. Both the linear and the quadratic terms are highly statistically significant, confirming beyond reasonable doubt that the relationship is indeed concave. The resultant profile of marginal effects is shown as the baseline in Figure 7 (solid bold line), with a 95 percent confidence interval. While there are considerable positive impacts of moving to higher ranked neighborhoods from the bottom part of the neighborhood rank distribution, there are at least as large negative effects at the top. The turning point is located at the center of the distribution; hence, the optimal childhood neighborhood (in terms of maximizing GPA score) appears to be a medium one, with average rank around 10-11. It is notable that this also covers the average rank level of 10.5 that would arise with random assignment; i.e. with zero residential segregation.

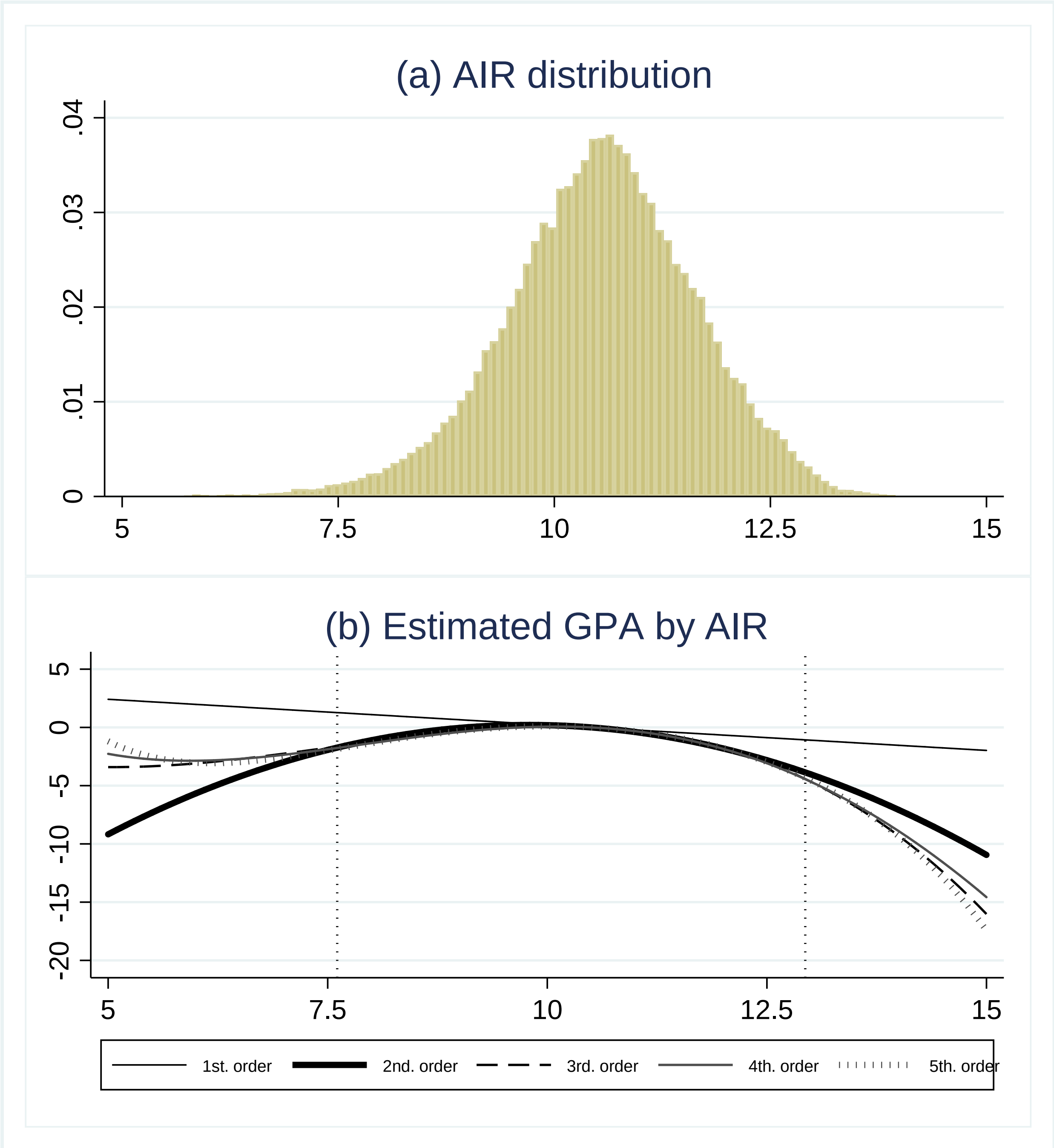

Figure 6. Distribution of offspring's average childhood neighborhood rank $(\mathbf{AIR}_0^{15})$ and its estimated impact on GPA score percentile

Note: Mean (median) AIR in panel (a) is 10.5 (10.6). First percentile is 7.6, 99th percentile is 12.9 (indicated with vertical dotted lines in panel (b)).

Table 1. Effects of childhood neighborhood on GPA score rank (within commuting zone) at age 15/16

	I (Baseline)	II	III	IV	V	VI
Neighborhood charac-teristics own childhood						
Rank (AIR_0^{15})	8.042***	8.133***	8.089**	7.332**	7.134**	6.434**
	(3.097)	(3.137)	(3.136)	(3.095)	(3.104)	(3.146)
Rank squared	-0.412***	-0.411***	-0.412***	-0.375**	-0.365**	-0.350**
	(0.149)	(0.151)	(0.150)	(0.148)	(0.149)	(0.149)
Immigrant share						-5.518
						(7.311)
Schoolmate characteris-tics						
Avg. earnings rank of parents			-0.651***	-1.142***	-1.146***	-1.191***
			(0.180)	(0.171)	(0.171)	(0.171)
Immigrant share						-2.951*
						(1.678)
Average GPA score rank among schoolmates				0.252***	0.252***	0.252***
				(0.023)	(0.023)	(0.023)
Own parents' (time-varying) rank					-0.125	-0126
					(0.139)	(0.139)
School-fixed effects	No	Yes	Yes	Yes	Yes	Yes
N	227,202	227,202	227,088	227,088	227,088	227,088
R squared	0.7551	0.7591	0.7591	0.7598	0.7598	0.7599
R squared adjusted	0.5405	0.5433	0.5433	0.5448	0.5447	0.5448

Note: All models include family fixed effects and also contain controls for within family birth order (6 dummy variables) and sex. Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

Although the complete marginal effect profile appears to be robustly estimated, it can be argued that the marginal effects estimated at high ranks are less disputable than the positive effects estimated at low ranks. First, as noted above, any unaccounted for shocks triggering residential decisions are, if anything, likely to bias the marginal effects upwards. While this in principle could imply that we overstate the positive marginal impacts at low ranks, it can hardly account for the negative effects estimated at higher ranks. Second, it is notable that all the models estimated with higher order polynomials indicate larger negative marginal effects at the top, but smaller positive effects at the bottom of the neighborhood rank distribution; see Figure 6.

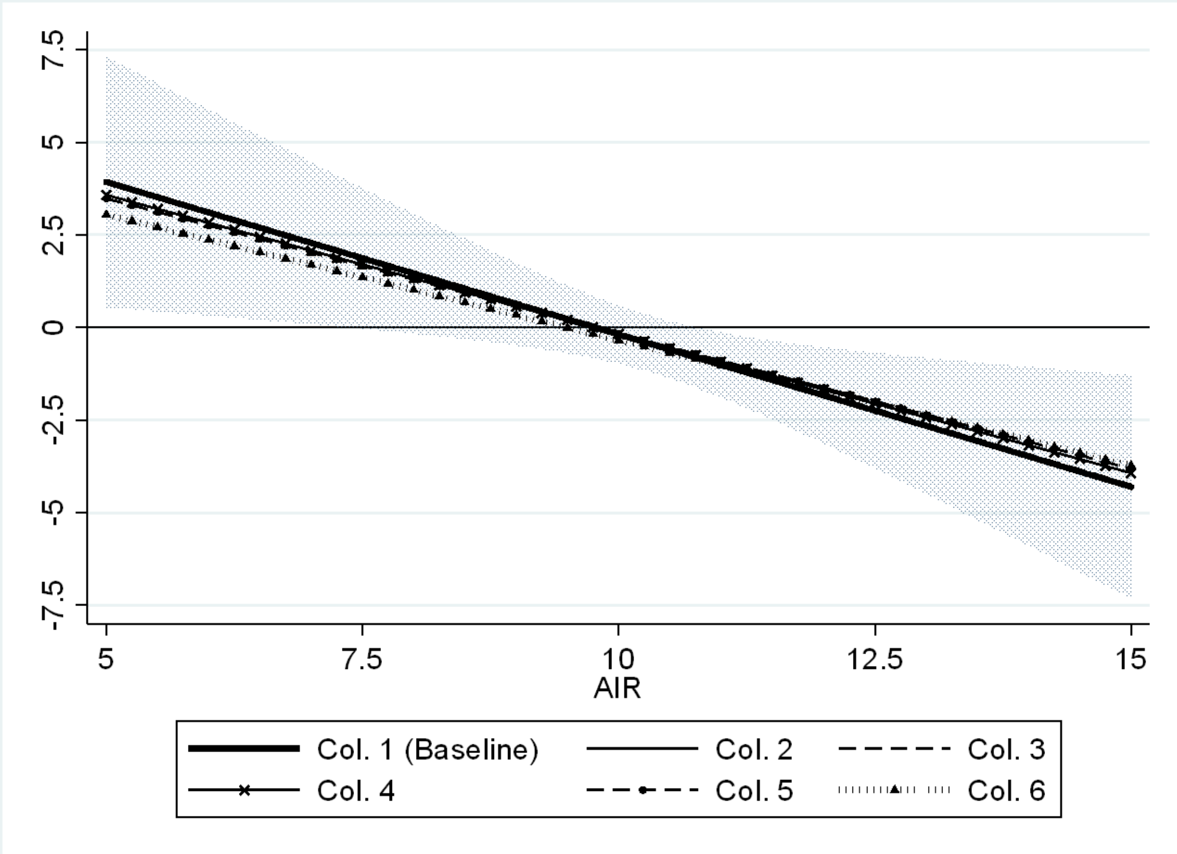

Figure 7. Estimated marginal impact of average childhood neighborhood rank $(\mathbf{AIR}_0^{15})$ on GPA score percentile with 95% point-wise confidence intervals for the baseline model.
Note: Column numbers refer to the columns in Table 1. The number of observations is 227,202 (columns 1-2) or 227,088 (columns 3-5).

To interpret the magnitudes of the estimated marginal effects, recall that AIR_0^{15} is measured in vigintiles, whereas GPA score is measured in percentiles. Hence, for example, the marginal effect approximately equal to 2 at $\mathrm{AIR}_0^{15} = 7.5$ implies that moving to a neighborhood where the adult population on average is ranked 1 decile (2 vigintiles) higher from such a low-class neighborhood improves the GPA score by 4 percentiles, ceteris paribus. Correspondingly, the effect close to minus 2 at $\mathrm{AIR}_0^{15} = 12$ implies that the same upwards movement from such a high-class neighborhood reduces the GPA score by 4 percentiles.

As discussed above, a potential concern regarding this model is that teachers' assignment of GPA scores to some extent may adapt to the student's ability levels, such that it is easier to obtain a good grade if co-students perform poorly. While this does not invalidate the causal nature of the estimated marginal effects, it does induce some ambiguity with respect to its interpretation. The vast majority of Norwegian children attend their local primary school; hence children from the same neighborhood typically also attend the same school. However, the neighborhoods examined in this paper are much smaller than the school districts, and many school districts cover neighborhoods with quite different socioeconomic statuses. The average (median) number of neighborhoods belonging to a primary school's catchment area is 13.1 (11), and the average (median) inhabitant rank distance between the highest and the lowest ranked neighborhood belonging to the same catchment area is 3.5 (3.4).

To sort out neighborhood effects operating through the neighborhood's influence on primary school choice, we add into the model controls for school and schoolmate characteristics; see Table 1, columns II-IV, with the resultant marginal neighborhood effects also illustrated in Figure 7. Note that school- and schoolmate characteristics always refer to the final year of primary school; i.e. at age 15/16. First, in Column II we add in school-fixed effects. This hardly changes the estimated impacts of childhood neighborhood at all. However, the inclusion of school-fixed effects does not necessarily solve the problem of fluctuating grade standards if these standards vary from year to year due to variation in the pupil composition. Therefore, in Column III we also control for the average earnings rank of the schoolmates' parents. In doing so, we first compute each parent's average earnings rank taken over years with offspring in the dataset, and then compute the average of the resultant variable at the school-year level. Still, the estimated impacts of the childhood neighborhood remain the same. Moreover, it is notable that the prevalence of higher ranked co-students is estimated to have a significant negative effect on own achievement, confirming that higher relative position within a group is beneficial also in a classroom setting. Next, in Column IV we include as an additional control the average GPA score rank among schoolmates. Although this variable has a large and highly significant positive impact on GPA score (a one-point increase in the average rank of co-students raises own rank by 0.23), it does not change the estimated impacts of the childhood neighborhood. It makes the estimated negative impact of schoolmates' class background larger, however. Note that while schoolmates' class background capture all kinds of (positive and negative) peer effects arising from its correlation with their human capital resources, their average GPA score also picks up fluctuations in teacher quality and/or in the teacher's determination of GPA standards.

Note that while we have identified a clear concave (quadratic) relationship between childhood neighborhood rank and GPA score, we have entered all the control variables linearly, including the rank of schoolmates' parents. While this choice is practicable in the sense that it makes it easier to interpret the estimated coefficients, it also turns out that it is also supported by the data. In Appendix C, we report estimates based on models in which also the control variables enter through quadratic terms. As can be seen there, none of the added second order terms are significantly different from zero, and their inclusion does not noticeably change the estimated impacts of neighborhood rank.

As discussed above, we cannot rule out that siblings exposed to different neighborhoods have also been exposed to different family circumstances in a way that confounds our estimated neighborhood effects. For example, parental economic success (or failure) may have influenced residential decisions and at the same time affected offspring differently depending on their age at the time of the events in question. In order to assess the empirical relevance of this concern, we add into the model a control for the parents' time-varying socioeconomic status. This is done in the same fashion as for the neighborhood ranks, such that for each offspring, we compute the parents' average annual (age-specific) earnings rank (within the commuting zone) during the offspring's age 0-15. The result from this exercise is presented in Table 1, Column V. It indicates that the time-varying parental rank variable has no effect on the offspring GPA outcome, and that the inclusion of this variable does not change the estimated neighborhood effects.

We conclude from this exercise that the neighborhood effects reported here are robust with respect to controls for the school environment as well as for the family's own economic performance. As shown in Figure 7, the estimated marginal effect profiles resulting from the alternative models are hardly distinguishable. In particular, the identified turning point by which the marginal effect of residing in a higher ranked neighborhood becomes negative is almost exactly the same in all models; i.e. around 10.

As we show in Appendix A, a key driver of increased residential segregation in Norway over the years studied in this paper is the rising share of immigrants from lower income countries (developing countries and Eastern Europe). The main reason for this appears to be that immigrants from lower-income countries tend to obtain a poor rank in the relevant earnings distributions and are also heavily overrepresented in neighborhoods with low average inhabitant rank; see Figure 8. Hence, a natural question to ask is whether some of the causal influences of neighborhood class identified here in reality picks up some effects of being exposed to immigrants. To address this concern, we report in Column VI estimation results from a model where we have also controlled for exposure to immigrants from low income countries, both among neighbors during childhood (defined in exactly the same way as AIR_0^{15}, only with the neighborhood's immigrant share instead of income rank), and among schoolmates. The point estimates indicate a negative influence of high immigrant exposure, and for schoolmates the effect is also statistically significant at the 10 percent level. However, controlling for these variables does not alter either the estimated impact of neighborhood rank or the estimated impact of the schoolmates' class background.

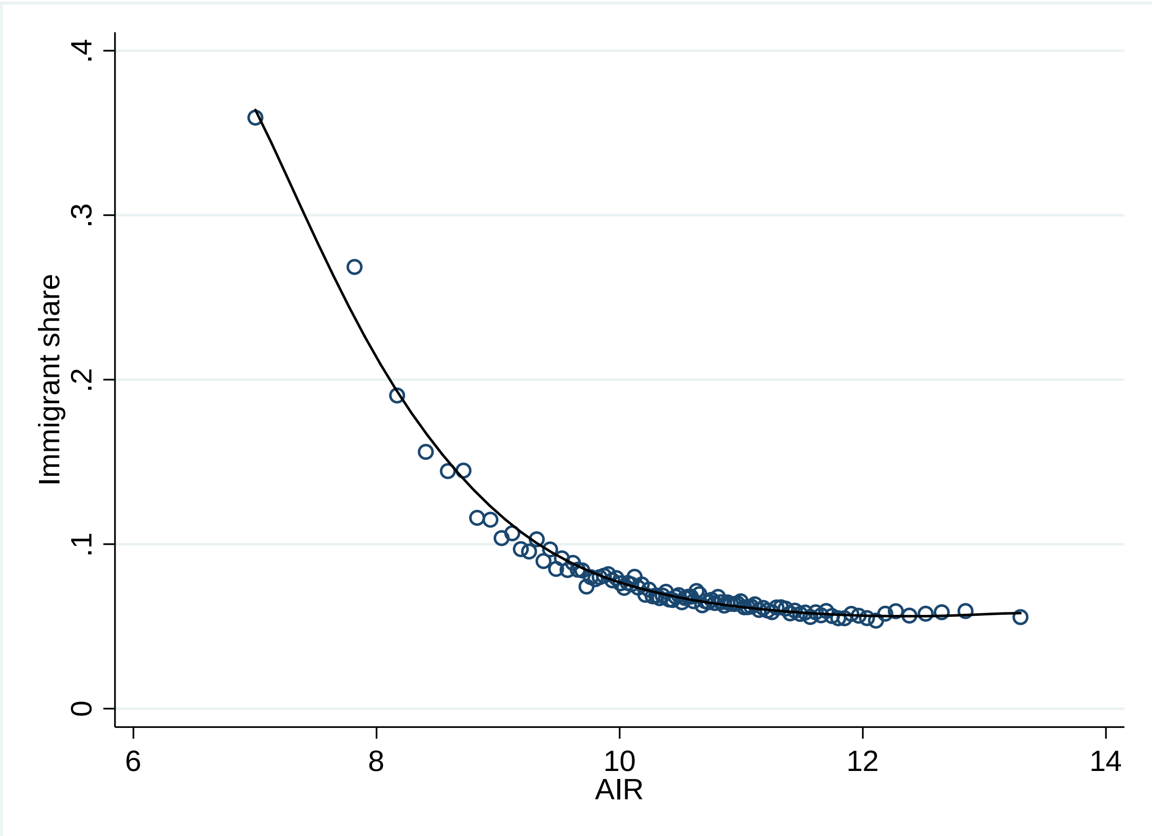

Figure 8. Immigrant shares in neighborhoods by average inhabitant rank $(\mathbf{AIR}_0^{15})$

Note: The figure shows average immigrant shares from low-income countries experienced in neighborhoods inhabited from birth to age 15 for each percentile in the AIR_0^{15} distribution. Low-income countries include all countries outside Western Europe, North-America, and Oceania. This graph is based on all offspring born between 1992 and 2000, not only those with siblings. The solid line is estimated with local polynomial (second order) regression.

4.3 Effect heterogeneity

In order to improve our understanding of the identified neighborhood effects, we now take a closer look at how these effects vary, depending on age of exposure, on gender, and on own family background. We start out this exercise by estimating separate concave functions for boys and girls and for the three different ages of exposure. More specifically, we divide childhood/adolescence into three phases; the preschool phase (AIR_0^5), the elementary school phase (AIR_6^{12}), and the junior high school phase (AIR_{13}^{15}), and estimate separate causal effects for each phase and gender. We focus on versions of the baseline model (corresponding to Column I in Table 1) here and in subsequent subsections, but we also report estimates based on models with all control variables included (corresponding to Column VI in Table 1).

Table 2. Effects of childhood neighborhood on GPA rank by gender age of exposure. Interaction models

	Baseline		All controls	
	I	II	III	IV
	Boys	Girls	Boys	Girls
Age 0-5				
Rank (AIR_0^{15})	1.780	3.194*	1.199	2.609
	(1.670)	(1.661)	(1.709)	(1.713)
Rank squared	-0.099	-0.170**	-0.076	-0.144*
	(0.081)	(0.081)	(0.083)	(0.082)
Age 6-12				
Rank (AIR_0^{15})	0.734	1.911	-0.084	1.018
	(2.540)	(2.488)	(2.582)	(2.495)
Rank squared	-0.325	-0.104	0.007	-0.061
	(0.125)	(0.122)	(0.126)	(0.122)
Age 13-15				
Rank (AIR_0^{15})	2.967	3.937**	3.081*	4.058**
	(1.824)	(1.811)	(1.853)	(1.855)
Rank squared	-0.147*	-0.193**	-0.151*	-0.198**
	(0.089)	(0.088)	(0.090)	(0.090)
School-fixed effects	No		Yes	
Restrictions tests				
Equal coeff. boys/girls	F(6,1257)=1.76 (p-value=0.106)		F(6,1256)=1.61 (p-value=0.142)	
Equal coeff. diff. ages	F(8,1257)=0.25 (p-value=0.982)		F(8,1256)=0.49 (p-value=0.864)	
N	227,202		227,088	
R squared	0.7552		0.7599	
R squared adjusted	0.5405		0.5448	

Note: Estimates are obtained from a single baseline regression (columns II and II) and a single model with all control variables included (columns III and IV). The separate effects by age and gender are obtained by interacting the neighborhood variable with gender and age of exposure. Both models include family fixed effects and controls for gender, birth year and birth order. The model with "all controls" also include the neighborhood's immigrant share, schoolmate characteristics (avg. earnings rank of parents, immigrant share, and avg. GPA score), and own parents' (time-varying) rank. Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

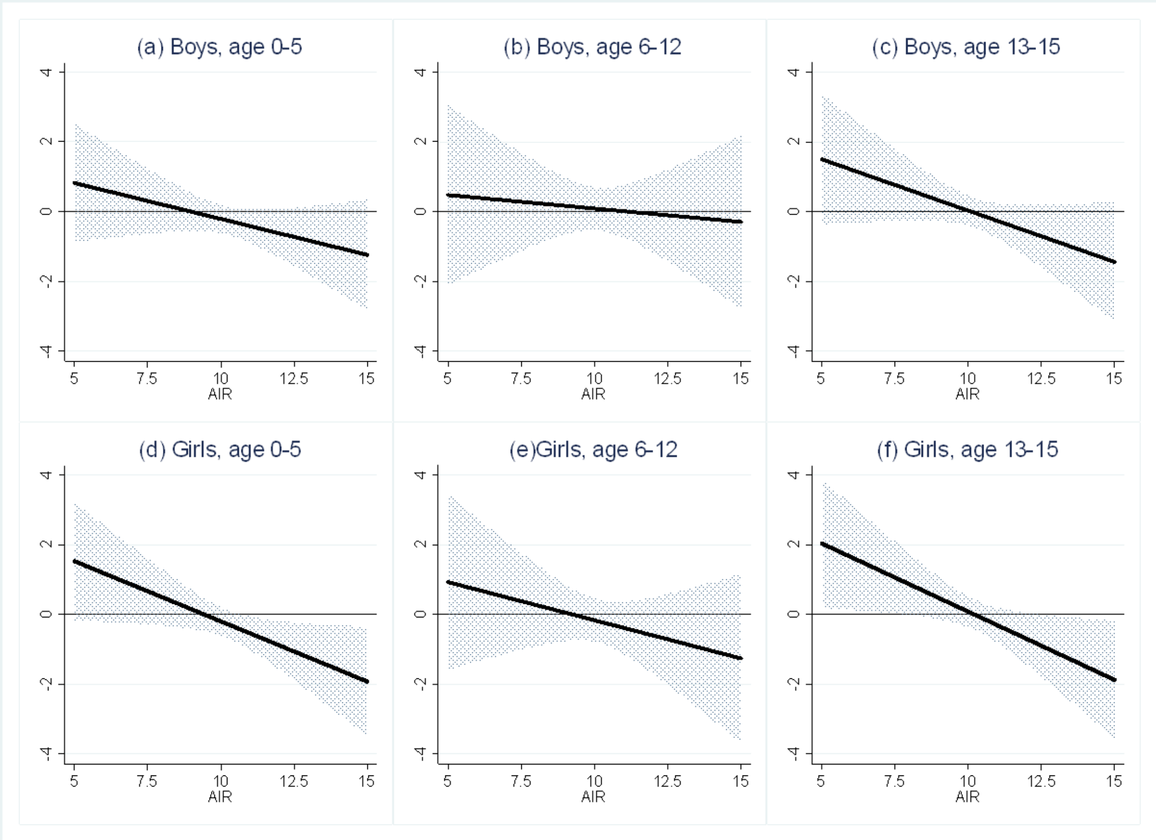

Figure 9. Estimated marginal impacts of average childhood neighborhood rank (AIR) on GPA score percentile with 95% confidence intervals. By gender and age of exposure.

Note: The estimates build on the baseline model (Table, 2, Columns I and II), with the linear and quadratic coefficients on the AIR-term interacted with indicator variables for the six combinations of age and gender. Total number of observations is 227,202. See also note to Table 2.

Table 2 presents the main estimation result from this exercise, and Figure 9 shows the six resultant marginal effect profiles. Unfortunately, the statistical uncertainty becomes too large to draw firm conclusions regarding effect heterogeneity. The main point to take home appears to be that the effects are similar both across childhood phases and gender. However, for both girls and boys, the results indicate that neighborhoods are most important during the junior high school period, followed by the pre-school period. And at all ages, neighborhood influences are more important for girls than for boys. While the differences across age groups are statistically insignificant (p-value=0.982 in the baseline model), the difference between boys and girls is borderline significant (p-value=0.106).

Does the impact of neighborhood class depend on own family background? To examine this topic within the setting of a model with family fixed effects, we need to use a family background characteristic that is constant across siblings. Hence, we compute a family rank which is the average of all annual ranks for (both) parents and for all available observation years in the data. We then divide the offspring population into quartiles based on this family rank measure and estimate the neighborhood impacts separately for the lowest quartile, the two medium quartiles, and the upper quartile (by means of interactions with AIR_0^{15}. The results are shown in Table 3 with estimated marginal effects illustrated in Figure 10. The point estimates indicate that neighborhood influences are of least importance for lower class offspring, and of highest importance for middle class offspring. For the lowest quartile, we actually find no evidence of a neighborhood influence at all. However, the statistical uncertainty is large, and the differences in coefficient estimates between the different rank quartiles are not statistically significant (p-value=0.382 in the baseline model).

Table 3. Effects of childhood neighborhood on GPA rank by own family background. Interaction models

	I Baseline	II All controls
Lowest quartile		
Rank (AIR_0^{15})	-0.953 (5.729)	-3.596 (6.14)
Rank squared	0.082 (0.299)	0.202 (0.312)
Quartile 2-3		
Rank (AIR_0^{15})	11.901** (5.315)	10.868** (5.293)
Rank squared	-0.607** (0.242)	-0.563** (0.251)
Upper quartile		
Rank (AIR_0^{15})	7.839 (6.483)	7.678 (6.454)
Rank squared	-0.418 (0.294)	-0.412 (0.292)
School-fixed effects	No	Yes
Restriction test		
Equal coeff. across rank quartiles	F(4,1257)=1.05 (p-value=0.382)	F(4,1267)=1.15 (p-value=0.334)
N	227,202	227,088
R squared	0.7551	0.7599
R squared adjusted	0.5405	0.5448

Note: Estimates are obtained from a single baseline regression (Column I) and a single model with all control variables included (column II). The separate effects by family background are obtained by interacting the neighborhood variable with parental rank indicators. Both models include family fixed effects and controls for gender, birth year and birth order. The model with "all controls" also include the neighborhood's immigrant share, schoolmate characteristics (avg. earnings rank of parents, immigrant share, and avg. GPA score), and own parents' (time-varying) rank. Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

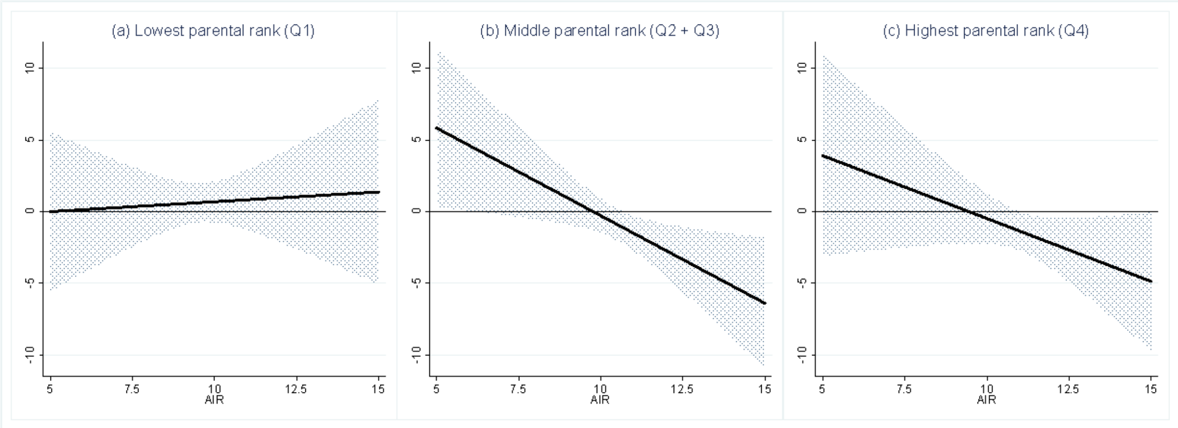

Figure 10. Estimated marginal impacts of average childhood neighborhood rank $(\mathbf{AIR}_0^{15})$ on GPA score percentile with 95% confidence intervals. By own family background.
Note: The estimates build on the baseline model (Table, 3, Column I), with separate linear and quadratic coefficients for each of the three AIR-variables. Total number of observations is 227,202. See also note to Table 3.

4.4 Movers and stayers

Up to now, our analysis has exploited all observed variation in siblings' AIR exposure; whether it has resulted from a move of a family from one neighborhood to another, or from changes in the same neighborhood's socioeconomic status. In order to examine the robustness of our findings with respect to these somewhat different sources of identification, we now estimate separate neighborhood effects for families who resided in the same neighborhood throughout our data period (stayers) and families who at some point moved (movers). The results are presented in Table 4, with estimated marginal effects shown in Figure 11. Although the estimated marginal effects are considerably larger for stayers than for movers, the differences are not statistically significant. The point estimates indicate that the marginal effect patterns are similar, however, with positive marginal effects at low AIR and negative effects at high AIR. The estimated turning points are also the same.

Table 4. Effects of childhood neighborhood on GPA rank by identification source (movers/stayers). Interaction models

	Baseline		All controls	
	I Movers	II Stayers	III Movers	IV Stayers
Neighborhood characteristics				
Rank (AIR_0^{15})	6.384*	17.622*	4.734	16.836*
	(3.395)	(9.331)	(3.414)	(9.309)
Rank squared	-0.330**	-0.884*	-0.259	-0.844*
	(0.163)	(0.459)	(0.162)	(0.457)
School-fixed effects	No		Yes	
Restriction test				
Equal coeff. movers/stayers	F(2,1257)=0.46 (p-value=0.629)		F(2,1256)=0.73 (p-value=0.483)	
N	227,202		227,088	
R squared	0.7590		0.7599	
R squared adjusted	0.5433		0.5447	

Note: Estimates are obtained from a single baseline regression (columns II and II) and a single model with all control variables included (columns III and IV). The separate effects by movers and stayers are obtained by interacting the neighborhood variable with mover-stayer status. Both models include family fixed effects and controls for gender, birth year and birth order. The model with "all controls" also include the neighborhood's immigrant share, schoolmate characteristics (avg. earnings rank of parents, immigrant share, and avg. GPA score), and own parents' (time-varying) rank. Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

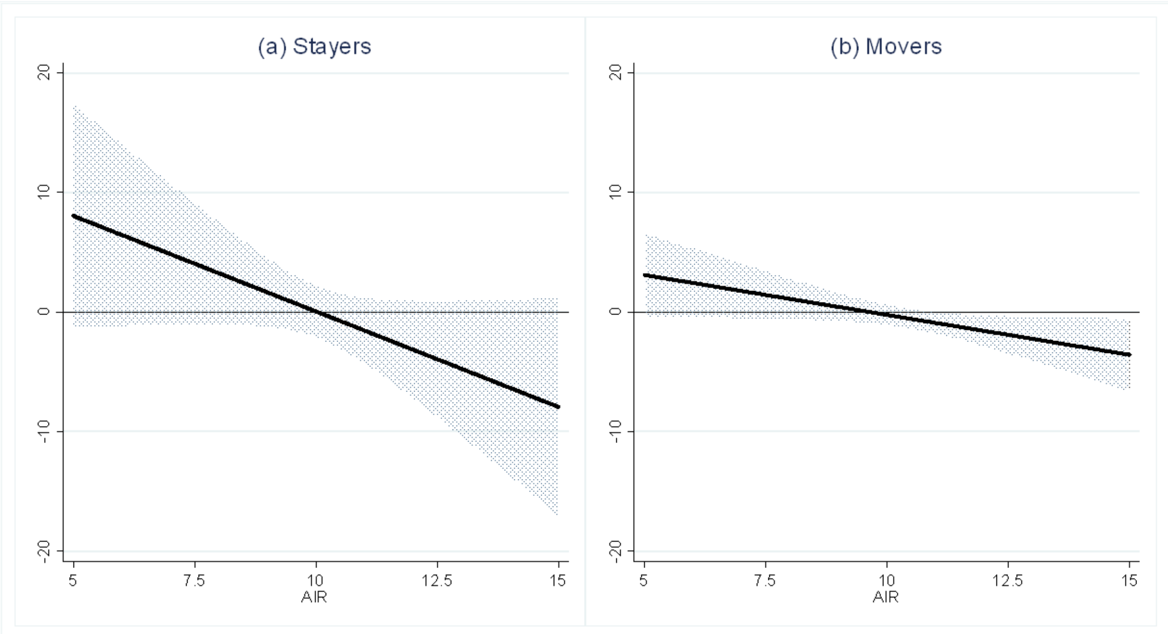

Figure 11. Estimated marginal impacts of average childhood neighborhood rank $(\mathbf{AIR}_0^{15})$ on GPA score percentile with 95% confidence intervals. By stayers and movers.

Note: The estimates build on the baseline model (Table, 4, columns I and II), with separate linear and quadratic coefficients for stayers and movers. There are 71,755 observations for stayers and 155,447 observations for movers. See also not to Table 4.

While we for efficiency-reasons have estimated the separate effects for movers and stayers within a joint regression model, using interaction terms between the rank variables and mover/stayer-indicators, we report results based on completely separate models in Appendix D. These are very similar to those reported in Table 4. Further, in Appendix E, we report separate estimates for movers and stayers based on models where neighborhoods are ranked on the basis of fixed individual (average) earnings ranks, implying that the identification of neighborhood effects comes from migration only (and not from rank changes within a fixed population). Again, the results are very similar to those reported in Table 4.

4.5 Longer term outcomes

So far, our analysis has exclusively focused on GPA score measured at age 15/16 as the outcome of interest. The main motivation behind this choice has been to ensure statistical power. Given that our data provide complete residential information (from birth to age 15) for offspring born after 1992 only, whereas outcomes must be measured no later than 2016, the number of siblings for which we both have outcome data and (non-negligible) variation in childhood neighborhood conditions quickly becomes limited as we raise the age at which the outcome is measured. The existing literature shows, however, that skills accumulated in early childhood are complementary to later learning (Cuhna et al., 2006); hence, it is probable that the effects identified for junior high school performance persist into higher ages. It would clearly be of interest to see whether our findings generalize to, say, high school graduation and/or later education, employment or earnings. The earliest age at which we can meaningfully establish graduation from high school for both the theoretical and the vocational tracks is by age 20. For such an outcome, we can only use siblings born between 1993 and 1996, i.e., with a maximum of three-year distance in age. This implies that the variation in childhood neighborhood conditions is limited.

Despite these limitations, we have estimated Equation (1) with a dummy variable indicating high-school graduation by age 20 as the outcome (66% have graduated at this time). We report the results from the baseline version of the model as well as for the model including all the control variables used above (i.e., corresponding to columns I and VI in Table 1). The resultant estimates are reported in Table 5, Columns I-II, and the marginal effect profile associated with the baseline model is shown in Figure 12, panel (a). Again, we estimate a concave effect of childhood neighborhood status, with positive marginal effects at low neighborhood ranks and negative effects at high ranks, and again the turning point appears to be in the middle of the rank distribution. Yet, the statistical uncertainty is too large for any substantive conclusions to be drawn. It is notable, however, that the average GPA score among schoolmates now has a precisely estimated zero effect, suggesting that its large influence on GPA score (see Table 1) primarily reflects fluctuations in GPA standards. It is also of some interest to note that childhood exposure to immigrants from low income countries apparently has a positive effect on high-school graduation.

Table 5. Effects of childhood neighborhood on outcomes measured at age 20

Outcome	High school graduation		Education/employment status	
	I Baseline	II All controls	III Baseline	IV All controls
Neighborhood characteristics own childhood				
Rank (AIR_0^{15})	0.177 (0.144)	0.255* (0.151)	1.078** (0.439)	1.199*** (0.462)
Rank squared	-0.008 (0.007)	-0.011 (0.007)	-0.049** (0.021)	-0.053** (0.022)
Immigrant share		0.708** (0.335)		1.499 (1.023)
Schoolmate characteristics				
Avg. earnings rank of parents		-0.007 (0.005)		0.006 (0.017)
Immigrant share		-0.011 (0.056		-0.043 (0.171)
Average GPA score rank among schoolmates		0.000 (0.001)		-0.001 (0.002)
School-fixed effects	No	Yes	No	Yes
N	55,898	55,885	55,898	55,885
R squared	0.8176	0.8247	0.8142	0.7599
R squared adjusted	0.2804	0.2843	0.2670	0.5448

Note: All models contain controls for birth-year, within family birth order (6 dummy variables) and sex. */**/*** indicates statistical significance at the 10/5/1 percent levels.

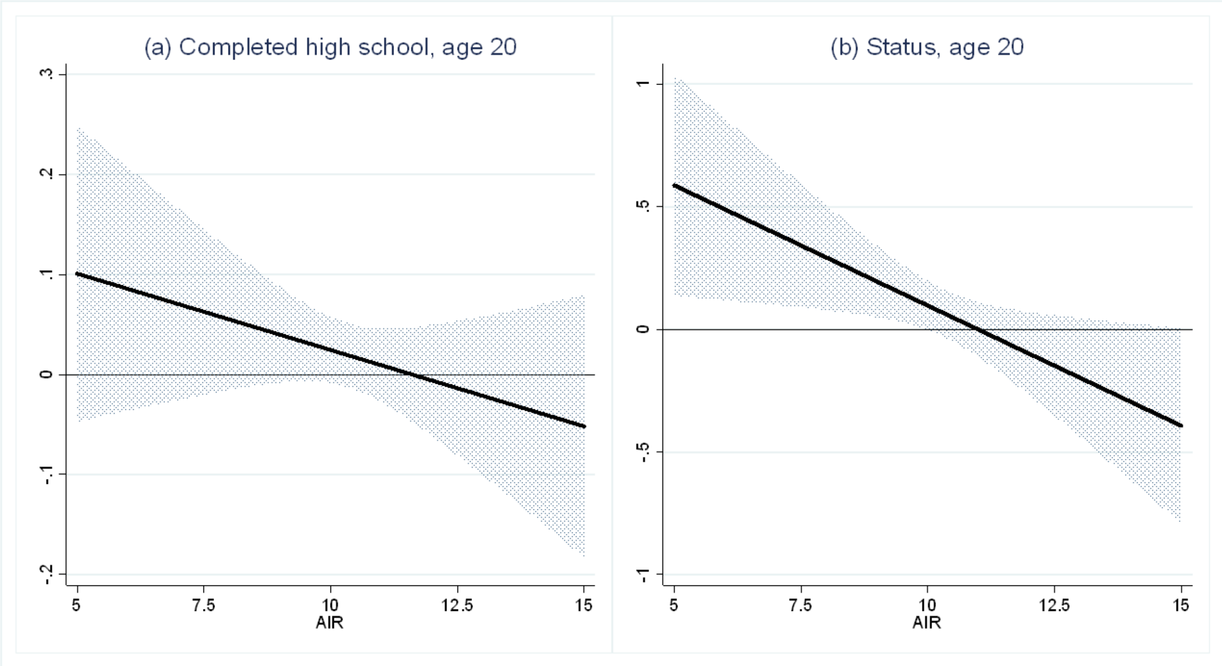

Figure 12. Estimated marginal impacts of average childhood neighborhood rank ($\mathbf{AIR}_0^{15}$) on high school graduation and status at age 20 with 95% confidence intervals.
Note: The estimates build on the baseline models (Table 5, columns I and III). The status variable used in panel (b) is a scalar variable describing the situation at age 20 taking the values 0 if not graduated and not in education or work; 1 if not graduated, but still in high school; 2 if graduated, but not in education or work; 3 if graduated and in work; and 4 if graduated and in higher education. The number of observations is 55,898.

In order to exploit the age-20 outcome data more efficiently, we have defined a more fine-grained cardinal outcome variable describing the education/employment status at this age. This variable takes the following values: 0 if not graduated and not in education or work at age 20 (27% of the observations); 1 if not graduated, but still in high school at age 20 (7%); 2 if graduated, but not in education or work at age 20 (34%); 3 if graduated and in work at age 20 (13%); and 4 if graduated and in higher education (19%). Re-estimating Equation (1) with this outcome gives the estimates reported in Table 2, Columns III-IV, and the associated marginal effect profile for the baseline version of the model is shown in Figure 12, panel (b). As can be seen, we again establish a statistically significant hump-shaped effect of childhood neighborhood status. And again, the turning point is in the middle of the neighborhood class distribution.

To examine outcomes at even higher ages, we obviously need to look at sibling cohorts born before the 1993-99 interval used so far. The price we have to pay for this is that we will have less than complete information about the neighborhoods inhabited at very low age (as residential information is available from 1993 only). However, given the apparent similarity in the effects of neighborhoods inhabited at different phases of childhood (conf. Section 4.3) it is arguably of interest to see how adult outcomes depend on the socioeconomic status of neighborhoods inhabited during adolescence also. To shed some light on longer term effects, we thus use data for the 1980-87 birth cohorts to examine the causal relationship between AIR_{13}^{15} and earnings/education outcomes measured at age 28-31. The statistical approach is the same as in the baseline model above; i.e., we use family fixed effects, birth-year fixed effects, and controls for birth order and gender. In addition, in a "full model" we control for commuting-zone-by-birth-year fixed effects, (this was not necessary in the models described above, as the GPA outcome is defined such that it by construction has the same distribution in all commuting zones and years).[8]

The first adult outcome we look at is the number of non-compulsory education years (NCE) obtained by age 28. The estimated neighborhood effects are reported in Table 6, Columns I-II, and the associated marginal effect profile is reported in panel A of Figure 13. Unfortunately, as the statistical uncertainty is very large for this outcome, we are not able to identify a clear causal relationship. The second adult outcome we look at is average labor earnings (including earnings from self-employment) at age 29-31, measured in inflation-adjusted "Basic amounts" (B).[9] [10] Here, a somewhat clearer picture of hump-shaped effects emerges, in line with what we have seen for GPA score at age 15/16; see Table 3, Columns III-IV and Figure 13, panel (b).

Finally, given that education and earnings outcomes inevitably have a somewhat ambiguous interpretation at age 29-31 when considered in isolation (low earnings at this stage may result either from failure to succeed in the labor market or from a very long and successful education), we have also constructed a summary status indicator applicable for this age. It takes the following values: 0 if no high school graduation by age 28 and average earnings during age 29-31 below 2B (14% of the observations); 1 if high school graduation and average earnings below 2B (29%); 2 if average earnings between 2B and 6B, but no master's

[8] Note that we cannot control for the school environment or schoolmate characteristics in this model, as these data are not available for the 1980-87 cohorts.

[9] A basic amount is currently (2017/2018) equal to NOK 93,634, which based on the average exchange rate in 2017 is equal to $11,332.

[10] For the 1987 (1986) birth cohort, we use earnings obtained at age 29 (29 and 30) only.

degree (26%); 3 if master's degree and earnings below 6B (6%); and 4 if earnings above 6B (24%). The results from using this as the dependent variable is shown in Table 6, Columns V-VI, with the marginal effect profiles illustrated in Figure 13, panel (c). They indicate a significant hump-shaped causal relationship between the socioeconomic status of the neighborhood inhabited during adolescence and overall economic success by age 28-31.

Viewed as a whole, the analysis of longer-term outcomes confirms the non-linearity of childhood neighborhood effects. In particular, it appears that the findings of positive marginal impacts at the bottom of the neighborhood class distribution and similarly sized negative impacts at the top, are highly robust.

Table 6. Effects of childhood neighborhood on outcomes measured at age 28-31

Outcome	Education (NCE) by age 28		Average earnings age 29-31		Education/earnings status by age 28-31	
	I	II	III	IV	V	VI
	Baseline	Full model	Baseline	Full model	Baseline	Full model
Neighborhood characteristics own childhood						
Rank (AIR_0^{15})	0.015	0.016	0.265*	0.232	0.177**	0.162**
	(0.118)	(0.121)	(0.145)	(0.147)	(0.078)	(0.079)
Rank squared	-0.002	-0.002	-0.013*	-0.012	-0.009**	-0.009**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.004)	(0.004)
N	196,449	196,449	196,449	196,449	196,449	196,449
R squared	0.6986	0.7028	0.5957	0.6004	0.6142	0.6191
R squared adjusted	0.4327	0.4336	0.2389	0.2386	0.2737	0.2743

Note: The status variable used in Columns V-VI takes the following values: 0 if no high school graduation by age 28 and average earnings age 29-31 < 2B (14% of the observations); 1 if high school graduation and average earnings < 2B (29%); 3 if average earnings 2B-6B, but no master's degree (26%); 4 if master's degree and earnings < 6B (6%); and 5 if earnings > 6B (24%). All models contain controls for birth-year, within family birth order (6 dummy variables) and sex. In the full models, the birth-year effects are estimated separately for each commuting zone. */**/*** indicates statistical significance at the 10/5/1 percent levels.

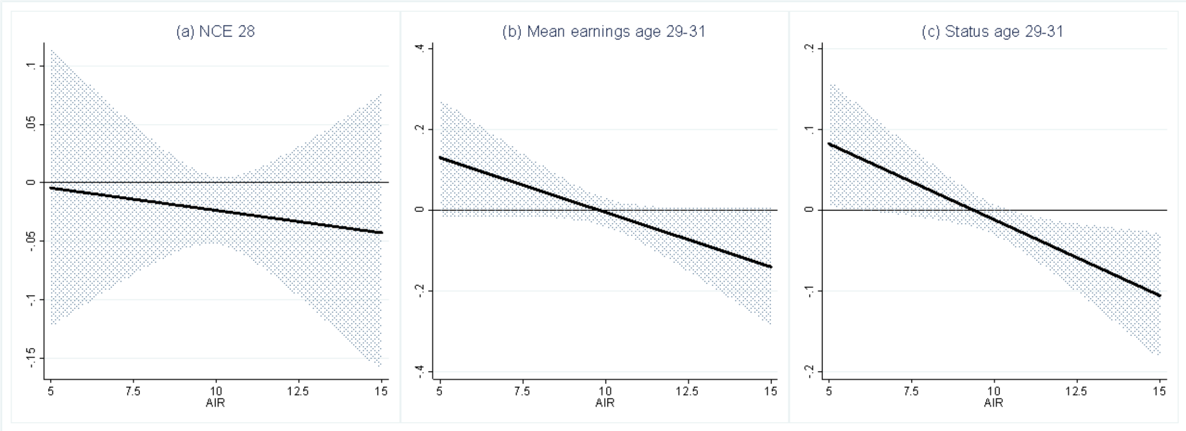

Figure 13. Estimated marginal impacts of average adolescent neighborhood rank $(\mathbf{AIR}_{12}^{15})$ **on outcomes measured at age 28-32 with 95% confidence intervals.**
Note: The estimates build on the baseline models (Table 6, columns I, III, and V). See note to Table 6 for definition of the status variable in panel (c). The number of observations is 196,449.

5 Concluding remarks

In this paper, we have shown that residential segregation has increased in Norway since the turn of the century. This implies that fewer children grow up in diverse middle class neighborhoods and more children grow up in either lower or upper class neighborhoods. We have also provided evidence showing that there is a distinct concave causal relationship between the class rank of childhood neighborhoods and subsequent performance at junior high school (in terms of GPA rank), and it is a robust finding that the best performance is achieved when growing up in middle class neighborhoods. We have also shown that the childhood neighborhood effects are persistent, and influence education and earnings outcomes at least up to age 28-31. Putting these results together, it appears to be the case that the current trend toward more residential segregation is harmful for *average* child development as reflected in early school performance. It does not necessarily increase the inequality between high –and low status offspring, however. Our results therefore turn upside down the popular notion that while segregation is certain to increase inequality, it has indeterminate effects on average child development; see, e.g., Mayer (2002).

Based on the existing literature, we interpret the favorable effects of moving from low to middle class neighborhoods as a reflection of positive peer effects arising from socializing with people who are resourceful in terms of human capital and family support, and also of being more exposed to educated and employed role models and less exposed to children and adolescents with social and behavioral problems. We interpret the adverse effect of moving even further up in the neighborhood hierarchy as reflecting the negative influence of experiencing a declining relative position, which can arise both due to lower attention from peers and teachers and due to lower self-confidence and educational ambitions.

The neighborhood effects identified in this paper are of direct relevance for parents making residential decisions with an eye to possible consequences for their offspring. Our results indicate that the widespread view that it is best for the kids to grow up in wealthy neighborhoods is misplaced. To the contrary, parents may actually do a disservice to their kids by placing them in an upper class environment. Our results are also of relevance for city planners and developers making decisions about new housing projects. The finding that neighborhoods with a representative socioeconomic composition provide the best environment for childhood development suggest that neighborhoods can benefit from having a diverse housing standard, allowing people from different classes to live together. According to our results, offspring from both lower and upper class families could benefit from living together in the same neighborhoods instead of segregating into lower and upper class neighborhoods.

Neighborhood effects identified on the basis of Norwegian data can of course not automatically be generalized to other countries. Norway is a country with a relatively ambitious welfare state, low overall earnings inequality, and low (absolute) poverty rates. Tax and transfer systems are designed to ensure equal standards of schools and childcare institutions across neighborhoods, and the overall degree of residential segregation is probably smaller than in many other countries. Yet, it is hard to see why the mechanisms responsible for generating a hump-shaped relationship between a neighborhood's socioeconomic status and offspring educational performance should be completely absent in other countries. In any way, a promising avenue for future research would be to bring in a more comparative perspective in the analysis of neighborhood effects, and in particular to identify how these effects interact with the overall degree of inequality and the extent to which local wealth –and earnings levels correlate with the standards of local amenities and public safety.

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Appendix A: Why has residential segregation increased?

We focus on four potential explanatory forces related to trends in earnings inequality, educational attainment, employment, and immigration patterns, respectively. To study their influence on segregation, we exploit the variation in average rank distance (*ARD*) across commuting zones over time, and define the following variables at the commuting-zone-and-year level – all based on the population aged 30-60 described above:

i) Earnings inequality: The population-weighted average of age-gender-specific Gini coefficients computed for the commuting zones' distributions of annual earnings levels.
ii) Education: The average number of attained non-compulsory schooling years (NCE).
iii) Employment: The fraction of residents employed.
iv) Immigration: The fraction of residents with immigrant background from three different regions, respectively: 1) Less developed countries (LDC), 2) Eastern Europe, and 3) Other (rich world) countries.

The trends in the national population-weighted averages of these regional variables are displayed in Figure A1. The degree of earnings inequality (panel (a)) has fluctuated with no apparent trend, whereas average educational attainment (panel (b)) has increased steadily over the whole period. Employment (panel (c)) has increased over time, with fluctuations inversely related to those of inequality. Finally, the fraction of immigrants has increased sharply, particularly from Eastern Europe (after the expansion of the European common labor market in 2004) and from less developed countries.

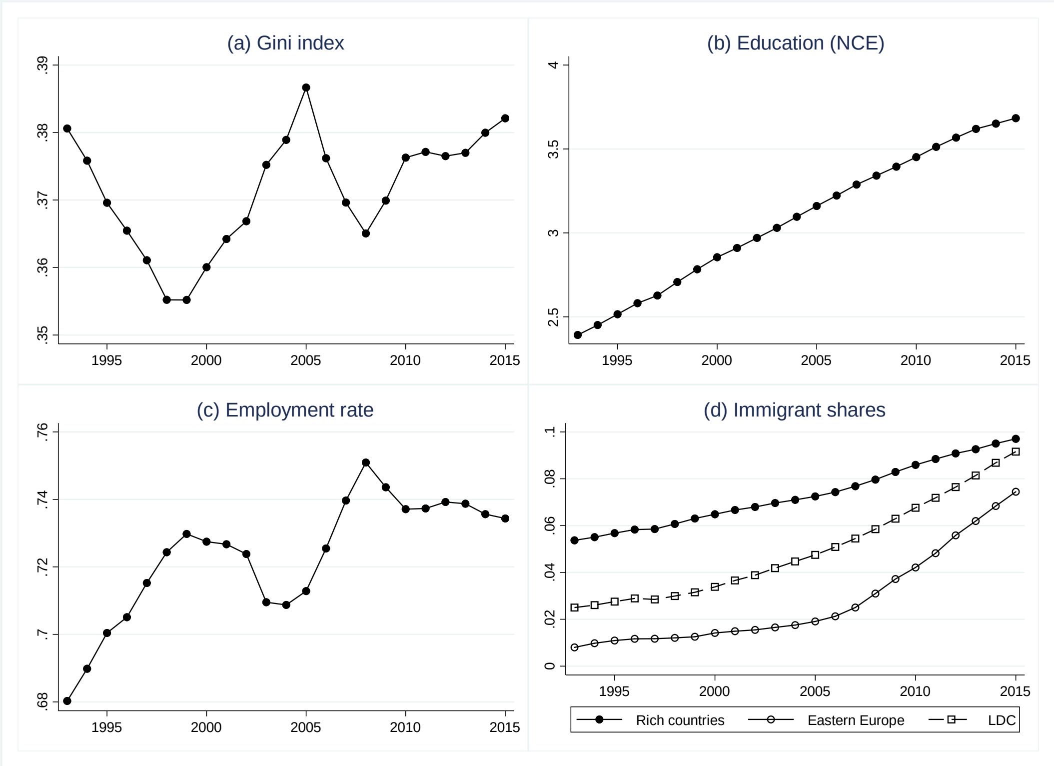

Figure A1. National averages of regional characteristics. By year.
Note: See the numbered items in the text for definitions. In panel (d), we use the term LDC to denote immigration shares from less developed countries, which here includes all countries outside Europe, North America, and Oceania.

With 160 different commuting zones and 23 years of data, we have in total 3,680 annual observations of neighborhood segregation within commuting zones. Let ARD_{rt} denote the average rank distance within neighborhoods in commuting zone *r* in year *t,* and let $\{EGINI_{rt}, EDU_{rt}, EMP_{rt}, IMM_{rt}\}$ denote the four corresponding explanatory factors discussed above (we use the label *EGINI* here to emphasize that this is the Gini coefficient calculated over earnings levels and not ranks). We then specify the following linear regression model:

$$ARD_{rt} = \alpha_r + \lambda_t + \beta_1 EGINI_{rt} + \beta_2 EDU + \beta_3 EMP + \beta_4 IMM_{rt} + \varepsilon_{rt}. \qquad \text{(A1)}$$

The model is estimated with population-weighted OLS. Table A1 presents the results from a series of specifications where we have added into the model the explanatory variables in a step-by-step fashion, and Figure A2 shows the resultant estimated time trends (the λ_t coefficients). Higher earnings inequality is associated with more residential segregation, whereas higher average education and employment levels are associated with less segregation. When we control for all these factors, we obtain an estimated time trend that indicates even larger increases in residential segregation. Higher fractions of immigrants from less developed countries and from Eastern Europe are also associated with higher residential segregation, whereas the fraction of immigrants from other rich countries appears to be unassociated with segregation. And when controlling for immigrant levels, it is notable that the influence of all the other control variables diminishes considerably (and become statistically insignificant for all but one), while the estimated time trend is reversed. That is, controlled for migrant rates, there are no indications of rising residential segregation within Norwegian commuting zones.

Table A1. Average rank distance within neighborhoods by commuting zone and year

	I	II	III	IV	V
Inequality (EGINI)		-1.500***	-1.338***	-0.710**	-0.212
		(0.336)	(0.265)	(0-298)	(0.219)
Education			0.075**	0.060*	0.019
(EDU)			(0.037)	(0.032)	(0.023)
Employment (EMP)				0.538*	0.217*
				(0.299)	(0.111)
Immigrant shares (IMM)					
Less developed countries					-1.248***
					(0.217)
Eastern Europe					-0.612***
					(0.212)
Other rich countries					0.194
					(0.405)
Region-fixed effects	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes
N	3667	3667	3667	3667	3667
R squared	0.935	0.944	0.946	0.947	0.961
R squared adjusted	0.932	0.941	0.943	0.944	0.959

Note: Standard errors are clustered at the commuting zone level. */**/*** indicates statistical significance at the 10/5/1 percent levels

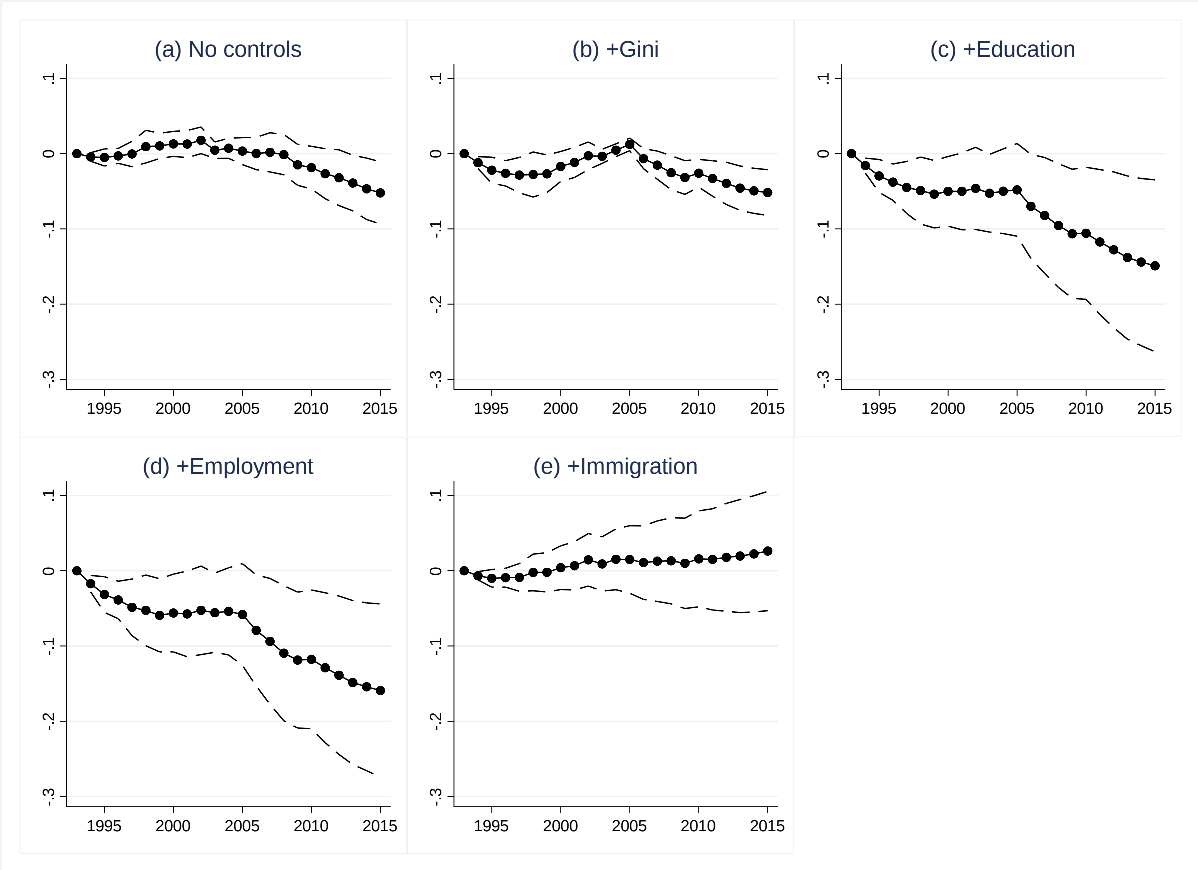

Figure A2. Estimated time trends in ARD within commuting zones resulting from a step-wise inclusion of explanatory variables.

Note: Dotted lines show the 95% confidence intervals based on standard errors clustered at the commuting zone level.

Appendix B: Socioeconomic status or diversity?

Neighborhoods with different socioeconomic ranks also differ systematically in terms of socioeconomic diversity. We illustrate this systematic relationship in Figure A3, where we have plotted average rank diversity (ARD) for each percentile in the (population-weighted) average inhabitant rank (AIR) distribution. The figure shows that diversity tends to rise with socioeconomic rank up to an AIR-level around 11-12, after which it stabilizes and then declines at the very top. Higher middle class and upper class neighborhoods are generally more diverse than lower class neighborhoods.

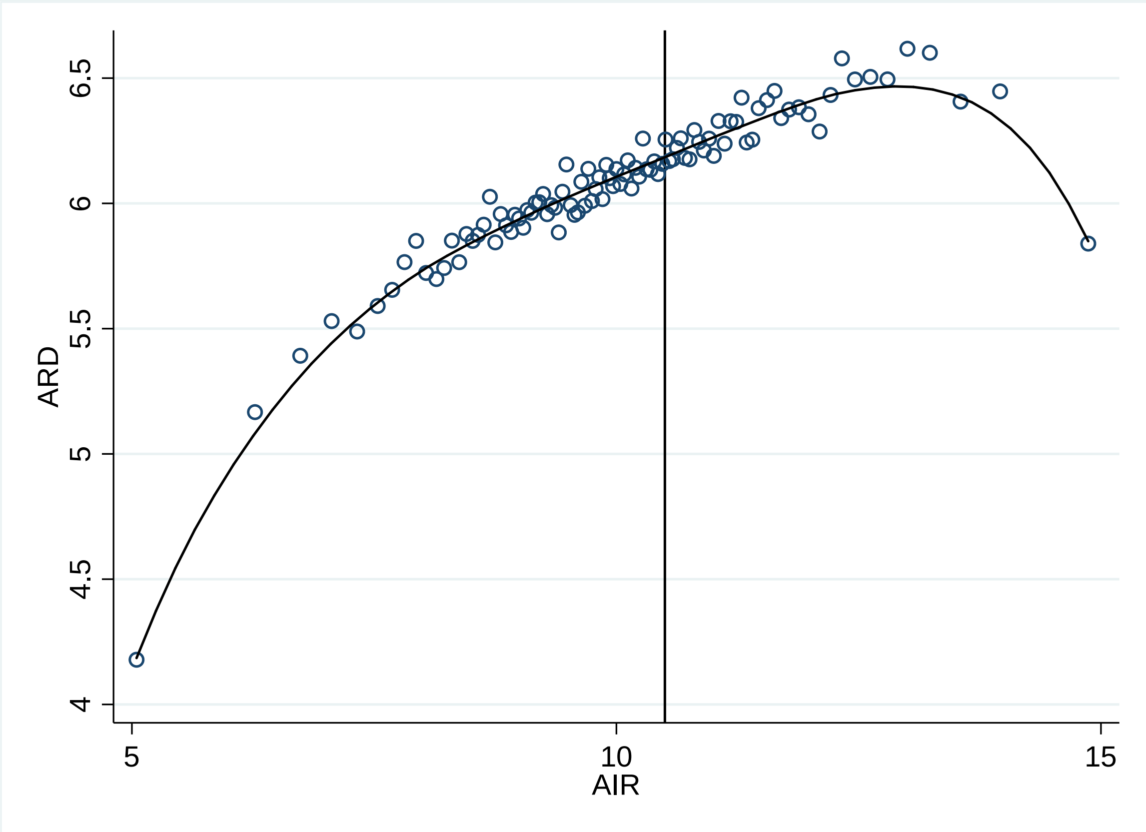

Figure A3. Average neighborhood rank distance (ARD) for each percentile in the distribution of average inhabitant ranks (AIR).
Note: Percentiles are population based, such that there is exactly one percent of the population behind each data point.

To examine whether the non-linear effects of the childhood neighborhood's socioeconomic status capture effects of neighborhood diversity, Table A2 present average estimated neighborhood effects on GPA score when neighborhood diversity is included as an additional explanatory variable. This variable is defined in exactly the same way as average inhabitant rank, such that it measures the average rank distance in neighborhoods inhabited from birth to age 15. We show results for the baseline model, as well as for the model with all covariates included. In addition, we present in Columns III and V versions of these models where neighborhood rank only enters linearly.

The resultant point estimates indicate that neighborhood diversity has a positive effect on offspring's GPA outcomes. None of the ARD estimates are significantly different from zero, however, even when AIR is restricted to enter the model linearly. When ARD is added to a quadratic-in-AIR model, the estimated concavity in AIR becomes a bit weaker, but again the statistical uncertainty is too large for any substantive conclusions to be drawn.

Table A2. Effects of childhood neighborhood on GPA score rank (within commuting zone) at age 15/16

	Model without ARD (repeated from Columns I and VI in Table 1)		Models with ARD included			
	I Baseline	II All controls	III Linear in AIR Baseline	IV Quadratic in AIR Baseline	V Linear in AIR All controls	VI Quadratic in AIR All controls
Neighborhood characteristics own childhood						
Rank (AIR_0^{15})	8.042*** (3.097)	6.434** (3.146)	-0.561 (0.396)	6.905** (3.321)	-0.762 (0.461)	5.334 (3.419)
Rank squared	-0.412*** (0.149)	-0.350** (0.149)		-0.359** (0.158)		-0.290* (0.161)
Diversity (ARD_0^{15})			1.547 (1.020)	0.843 (1.085)	1.553 (1.023)	0.976 (1.099)
Immigrant share		-5.518 (7.311)			-7.970 (7.319)	-5.979 (7.377)
Schoolmate characteristics						
Avg. earnings rank of parents		-1.191*** (0.171)			-1.196*** (0.172)	-1.192*** (0.171)
Immigrant share		-2.951* (1.678)			-2.957* (1.680)	-2.942* (1.678)
Average GPA score rank among schoolmates		0.252*** (0.023)			0.252*** (0.023)	0.252*** (0.023)
Own parents' (time-varying) rank		-0126 (0.139)			-0115 (0.139)	-0119 (0.140)
School-fixed effects	No	Yes	No	No	Yes	Yes
N	227,202	227,088	227,202	227,202	227,088	227,088
R squared	0.7551	0.7599	0.7551	0.7551	0.7599	0.7599
R squared adjusted	0.5405	0.5448	0.5404	0.5404	0.5447	0.5447

Note: All models include family fixed effects and also contain controls for within family birth order (6 dummy variables) and sex. Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

Appendix C: Neighborhood effects with quadratic control variables

In Section 4.1 above, we included all control variables in the regression models linearly, whereas the central average inhabitant rank (AIR) variable was allowed to influence GPA outcomes through a more flexible (quadratic) specification. For some of the control variables, this is not an obvious choice. For example, as neighborhood rank exposure clearly affects offspring outcomes non-linearly it may be suspected that the same could be the case for the parental ranks of schoolmates. In Table A3, we report estimates for a model with all controls entered through quadratic functions. As can be seen, none of the added second order terms are even close to being statistically significant. At the same time, the inclusion of these terms does not noticeably change the estimated impacts of neighborhood rank. If anything, it makes the estimated concavity of this relationship a bit stronger.

Table A3. Effects of childhood neighborhood on GPA rank with quadratic terms on control variables

	I Complete model (repeated from Table 1, Column VI)	II With quadratic terms on control variables
Neighborhood characteristics own childhood		
Rank (AIR_0^{15})	6.434** (3.146)	7.880** (3.248)
Rank squared	-0.350** (0.149)	-0.412*** (0.155)
Immigrant share	-5.518 (7.311)	-0.190* (0.115)
Immigrant share squared		0.303 (0.206)
Schoolmate characteristics		
Avg. earnings rank of parents	-1.191*** (0.171)	-0.802 (1.377)
Avg. earnings rank of parents squared		-0.017 (0.065)
Immigrant share	-2.951* (1.678)	-3.972 (2.992)
Immigrant share squared		-1.850 (4.900)
Average GPA score rank among schoolmates	0.252*** (0.023)	0.179 (0.166)
Average GPA score rank among schoolmates squared		0.001 (0.002)
Own parents' (time-varying) rank	-0126 (0.139)	-0.604 (0.493)
Own parent's rank squared		0.022 (0.022)
School-fixed effects	Yes	Yes
N	227,088	227,088
R squared	0.7599	0.7599
R squared adjusted	0.5448	0.5448

Note: Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

Appendix D: Additional evidence on stayers and movers

In Section 4.4 above, we reported separate neighborhood effect estimates for movers and stayers based on a joint regression models, with the separate effects on GPA score obtained by the use of interaction terms. In Table A4 below, we report corresponding estimates based on completely separate models for movers and stayers. The estimated neighborhood effects turn out to be very similar to those reported in Section 4.4. However, from the estimates reported in Table A4, we can also examine differences between movers and stayers in the estimated influence of other characteristics. It is notable that while the earnings ranks of the schoolmates' parents have the same effect on movers and stayers, the influence of exposure to immigrants appears to be different. For movers, we find a significant negative effect of the schoolmate immigrant share, but no effect of exposure to immigrants in the neighborhood, whereas for stayers, we find exactly the opposite pattern: A negative effect of exposure to immigrants in the neighborhood, but no effect of the schoolmate immigrant share.

Table A4. Effects of childhood neighborhood on GPA rank by identification source (movers/stayers). Separate models.

	Movers		Stayers	
	I Baseline	II All controls	III Baseline	IV All controls
Neighborhood characteristics				
Rank (AIR_0^{15})	6.123* (3.348)	5.326 (3.444)	16.745* (8.367)	15.673 (9.700)
Rank squared	-0.317** (0.161)	-0.274* (0.163)	-0.833* (0.462)	.0.820* (0.474)
Immigrant share		1.049 (7.906)		-41.512** (17.843)
Schoolmate characteristics				
Avg. earnings rank of parents		-1.190*** (0.211)		-1.208*** (0.298)
Immigrant share		-4.002** (1.982)		-0.364 (3.040)
Average GPA score rank among schoolmates		0.276*** (0.027)		0.211*** (0.036)
Own parents' (time-varying) rank		-0.198 (0.164)		0.057 (0.273)
School-fixed effects	No	Yes	No	Yes
N	155,447	155,408	71,755	71,730
R squared	0.7598	0.7657	0.7415	0.7492
R squared adjusted	0.5502	0.5548	0.5124	0.5177

Note: Estimates are obtained from four separate models. All models include family fixed effects and controls for gender, birth year and birth order. The model with "all controls" also include the neighborhood's immigrant share, schoolmate characteristics (avg. earnings rank of parents, immigrant share, and avg. GPA score), and own parents' (time-varying) rank. Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

Appendix E: Neighborhood ranks based on constant individual ranks

In this appendix, we report estimated neighborhood effects on GPA score based on neighborhood ranks computed from constant individual ranks. The constant ranks are obtained in the following way: For all adults used to rank the neighborhoods, we first compute the average annual age-specific rank within the commuting zone. This constant individual rank is then used to rank each neighborhood each year on the basis of each year's adult population. This rank measure eliminates all neighborhood rank changes that result from changes in a given population's average rank, such that a neighborhood's rank can only change through in- or out-migration.

Table A5. Effects of childhood neighborhood on GPA rank with neighborhood ranks based on fixed parental ranks. Separate models.

	All		Movers		Stayers	
	I Baseline	II All controls	III Baseline	IV All controls	V Baseline	VI All controls
Neighborhood characteristics						
Rank (AIR_0^{15})	8.782** (3.589)	7.054* (3.634)	7.675** (3.703)	6.944* (3.791)	17.437 (13.016)	14.318 (13.685)
Rank squared	-0.447*** (0.170)	-0.372** (0.170)	-0.390** (0.176)	-0.349** (0.178)	-0.886 (0.626)	-0.796 (0.649)
Immigrant share		-6.242 (7.408)		1.404 (7.911)		-45.838** (18.554)
Schoolmate characteristics						
Avg. earnings rank of parents		-1.190*** (0.171)		-1.188*** (0.211)		-1.203*** (0.298)
Immigrant share		-2.932* (1.677)		-3.997** (1.981)		-0.367 (3.040)
Average GPA score rank among schoolmates		0.252*** (0.023)		0.276*** (0.027)		0.211*** (0.036)
Own parents' (time-varying) rank		-0.124 (0.139)		-0.197 (0.164)		0.066 (0.273)
School fixed effects	No	Yes	No	Yes	No	Yes
N	227,202	227,088	155,447	155,408	71,755	71,730
R squared	0.7551	0.7599	0.7598	0.7657	0.7415	0.7492
R squared adjusted	0.5405	0.5447	0.5502	0.5548	0.5124	0.5177

Note: Estimates are obtained from six separate models. All models include family fixed effects and controls for gender, birth year and birth order. The model with "all controls" also include the neighborhood's immigrant share, schoolmate characteristics (avg. earnings rank of parents, immigrant share, and avg. GPA score), and own parents' (time-varying) rank. Standard errors are clustered at the school level. */**/*** indicates statistical significance at the 10/5/1 percent levels.

Table A4 report estimated neighborhood effects on offspring GPA score based on this modified rank measure, for the whole sample as well as for movers and stayers separately. It turns out that this modification of the source of identification does not change the results to any noticeable extent.