Paths of Persistence? Adolescence socioeconomic segregation and high-status jobs in adulthood

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Abstract. The topic of how neighborhood environments shape future outcomes for children has generated significant scholarly attention in recent years. This study contributes to the existing literature by examining the long-term influence of different sorts of neighborhood segregation experienced during adolescence on the likelihood of attaining high-skilled occupations during mid-prime working age. Using a full-population microdata for Sweden, we control for intergenerational persistence in labor market outcomes and complement this with military enlistment data on individual IQ. The identification further relies on the fact that the place of residence during adolescence is parent-determined, and the main estimates are based on individuals who relocate to another municipality. Our findings reveal that growing up in neighborhoods marked by poverty and low education reduces the likelihood of pursuing occupations that require advanced higher education. Conversely, obtaining managerial positions appears to be less influenced by socioeconomic background, and we find few effects of ethnic segregation. We further show that higher education and moving to metropolitan areas can mitigate neighborhood disadvantages, highlighting the need for opportunities in spatial mobility and university studies for disadvantaged youth.

Socioeconomic disadvantages at the family level are, however, more persistent and challenging to overcome.

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1. Introduction

“Neighborhood effects”—the effects on individual level socioeconomic outcomes and life-time trajectories of the behaviors and characteristics of members of an individual’s residential community—have long been a phenomenon of interest in urban studies (Park, 1915; Wirth, 1938; Sampson et al., 2002; Stokes, 2019; Chyn and Katz, 2021; Malmberg et al., 2023; Abrahamson, 2013). In particular, the effects of a neighborhood’s characteristics on the health of its residents have received much attention (Diez Roux, 2001; Finch et al., 2010; Duncan and Kawachi, 2018; Fortson and Sanbonmatsu, 2010). Additionally, recent work on vaccination rates and responses to the Covid-19 pandemic has examined the influence of neighborhood and peer effects (Klaesson et al., 2023; Mellander et al., 2023).

The social determinants of individual behaviors and aggregate outcomes has also been a growing interest among economists (Angrist, 2014; Blume and Durlauf, 2001; Durlauf, 2004; Becker, 1974; Golub and Jackson, 2010; Becker and Murphy, 2009; Cutler and Glaeser, 1997; Calvó-Armengol et al., 2009; Glaeser et al., 2000). While economics has typically studied aggregate behavior as the outcome of individual decisions made interactively, and sociology has focused on the role of social influences on individual behavior, social scientists now recognize that when making decisions with significant economic consequences, individuals can be directly influenced by the choices and characteristics of others around them (Durlauf and Ioannides, 2010; Ioannides and Topa, 2010). This dynamic creates information feedback loops between individual and group choices based on the past choices of some people, which then affects the current social context and hence future choices of others (Akerlof, 1997; Topa and Zenou, 2015; Topa, 2011).

Starting with the seminal empirical study of Kain (1968), neighborhood effects have been extensively studied in the context of employment outcomes, often focusing on individuals participation in the labor market (Hémet and Malgouyres, 2018; Clampet-Lundquist and Massey, 2008; Musterd and Andersson, 2006). Neighborhood characteristics—including concentrated poverty or affluence, high quality schools or schools with inadequate funding and lacking in qualified teaching personnel, the success of failure of schools in mixing students from different social backgrounds, the presence or absence of role models and peers—have been identified as greatly influencing the educational attainment of neighborhood residents (Garner and Raudenbush, 1991; Wodtke et al., 2011; Hedefalk and Dribe, 2020; Andersson and Malmberg, 2015; Laliberté, 2021; Wodtke et al., 2023; Troost et al., 2023; Levy, 2021; Andersson and Subramanian, 2006; Chetty et al., 2016; Chetty and Hendren, 2018). Educational attainment in turn significantly shapes employment and income pathways[1] (Jefferson, 2008; Teichler, 2001; Chetty et al., 2020).

The search for a job is heavily influenced by seekers' access to information about the labor market and the availability of different types of jobs (Stigler, 1962; Pissarides, 2011; Albrecht, 2011). Access to this type of information is in turn heavily influenced by the social structures that individuals are embedded in and their connections with friends, neighbors, and professional acquaintances (Ioannides and Loury, 2004; Jahn and Neugart, 2020). Neighborhoods which are socially isolated, and which concentrate poverty and unemployment, affect the quantity and quality of job contacts available to local residents (Elliott, 1999). Socially and economically disadvantaged neighborhoods thus affect individuals' probability of employment and, consequently, their earnings (Jahn and Neugart, 2020; Vandecasteele and Fasang, 2021; Eilers et al., 2022; Galster et al., 2008).

[1] https://www.oecd.org/education/education-at-a-glance

Some prior studies also show *long-term* economic effects of youths' exposure to disadvantaged neighborhoods (Galster et al., 2007; Chetty and Hendren, 2018; Brattbakk and Wessel, 2013; Brännström, 2005; Baum-Snow et al., 2019), while other studies contradict such findings (Oreopoulos, 2003). Overall, long-term effects on income appear to be relatively small, or even nil, in the Nordic countries (Lindahl, 2011).

Participation in the labor market and earning an income entail having a job which implies having an *occupation*. An occupation is the kind of work a person does to earn a living, and occupations represent bundles of specific tasks and required skills, capabilities, training, and education. Individuals may thus face barriers to entry or exit from certain occupations depending on their education, skills, experiences, gender, ethnicity, or other factors (Banerjee and Newman, 1993). Family background, culture, social norms, ties, and connections can also influence occupational choices and outcomes (Doepke and Zilibotti, 2008; Heckman and Landersø, 2022). Individuals may rely on their friends, relatives, or acquaintances to obtain information, referrals, or recommendations about job opportunities, employers, or occupations (Dolton et al., 1989). Thus, it is reasonable to expect neighborhoods' socioeconomic milieu to influence individuals' occupational choices. However, there has been relatively little research attention given to the interplay between neighborhood effects and occupational outcomes, particularly from a long-term perspective. This is quite astounding considering that "*Occupational choices are important for individuals and societies because they influence individual lifetime earnings and social status as well as the technological progress and economic growth of society*." (Zhan (2015), p. 44).

We contribute to this research gap by studying the extent to which the neighborhood in which an individual grows up may influence the likelihood of obtaining a high-status job later in life. The neighborhood social environment may not only serve as a space where an individual forges future networks that can facilitate job finding later in life, but it may also be imbued with cultures and norms that shape an individual's behavior, form their personality, influence educational choices, and consequently affect future labor market outcomes. Here we report on an investigation into the long-term impacts of residing in disadvantaged neighborhoods during adolescence (at age 16) on the occupational choices of males in the 40-44 age group, which represents their mid-prime working years[2]. Specifically, we aim to determine how socioeconomic and ethnic segregation affect individuals' likelihood of obtaining high-skilled jobs—those occupations that offer the highest incomes. Since occupational choices reflect psychological temperament and cognitive capabilities, an investigation into neighborhood effects and occupational choice is bound to be more revealing if it takes into account at what development stage an individual experiences the effects. We focus on adolescence since it has been identified as a critical period during which individuals' personalities and behavioral traits are formed (Heckman and Mosso, 2014). It constitutes a critical phase in one's life cycle when we can expect to be more influenced—both in the short and long term—by our neighborhood environment (Chyn and Katz, 2021). While cognitive abilities and general behavioral patterns may form during early youth, it is typically during later adolescence and the early stages of adulthood that individuals start to think more critically and practically about educational choices and preferred career paths (Chickering and Reisser, 1993).

While Sweden lacks social experiments similar to the Moving to Opportunity program conducted in the United States in the 1990s[3], which has been extensively exploited in

[2] The prime working age is often defined as 25-54 (https://www.bls.gov/opub/btn/volume-8/male-nonworkers-nlsy.htm; https://data.oecd.org/emp/employment-rate-by-age-group.htm).
[3] The exception may be the Swedish settlements policies of the mid-1980s to early 1990s, providing a random allocation of refugees across municipalities (see, e.g., Edin et al. (2004); Åslund et al. (2011)). In this paper, the interest is however not on the performance of refugees, who comprise a relatively small population group. A further downside of studying refugees is that it is not possible to control for intergenerational effects.

research on neighborhood effects for reasons of exogenous variation (Chetty et al., 2016; Clampet-Lundquist and Massey, 2008; Ludwig et al., 2013; Jens Ludwig et al., 2008; Aliprantis, 2017; Sampson, 2008), we have access to rich geocoded, full-population register data dating back to 1990. These data enable us to follow individuals over long periods and allow for matching with other data sources. Consequently, we can identify the geographic context within which each individual grows up and where he/she resides in adulthood. Furthermore, we can identify parents and their neighborhood choices, which to some extent can be considered exogenous to the child. Additionally, we incorporate a control for the cognitive abilities (commonly denoted as IQ) of the individuals, derived from matched enlistment data for military services conducted at ages 18-19. This measure aims to capture analytical skills and personality traits that remain unobserved in register data and are unaffected by skills acquired during higher education. Moreover, it serves as a control for the spatial sorting of individuals in adulthood.

Our research reveals that the characteristics of residential neighborhoods during adolescence significantly impact the probability of securing a high-skilled job later in life. Despite the greater influence of individuals' own cognitive ability and their parents' socioeconomic background, residing in a marginalized neighborhood during adolescence tends to negatively influence the likelihood of attaining a more advanced occupation as an adult. Specifically, growing up in a neighborhood characterized by low educational and income levels implies a reduced likelihood of being employed in occupations requiring advanced levels of education later in life. We further show that this primarily stems from a lower probability of youth in distressed areas to pursue higher education to start with, as well as a lower probability to move to metropolitan areas that offer more and diverse job opportunities (Duranton and Puga, 2004). An important implication may thus be that individuals may overcome the negative influence on occupational outcomes of neighborhood deprivation by university studies and spatial mobility. From this follows empirical support for policy measures, particularly focusing on paths to higher education (which often takes place in larger regions), aimed at disadvantaged areas to increase the current and future opportunities of the youth who happen to spend their adolescence in such places.

The rest of the paper is organized as follows. Section 2 focuses on the distinctiveness of the Swedish educational system. Section 3 presents the empirical strategy, including data, variables, and our estimation approach. Section 4 presents and analyses the empirical results, while section 5 concludes the paper.

2. The Swedish context

Despite its small population size and the distinctiveness of its political and economic heritage, Sweden provides a very congenial setting for studying how neighborhood effects influence future occupational choices. Higher education in Sweden is publicly financed and provided freely for all citizens. Additionally, students are eligible for both a study grant and a study loan under relatively advantageous conditions, including favorable interest rates and repayment schemes. Moreover, elementary education in Sweden is provided equally and is compulsory until the age of 15 (grades 1-9). From the age of 16, upon entering high school (known as "gymnasium" in Swedish), students have the option to choose between various academic programs, such as those focusing on natural sciences or social sciences, as well as vocational programs preparing them for occupations in sectors like hotels and restaurants or construction. A distinctive aspect specific to the Swedish context is that, following the high school reform of 1991, all programs—both academic and vocational—are designed to provide students with basic eligibility for university studies (Erikson, 2017). This implies that every potential educational path and occupational career choice is theoretically accessible to everyone, regardless of their socioeconomic background. Furthermore, individuals are not necessarily confined to specific career paths based on their high school choices.

Because of its institutional settings, we might anticipate that upward social mobility is more achievable in the Swedish setting as compared to many other countries. Therefore, Sweden can be considered *a least likely case*. This implies that if we discover that the socioeconomic spatial setting affecting upbringing in turn affects occupational choices, it is likely to be even more significant in countries where access to higher education relies on private funds or scholarships.

3. Empirical strategy

Despite the equal educational opportunities discussed above, based on prior research on Sweden on long-term neighborhood effects on various life outcomes such as education, income, employment, and self-employment (Andersson, 2004; Andersson and Subramanian, 2006; Andersson and Malmberg, 2015; Wixe, 2020), we anticipate differences also in occupational choices among individuals from diverse socioeconomic backgrounds. We assess the characteristics of the residential neighborhood, in terms of poverty, educational attainment, and ethnic composition, when an individual is aged 16. Since, for most adolescents, the neighborhood of residence is determined by their parents, these neighborhood characteristics can be viewed as largely exogenous from the adult individual's perspective. This is important given the concerns about selection bias when studying neighborhood effects. Selection bias occurs when the process by which individuals or households are matched to specific neighborhoods is not independent of the outcomes being studied. That is, it arises when people nonrandomly choose to live in certain neighborhoods based on their preferences, income, and the availability of alternative housing options. Households do not randomly decide where to live. Instead, they consider factors like affordability, personal social, political, and cultural preferences, and family needs. As a result, individuals and families self-select into neighborhoods based on their circumstances and (ethnic) preferences (Aliprantis et al., 2024; Wixe and Rouchy, 2024; Ioannides and Zabel, 2008; Bayer et al., 2004; Borjas, 1998). The observed relationship between neighborhood characteristics and outcomes could thus be influenced by unmeasured individual traits. For instance, families with specific socioeconomic backgrounds or educational levels may be more likely to choose certain neighborhoods. If these unobserved characteristics also affect outcomes, it can lead to biased assessment of neighborhood effects (Sampson et al., 2002; Hedman and Van Ham, 2011; Van Ham et al., 2018; Heckman and Landersø, 2022). By focusing on neighborhood characteristics determined by the parents, which are logically not influenced by the future occupations of their children, we largely avoid such biases.

Nevertheless, a further caveat is the intergenerational persistence in labor market (and socioeconomic) outcomes shown by prior studies, wherein the socioeconomic status of parents giving rise to their spatial sorting, impact also the outcomes of their offspring well into adulthood (Lo Bello and Morchio, 2022; Björklund and Jäntti, 2012; García-Mainar and Montuenga, 2020; Chetty et al., 2020; Chetty et al., 2014; Case and Katz, 1991; Nicardo et al., 2024; Corcoran et al., 1990). Ginther et al. (2000) and Heckman and Landersø (2022) show that exclusion of family controls leads to a rather substantial upward bias in estimates of long-term neighborhood effects on children's educational outcomes and future income, respectively. To avoid overestimating the influence of neighborhood quality during adolescence, we thus control for the education level, income, and ethnic background of the parents in the individual's adolescent years.

Additionally, we incorporate a control for the cognitive abilities (often denoted as IQ) of the individuals themselves, derived from enlistment data for military services conducted at ages 18-19. This measure is argued to encompass analytical skills and personality traits that remain unobserved in register data and are uninfluenced by skills acquired during higher education studies. These cognitive abilities also serve as a means to control for the spatial sorting of individuals in adulthood. As enlistment was mandatory for men at the time, while women are heavily underrepresented in the (enlistment) data, we limit our analysis to males. Keuschnigg et al. (2023) show a strong association between this specific measure of cognitive ability and occupational success of males in Sweden.

3.1. Data and study population

We utilize longitudinal full-population microdata from Statistics Sweden, encompassing all individuals aged 16 and above. This dataset provides comprehensive information on individual characteristics, including age, gender, ethnic background, family status, education, income, and occupation. Moreover, the data establish connections between individuals and their parents, enabling us to control for parental peer effects in labor market choices. To ensure that our estimates of long-term neighborhood effects do not capture the effect of one's current place of residence, we conduct our baseline estimations exclusively on what are known as "movers". These individuals have changed their municipality of residence by 2019 from where they lived at age 16, thereby residing in a different neighborhood as well. The dataset spans back to 1990, allowing us to measure the quality of individuals' neighborhoods during their adolescent years, which we define as age 16. Meanwhile, we measure occupational outcomes in 2019 to circumvent potential adverse effects resulting from the COVID-19 pandemic (the dataset spans up to 2021).

We select individuals aged 40-44 in 2019 with a known occupation. We commence at age 40, as individuals at this age are typically established in the labor market and are past their years of studying. We conclude at age 44 because this represents the oldest age group for whom we can measure neighborhood characteristics at age 16, and who are covered by the high school reform of 1991. Consequently, individuals not available in the data at age

16—such as those who immigrated to Sweden at older ages—are excluded from our study. As discussed above, our focus is solely on males due to the availability of enlistment data, capturing cognitive abilities and personality traits that are otherwise unobservable in register data, for the vast majority of this group. The final exclusion is of individuals residing in the same municipality in 2019 (aged 40-44) as they did at age 16 (1991-1995). These criteria result in 99,289 observations.

3.2 Variables

3.2.1. Occupations

The dependent variable concerns the occupation of the individual, based on the occupational codes denoted SSYK 2012 by Statistics Sweden, corresponding to the international standard classification of occupations ISCO-08. We focus on the 1-digit-level major groups: 'Managers' (group 1), 'Occupations requiring an advanced level of higher education' (group 2), and 'Occupations requiring higher education qualifications or equivalent' (group 3). These occupations necessitate an ISCO skill level of 3 (groups 1 and 3) or 4 (groups 1 and 2), which we denote as “high-skill occupations”. Occupation groups 4-9 are classified as skill level 1 or 2, thus denoted as “low-skill occupations”. Additionally, we distinguish between 2-digit subgroups within the major groups, as presented in Table 1. Table 1 also displays the number and proportion of individuals within our population of interest who belong to each occupational group.

Table 1. Occupational Classifications According to SSYK 2012/ISCO-08.

Group	Name	Number of individuals	Share of individuals (%)
1	Managers	14,218	14.32
	Of which		
11	Legislators, chief executives, and senior government Officials	1,199	8.43
12	Administrative and commercial managers	4,871	34.26
13	Production and specialized services managers	5,097	35.85
14	Education managers	398	2.80
15	Health and other services managers	1,204	8.47
16	Financial and insurance services branch managers	324	2.28
17	Hotel, restaurant, retail, and other services managers	1,125	7.91
2	Occupations requiring advanced level of higher education	33,434	33.67
	Of which		
21	Occupations requiring advanced academic competence in science and technology	7,642	22.86
22	Occupations requiring advanced academic competence in health care	2,590	7.75
23	Occupations requiring advanced academic competence in education	4,673	13.98
24	Occupations requiring advanced academic competence in finance and management	6,765	20.23
25	Occupations requiring advanced academic skills in information and communications technology (ICT)	9,101	27.22
26	Occupations requiring advanced academic skills in law, culture, and social work etc.	2,663	7.96
3	Occupations requiring higher education qualifications or equivalent	20,539	20.69
	Of which		
31	Occupations requiring higher education qualification or equivalent in technology	6,069	29.55
32	Occupations requiring higher education qualification or the equivalent in healthcare and laboratory	514	2.50
33	Occupations requiring higher education qualification or equivalent in finance and management	9,853	47.97
34	Occupations requiring higher education qualification or the equivalent in culture, wellness, and social work	1,585	7.72
35	Occupations requiring higher education qualification or equivalent in information, communication (ICT), sound and light technologies, etc.	2,518	12.26
4-9	Other occupations	31,098	31.32
	Total	99,289	100

Source. Statistics Sweden[4]

[4] https://www.scb.se/dokumentation/klassifikationer-och-standarder/standard-for-svensk-yrkesklassificering-ssyk/

3.2.2. Neighborhood characteristics

We define neighborhoods according to Statistics Sweden's RegSO (regional statistical area) classification. This definition of neighborhoods is particularly suited to our research question because the purpose of the RegSO classification is specifically to facilitate statistical tracking of socioeconomic segregation. Under this definition, Sweden's territory is divided into 3,363 neighborhoods. To prevent issues of confidentiality, each neighborhood is designed to encompass a population deemed 'large enough,' resulting in relatively sizable neighborhoods in sparsely populated rural regions. Consequently, the RegSO classification can be argued to offer a more accurate representation of actual neighborhoods in urban areas compared to rural ones.

The primary independent variables of interest are the characteristics of the neighborhood of residence experienced at age 16 (i.e., years 1991-1995 for individuals aged 40-44, respectively). We measure socioeconomic status across three dimensions: (1) the proportion of the working-age (20-64) population in the neighborhood with low education, (2) the proportion of the working-age neighborhood population at risk of poverty, and (3) the proportion of the working-age neighborhood population born in non-Nordic/EU15 countries. To allow for non-linear effects and facilitate result interpretation we present the average marginal effects, and we categorize these proportions based on percentiles (5, 10, 25, 50, 75, 90, 95, 100) for each respective year. The bottom 5 percent of neighborhoods with the lowest proportions are classified as the lowest category (5), representing the 'least disadvantaged' neighborhoods, while the top 5 percent with the highest proportions are classified as the highest category (100), signifying the 'most disadvantaged' neighborhoods. This approach ensures that regardless of the year (1991-1995) for which neighborhood shares are calculated, each category comprises an identical number of neighborhoods. Hence, 'disadvantage' serves as a relative measure (cf. Alpizar et al. (2005); Layard et al. (2010); Ravallion and Chen (2019)), comparing neighborhoods within each specific year.

3.2.3. Control variables

The socioeconomic background of individuals is influenced not only by the neighborhood of residence during adolescence but significantly by the socioeconomic status of the parents as well. To avoid overestimating the impact of the neighborhood, we control for the disposable income, education level, and ethnic background of the father[5], assessed when the individual is of age 16. We further control for the type of municipality where the individual resided at age 16 (1991-1995), distinguishing between metropolitan municipalities, urban municipalities near larger cities, urban municipalities farther from larger cities, rural municipalities near larger cities, and rural municipalities farther from larger cities. This classification, developed by the Swedish Agency for Economic and Regional Growth, is based on population sizes and commuting patterns.

Additional control variables at the individual level, assessed in 2019, encompass age (40-44), family/civil status (single/married without/with children), and ethnic background (born in a non-Nordic/EU15 country). Notably, we account for cognitive abilities at the individual level using test results from military enlistment data. For the age groups examined in this study, enlistment was compulsory for all males and carried out at ages 18-19. All recruits underwent tests measuring verbal, spatial, logical, and technical abilities, with results aggregated to generate a general intelligence score (IQ) using a nine-point standard scale, with a mean of five and a standard deviation of two (known as the stanine method). Finally, since occupational choices are constrained by available job

[5] We have also examined the socioeconomic background of the mother, yielding comparable results concerning parental peer effects, albeit with a slightly smaller estimate regarding the parent's education level. However, the estimates related to the neighborhood become somewhat larger, indicating that the socioeconomic background of the father leads to more restrictive estimates.

opportunities, we introduce fixed effects at the local labor market level to control for variations in occupational structures across regions (Duranton and Puga, 2005; Koster and Ozgen, 2021).

Table A.1 in the appendix provides a summary of the independent variables employed in estimating long-term neighborhood effects on occupational choices.

3.3. Model and estimation strategy[6]

Given that the dependent variable—individual-level occupational outcomes—is in categorical form, we employ the multinomial logit model (MNL). The primary advantage of MNL models is in the ability to understand and quantify decision-making processes or outcomes when individuals are confronted with several mutually exclusive options, which are not binary but instead involve three or more distinct alternatives. By utilizing MNL models, we can analyze how various factors may influence the likelihood of each potential alternative outcome.

Consequently, the dependent variable is represented as y_i = 1,2,3 when analyzing 1-digit occupational groups and as y_i = 11-17, 21-26, 31-35 when examining 2-digit occupational groups (refer to Table 1). The baseline category consistently remains y_i = 0, corresponding to individuals belonging to occupational groups 4-9. Therefore, individuals in each high-skill occupational group (whether 1-digit or 2-digit) are compared to a reference group comprising individuals in low(er)-skill occupations. Moreover, we generate a binary variable where y_i = 1 if the individual belongs to any of the three high-skill 1-digit occupational groups.

We thus estimate the logarithm of the probability of having a high-skill occupation (k) versus holding a low-skill occupation (0), as indicated by the MNL in equation 1.

[6] This section loosely follows Mood (2010).

$$\ln\left(\frac{\Pr(y_i = k|\boldsymbol{X})}{\Pr(y_i = 0|\boldsymbol{X})}\right) = \alpha + \boldsymbol{X\beta^k}, \qquad (1)$$

where α is the intercept, $\mathbf{X}$ is a row vector containing the explanatory variables described in section 3.2.2 (neighborhood characteristics at age 16) and 3.2.3 (control variables). Since the estimated parameters, $\boldsymbol{\beta}$, of equation 2 are log-odds ratios, which are difficult to interpret, we present the results as average marginal effects (AMEs). To find the AMEs, the logistic model of equation 1 is transformed into the probability model shown by equation 2.

$$\Pr(y_i = k|\boldsymbol{X}) = p = \frac{\exp(\alpha + \boldsymbol{X\beta^k})}{1 + \sum_{j=1}^{K} \exp(\alpha + \boldsymbol{X\beta^j})} \qquad (2)$$

Where $j = 1, \dots, K$ includes all categories (including category k) but the baseline category ($y_i = 0$). When there are only two categories ($y_i = 1$ and $y_i = 0$), the outcome variable is binary and equation 1 and 2 translate into the simpler logit model.

The marginal effect of a specific explanatory variable such as X_1 is found by taking the derivative of p with respect to X_1, that is $\delta p/\delta X_1$. The marginal effect thus shows the change in predicted probability (of having a certain occupation) when the explanatory variable changes by a small amount (often interpreted as one unit). However, since the model is non-linear, the effect of X_1 on p depends on the specific value of X_1 as well as the values of all other explanatory variables. Instead of choosing specific values at which to evaluate the marginal effects we compute the *average* marginal effects (AMEs).

The Average Marginal Effect (AME), thus, illustrates the population-averaged impact of a particular explanatory variable on the likelihood of having a specific type of occupation. While AMEs can be calculated for all explanatory variables, they are more straightforwardly interpreted for binary and categorical variables compared to continuous ones. Regarding binary explanatory variables, the AME indicates the average alteration in the predicted probability as the binary variable transitions from 0 to 1. For categorical variables, the AME signifies the average change in predicted probability when an individual belongs to a specific category rather than the reference category. In the case of continuous explanatory variables, the AME demonstrates the average shift in predicted probability resulting from a "small" (often interpreted as a one-unit) change in the continuous variable.

We estimate equation 2 and compute the Average Marginal Effects (AMEs) for the study population identified in section 3.1. The results of these estimations are presented in the following section. Furthermore, considering that the RegSO classification might be less representative of actual neighborhoods in rural areas compared to urban areas within municipalities, we conduct robustness tests by including only individuals residing in urban neighborhoods at age 16. The definition of "urban" ["tätort" in Swedish] is however relatively generous, including all contiguous settlements with at least 200 inhabitants. Hence, a neighborhood can be "urban" even if the municipality it belongs to is classified as rural, see section 3.2.3 regarding the classification of municipalities. Estimates based on regressions including non-movers are also presented in the appendix.

Since occupational choices are closely linked to educational outcomes, we extend the analysis and explore further the role of higher education in explaining the hypothesized long-term neighborhood effects on occupational opportunities. Furthermore, we explore the role of geography in labor market opportunities, to analyze whether the potential long-term neighborhood effects are driven by individuals residing in or moving to larger (metropolitan) regions.

4. Empirical results on long-term neighborhood effects on occupational outcomes

First, we run estimations using the binary logit model to examine the extent to which the individual's neighborhood of residence at age 16 influences their occupation in 2019. Specifically, we focus on whether individuals hold managerial positions or occupations requiring (an advanced level of) higher education (occupational groups 1-3), or any other occupation (occupational groups 4-9). These distinctions correspond to whether an individual's occupation falls within skill levels 3-4 rather than skill levels 1-2. The results for this binary outcome are presented in specification 1 in Table 2.

We also run a MNL (Specifications 2a-c) to distinguish among the three occupation groups characterized by high skill levels. This analysis aims to understand how an individual's neighborhood of residence at age 16 influences the probability of holding different types of occupations: a managerial role (group 1), an occupation requiring an advanced level of higher education (group 2), or an occupation necessitating higher education or equivalent qualifications (group 3). These categories are again compared to occupations categorized under low skill levels (groups 4-9). Each occupation group (1-3) is thus compared to the reference group, which encompasses all other occupations except groups 1-3, excluding military workers. Additionally, Table A2 in the appendix presents the results for the control variables.

Table 2. Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019.

	(1) Logit		(2) Mlogit	
	Group 1-3	(a) Group 1	(b) Group 2	(c) Group 3
Low education (base=5%)				
10%	-.0123	-.0015	-.0195**	.0092
	(.0089)	(.0066)	(.0089)	(.0082)
25%	-.0220***	-.0051	-.0256***	.0090
	(.0077)	(.0058)	(.0077)	(.0071)
50%	-.0424***	-.0080	-.0396***	.0057
	(.0077)	(.0058)	(.0078)	(.0071)
75%	-.0565***	-.0081	-.0476***	-.0004
	(.0079)	(.0061)	(.0081)	(.0074)
90%	-.0564***	-.0094	-.0524***	.0056
	(.0084)	(.0066)	(.0087)	(.0080)
95%	-.0528***	-.0006	-.0507***	-.0013
	(.0099)	(.0083)	(.0107)	(.0095)
100%	-.0594***	-.0048	-.0538***	-.0006
	(.0104)	(.0087)	(.0112)	(.0100)
Poverty (base=5%)				
10%	-.0067	.0031	-.0031	-.0066
	(.0077)	(.0062)	(.0082)	(.0076)
25%	-.0060	.0062	-.0093	-.0028
	(.0066)	(.0054)	(.0070)	(.0065)
50%	-.0118*	.0063	-.0143**	-.0036
	(.0066)	(.0052)	(.0069)	(.0064)
75%	-.0245***	.0093	-.0235***	-.0106
	(.0066)	(.0054)	(.0070)	(.0065)
90%	-.0285***	.0064	-.0269***	-.0079
	(.0072)	(.0059)	(.0077)	(.0072)
95%	-.0316***	.0048	-.0297***	-.0070
	(.0091)	(.0078)	(.0099)	(.0091)
100%	-.0533***	.0053	-.0388***	-.0199**
	(.0101)	(.0085)	(.0110)	(.0098)
Ethnic (base=5%)				
10%	.0243***	.0080	.0200**	-.0039
	(.0089)	(.0084)	(.0101)	(.0095)
25%	.0108	.0028	.0190**	-.0112
	(.0074)	(.0069)	(.0083)	(.0079)
50%	.0267***	.0054	.0356***	-.0147*
	(.0074)	(.0068)	(.0082)	(.0078)
75%	.0226***	.0015	.0373***	-.0165**
	(.0076)	(.0069)	(.0084)	(.0080)
90%	.0120	-.0056	.0312***	-.0141*
	(.0081)	(.0073)	(.0089)	(.0084)
95%	.0023	-.0172**	.0439***	-.0248**
	(.0097)	(.0085)	(.0108)	(.0099)
100%	.0058	-.0195**	.0320***	-.0081
	(.0104)	(.0090)	(.0120)	(.0110)
Region type (age 16)	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Pseudo R2	0.1937	0.1098	0.1098	0.1098
Predicted probability	0.6868	0.1432	0.3367	0.2069

Notes. The number of observations is 99,289. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

To gain a better understanding of the magnitude and the economic significance of the estimates presented in Table 2, Figures 1-2 illustrate the predicted probability for each outcome for each level of the neighborhood variables.

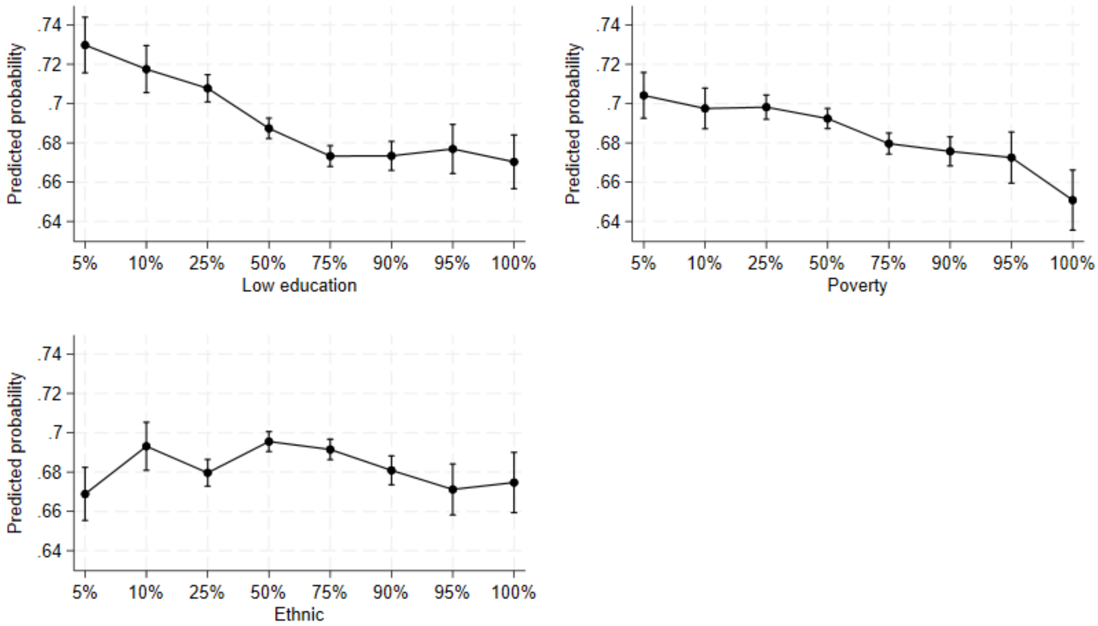

Figure 1. Predicted Probability of having an Occupation in Group 1-3 versus Group 4-9 in 2019 for Individuals Residing in Various Types of Neighborhoods at Age 16 (1991-1995).

In general, the probability of having a high-skill occupation is relatively high. Specifically, 68.7 percent of the male population under study is employed as either managers or in occupations requiring higher education (refer to Table 1). Nevertheless, as illustrated in Figure 1, the probability of holding one of these three occupation types diminishes if the individual resided in a socioeconomically disadvantaged area at age 16.

The predictive margin for individuals residing in the lowest 5 percent neighborhoods in terms of low education (denoted as the share of the working-age population with elementary school or less) is 73.0 percent. In contrast, this percentage decreases to 67.0 percent for individuals who lived in the highest 5 percent neighborhoods. This reflects an average marginal effect of -0.0594, as shown in Table 2, signifying an approximate decrease of 6 percentage points in the predicted probability.

In terms of poverty (measured as the share of the working-age population at risk of poverty), individuals who lived in the least impoverished neighborhoods at age 16 exhibit a predictive margin of 70.4 percent. In contrast, those residing in the most impoverished neighborhoods show a lower percentage at 65.1 percent. Consequently, individuals from the latter category are 5.3 percentage points less likely to have an occupation as a manager or one that requires (advanced) higher education in 2019. Both aspects that capture socioeconomic status align in the same direction—the socioeconomic status of the neighborhood experienced during adolescence manifests significant long-term effects on occupational outcomes later in life. Hence, despite previous studies on Sweden showing small or no long-term neighborhood effects on income (Brännström, 2005; Lindahl, 2011), we find quite substantial impacts on occupational choices. This is in line with theoretical underpinnings on information feedback loops between individual and group choices based on the past behavior of some people, which affects future choices of others (Akerlof 1997; Topa and Zenou 2015; Topa 2011). The negative relationship between neighborhood socioeconomic status and probability to gain a high-skilled job may also be explained by weaker employment-enhancing network attachments resulting from growing up in poorer areas with low employment rates (cf. Elliott 1999; Eilers et al. 2022).

The findings related to ethnic segregation (measured as the share of the population born in non-Nordic/EU15 countries) present a different story. There is no significant difference in the predicted probability of having a high-skill occupation for individuals residing in the most ethnically segregated neighborhoods, representing the 90-100% range in Table 2 and Figure 1, compared to those residing in the least ethnically segregated neighborhoods (5%). However, individuals living in certain 'medium' ethnically segregated neighborhoods are more inclined to have a high-skill occupation compared to those in 'extreme' neighborhoods at either end of the distribution, showing marginal effects of approximately 2.5 percentage points. It's crucial to remember that residential segregation patterns in Sweden during the early 1990s differed significantly and were far less pronounced than the patterns observable in present times (Aldén et al., 2015; Wixe and Pettersson, 2020). Additionally, the relationship between socioeconomic and ethnic segregation has evolved over time. In the early 1990s, the correlation between them was relatively weak, whereas in subsequent years, ethnic and socioeconomic segregation have become more closely intertwined (Wixe and Pettersson, 2020). The data utilized in this paper indicates that during 1991-1995 (the period for which neighborhood characteristics are evaluated), the average correlations at the neighborhood level between ethnic composition and low education, ethnic composition and poverty, and low education and poverty are 0.10, 0.39, and 0.20, respectively. Comparatively, the corresponding bivariate correlations in 2019 are significantly higher, 0.63, 0.74, and 0.70, respectively.

Table 2, specifications 2a-c, and Figure 2 indicate that the outcomes for long-term neighborhood effects on high-skill occupations are predominantly influenced by group 2—Occupations requiring an advanced level of higher education. Individuals residing in the most educationally disadvantaged neighborhoods at age 16 are 5.4 percentage points less likely to have these occupations compared to those in the least disadvantaged neighborhoods (specification 2b).

The average marginal effects and the (green) curve depicted in Figure 2 demonstrate an almost linear relationship between neighborhood education levels and the likelihood of having an occupation requiring advanced higher education. Consequently, the higher the proportion of low-educated individuals in the neighborhood during adolescence, the lower the likelihood of having an occupation demanding an advanced level of higher education in adulthood. A similar trend is observed for neighborhoods disadvantaged in terms of poverty, although the marginal effects are somewhat smaller (up to 3.9 percentage points) and only become significant after the 25th percentile.

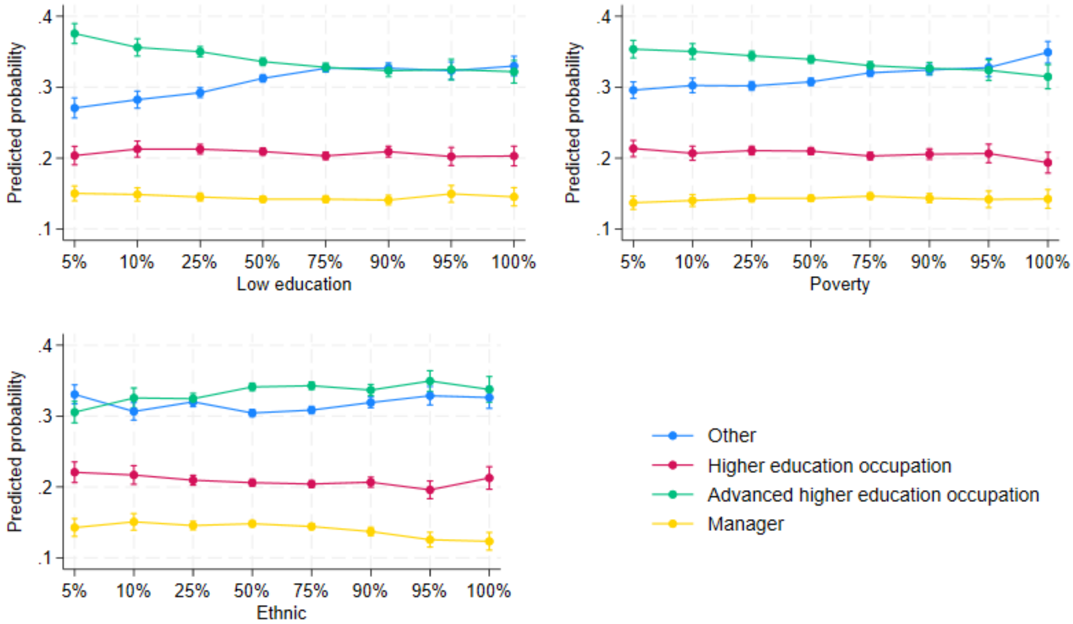

Figure 2. Predicted Probability of having an Occupation in the Respective Group 1-3 versus Group 4-9 (Denoted 'Other' in the Figure) in 2019 for Individuals Residing in Various Types of Neighborhoods at Age 16 (1991-1995).

It's interesting to note that individuals who lived in neighborhoods with higher proportions of non-Nordic/EU15 populations are more inclined to have occupations requiring advanced higher education. For individuals residing in neighborhoods above the 25th percentile, the average marginal effect ranges between 3.1 and 4.4 percentage points (specification 2b), showing a different pattern from the linear change observed in the socioeconomic variables.

Conversely, individuals who resided in the most ethnically segregated neighborhoods (above the 90th percentile) during adolescence are less likely to become managers as adults. The predicted probability of being a manager decreases by nearly 2 percentage points from the least to the most ethnically segregated neighborhoods (specification 2a). Considering that the overall probability of being a manager is less than half the probability of having an occupation requiring advanced higher education (refer to Table 1), this effect is comparable to the impact of socioeconomic disadvantage on the likelihood of having an occupation requiring an advanced level of higher education, as discussed earlier.

Moreover, with the exception of the most ethnically segregated neighborhoods, ethnic segregation also tends to exhibit a negative long-term effect on the likelihood of having an occupation requiring higher education or equivalent (specification 2c). The average marginal effects for socioeconomic disadvantage, however, are consistently insignificant for both occupation group 1 (managers) and group 3 (higher education occupations). Hence, our results show that it is the occupations that requires an individual to have taken an *advanced* educational path that are less prevalent among those growing up in socioeconomically weaker neighborhoods, while positions as managers and jobs requiring less-advanced higher education are more accessible no matter one's socioeconomic background. This supports the strong relationship between neighborhood environments and individual educational choices shown by several prior studies (Garner and Raudenbush, 1991; Wodtke et al., 2011; Hedefalk and Dribe, 2020; Andersson and Malmberg, 2015; Laliberté, 2021; Wodtke et al., 2023; Troost et al., 2023; Levy, 2021; Andersson and Subramanian, 2006; Chetty et al., 2016; Chetty and Hendren, 2018).

4.1. Estimations on 2-digit occupational groups

Subsequently, we perform similar multinomial regressions (MNL) as previously conducted, dividing the three 1-digit groups into 18 two-digit groups (see Table 1). Due to the relatively fewer observations in each category, the estimations fail to converge when incorporating regional fixed effects. Therefore, these are substituted with regional types, distinguishing between metropolitan, urban, and rural municipalities.[7] The results for different occupational groups with a significant result for neighborhood characteristics are visualized in Figure 3. The full estimation results for the 2-digit occupational groups are presented in the Appendix Table A3-5. Table 2 above showed that, in general, the likelihood of becoming a manager is not notably influenced by the socioeconomic status of neighborhoods during individuals' adolescence. However, Figure 3 (upper left) and Table A3 present a slightly more nuanced scenario. Individuals residing in neighborhoods with higher shares of low-educated individuals at age 16 tend to have reduced likelihoods of becoming legislators, chief executives, and senior government officials (group 11), administrative and commercial managers (group 12), as well as financial and insurance services branch managers (group 16). Given the relatively low average predicted probability of belonging to these specific occupation groups, as reported at the table's end, the marginal effects are notably significant. For instance, the average predicted probability of being an administrative or commercial manager (group 12) is 4.9 percent. Relative to having a low-skill occupation, the probability of being such a manager decreases by approximately one percentage point for individuals residing in neighborhoods with the highest share of low-educated individuals (above the 75th percentile) compared to those residing in neighborhoods with the lowest share of low-educated individuals (up to the 5th percentile).

[7] We have run three additional estimations only splitting one 1-digit group (into 2-digit groups) at a time and including region fixed effects. With this approach, the estimation splitting group 2 (but not group 1 and 3) converges and shows very similar results as when including all 2-digit groups (within group 1-3) at the same time and replacing region FE with region types, that is, the results presented in Table A4.

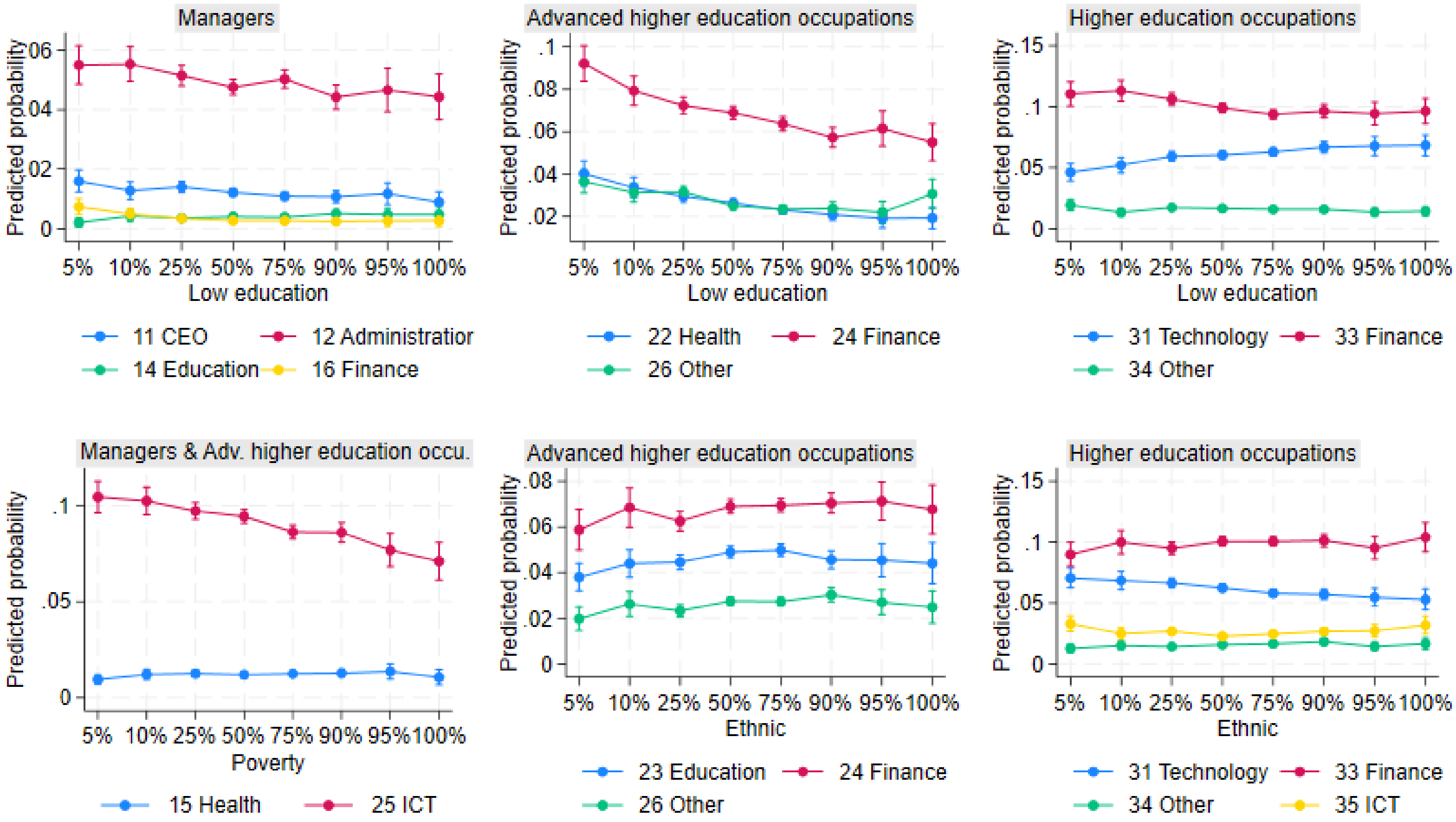

Figure 3. Predicted Probability of having an Occupation in the Respective Subgroup, 11-17, 21-26, 31-35, versus Group 4-9 in 2019 for Individuals Residing in Various Types of Neighborhoods at Age 16 (1991-1995).

Moreover, the predicted probability of being a financial and insurance services branch manager (group 16) is generally very low (0.33 percent) and even lower (as low as 0.24 percent) for individuals who did not reside in neighborhoods with the highest educational advantages. For those in the base category (up to the 5th percentile), the predicted probability is 0.74 percent, which is three times larger. Conversely, this trend is reversed for managers within education (group 14). Figure 3 (upper left) and Table A3 illustrate that individuals residing in neighborhoods with the lowest shares of low-educated individuals (again, the base category) are the least likely to become education managers. However, there is no linear decreasing trend observed when increasing the share of low-educated individuals (moving down the percentiles). Although the predicted probability for each percentile differs statistically from the base category (5%), they do not statistically differ from each other.

Figure 3 (upper middle) and Table A4 indicate that the negative long-term effect of socioeconomic disadvantage, particularly in terms of education, on the likelihood of having an occupation requiring an advanced level of higher education is chiefly influenced by occupations within health care (group 22), finance and management (group 24), and law, culture, and social work (group 26). Once more, the average marginal effects demonstrate considerable impact on the average predicted probabilities.

Concerning health and finance, a discernible linear decreasing trend as seen in Figures I and II is evident. Specifically, the predicted probability of having an advanced occupation within health care significantly drops for those residing in neighborhoods with the highest shares of low-educated individuals at age 16, reaching a mere 1.9 percent in contrast to 4.0 percent for individuals who resided in the least low-educated neighborhoods.

Figure 3 (lower left) and Table A4 show that the negative impact of residing in poorer neighborhoods at age 16 on the likelihood of having an occupation requiring an advanced level of higher education primarily affects occupations within information and communications technology (group 25). The probability of having such an occupation decreases from 10.4 percent for individuals residing in the least poor neighborhoods (up to the 5th percentile) to 7.1 percent for those in the poorest neighborhoods (above the 95th percentile).

Moreover, Figure 3 (lower middle) and Table A4 highlight that the positive influence of residing in more ethnically segregated neighborhoods is prominent in advanced occupations within education (group 23), finance (group 24), and 'other' (group 26). However, this trend doesn't hold true for individuals residing in neighborhoods with the highest shares of non-Nordic/EU15 populations (above the 90/95th percentile). Interestingly, Table A4 shows that experiencing socioeconomic and ethnic segregation during adolescence doesn't appear to significantly influence the probability of having an occupation requiring advanced academic competence in science and technology (group 21), except for individuals who resided in the most ethnically segregated neighborhoods (above the 95th percentile).

Previously, Table 2 indicated that the likelihood of an individual having an occupation requiring higher education or equivalent is generally unaffected by the socioeconomic status of their neighborhoods at age 16. However, upon further examination of the 2-digit groups in Figure 3 (upper right) and Table A5, it becomes evident that individuals who resided in low-education neighborhoods are less likely to hold occupations requiring higher education qualifications or equivalent, specifically within finance and management (group 33). This finding suggests that Figure 3 and Tables A.3.a-c consistently demonstrate that individuals who lived in neighborhoods with higher shares of low-educated individuals at age 16 tend to have reduced probabilities of holding high-skill occupations within finance and related activities.

Conversely, individuals who resided in low-educated neighborhoods are more likely to have higher education occupations in technology (group 31). However, these occupations are less probable for individuals who lived in neighborhoods with higher shares of non-Nordic/EU15 populations. Notably, ethnic segregation, particularly at least medium levels, appears to have a somewhat adverse effect on obtaining a higher education occupation within information, communication (ICT), sound and light technologies, etc. (group 35).

The effects concerning ethnic segregation, however, exhibit some ambiguity. There's a tendency for somewhat positive effects on occupations requiring higher education or equivalent in finance and management (group 33), as well as in culture, wellness, and social work (group 34). As discussed previously, we have observed positive long-term effects of ethnic segregation for some occupations requiring advanced levels of higher education.

4.2. Urban residents and non-movers

As RegSO areas cover relatively large geographical zones in rural areas outside densely populated cities and towns, they might be less reflective of actual neighborhoods. To test the robustness of our findings, we re-estimate the specifications in Table 2, focusing solely on individuals who resided in the urban areas of municipalities at age 16. The updated results are outlined in Table A.4 in the appendix.

In the logit estimation (specified as 1i), the outcomes remain robust concerning the neighborhood's share of low education. However, when restricting the analysis to urban residents, the significance and impact of poverty on outcomes diminish to some extent. Conversely, individuals who lived in the two most ethnically segregated types of neighborhoods at age 16 exhibit a lower likelihood of having a high-skill occupation later in life. This suggests a persistent adverse effect of residing in neighborhoods with the highest shares of non-Nordic/EU15 populations.

The MNL estimations (specified as 2i) echo the findings of specification 2 in Table 2. The negative impact of ethnic segregation primarily affects managers (2ia) and individuals in occupations requiring higher education qualifications (2ic). However, the effect remains positive for individuals in occupations requiring an advanced level of higher education (2ib).

Table A5 in the appendix presents the results concerning neighborhood variables obtained from estimations that include non-movers. These individuals remained in the same neighborhood or at least the same municipality in 2019 as they did at age 16. This substantially increases the number of observations, leading to a notable increase in the significance and magnitude of the average marginal effects.

Specifically, there is an approximate doubling of the average marginal effects derived from residing in the most socioeconomically disadvantaged neighborhoods, significantly impacting the probability of having a high-skill occupation (as indicated in specification 1ii). Furthermore, the inclusion of non-movers indicates that socioeconomic disadvantage also diminishes the likelihood of acquiring occupations requiring higher education (group 3, as seen in specification 2iic) and attaining managerial positions (group 1, as observed in specification 2iia, specifically associated with low education). However, it's important to note that these effects may not represent long-term neighborhood impacts, as there might be a correlation across time regarding locational characteristics. The results even point to an overestimation of long-term neighborhood effects when including non-movers, mainly deriving from biased estimates on group 1 and 3.

Nevertheless, the results regarding group 2 (Occupations requiring an advanced level of higher education) demonstrate consistency in both sign, size, and significance between Table 2 (specification 2) and Table A.5 (2iib). That socioeconomic disadvantage at neighborhood level experienced during adolescence is detrimental for obtaining occupations requiring advanced higher education thus seems to be a robust result.

4.3. The role of higher education

The results above point to the strongest long-term neighborhood effects on occupations requiring an advanced level of higher education (group 2). It is thus plausible that the link between the neighborhood characteristics experienced at youth and high-status jobs goes through higher education studies. Indeed, previous literature point to significant neighborhoods effects on educational choices and outcomes in particular (Garner and Raudenbush, 1991; Wodtke et al., 2011; Hedefalk and Dribe, 2020; Andersson and Malmberg, 2015; Laliberté, 2021; Wodtke et al., 2023; Troost et al., 2023; Levy, 2021; Andersson and Subramanian, 2006; Chetty et al., 2016; Chetty and Hendren, 2018). To explore the role of higher education as the mechanism between our neighborhood characteristics and high-skilled jobs, we start off by estimating the long-term neighborhood effects on the probability of being highly educated (that is, having engaged in at least three years of higher studies, corresponding to a bachelor education). The results are presented in Table A8 (specification 4) and visually in Figure 4, where the underlying estimation corresponds to specification 1 in Table 2, the only difference being that the binary outcome is now being highly educated or not (instead of having a high-skill occupation or not). Furthermore, in Table A8 (specification 5), we present results from multinomial logit estimations, separating various types of higher education – short higher education (1-2 years), bachelor (at least 3 years but less than 5), master (at least 5 years), PhD (postgraduate education) – versus the base category that includes individuals with at most high school studies (note that the reference category varies across specification 4 and 5).

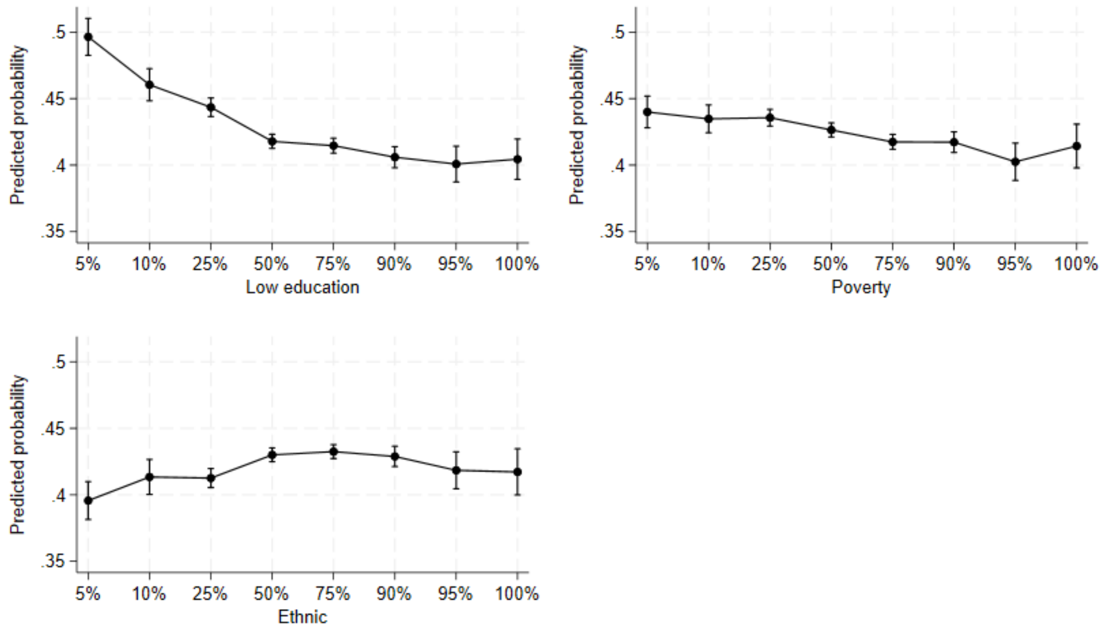

Figure 4. Predicted Probability of having at least Three Years of Higher Education in 2019 for Individuals Residing in Various Types of Neighborhoods at Age 16 (1991-1995).

Figure 4 (Table A8) shows a similar pattern to Figure 1 (Table 2, specification 1), there is a relatively strong negative relationship between socioeconomic disadvantage experienced during adolescence and the probability of being highly educated as an adult. The relationship with neighborhood type is particularly pronounced for low education, which points to the importance of having (educated) role models in the community (Durlauf, 2004; Ioannides and Topa, 2010). Individuals who resided in the neighborhoods with the highest shares of low educated are close to 10 percentage points less likely to pursue higher education themselves. Table A8 shows that the relatively strongest marginal effects are found for master studies (spec 5c) followed by bachelor studies (spec 5b). There are however relatively few individuals who have engaged in master and PhD studies, therefore, in the remaining analysis we focus on the group of individuals with *at least* bachelor studies, i.e., the so called highly educated.

Next, we estimate the long-term neighborhood effects on occupational choices for highly educated individuals, presented in Table A9, as well as for non-highly educated individuals, presented in Table A10. As can be noted from Table A9 (specification 1iii), a striking 93.98 percent of highly educated individuals have a high-skill occupation. Among individuals lacking higher education (equivalent to at least bachelor studies), 50 percent have a high-skill job (specification 1iv). Unsurprisingly, the decrease in probability primarily stems from a lower percentage being employed in occupations requiring *advanced* higher education. Figure 5 summarizes the results on neighborhood characteristics from the logit estimations (specification 1iii and 1iv).

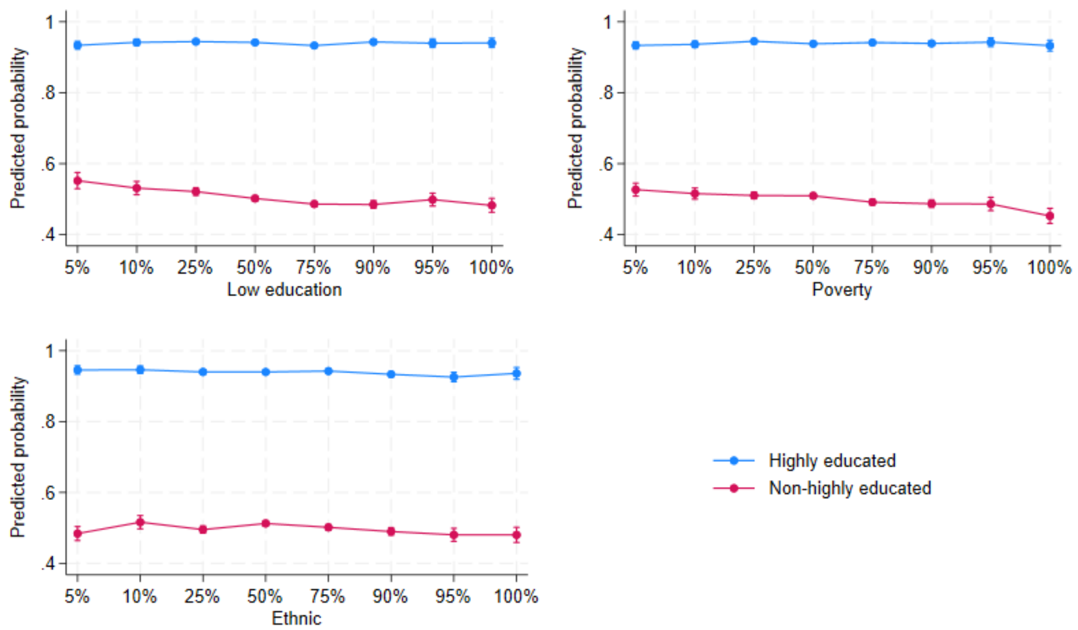

Figure 5. Predicted Probability of having an Occupation in Group 1-3 versus Group 4-9 in 2019 for Highly Educated and Non-Highly Educated Individuals Residing in Various Types of Neighborhoods at Age 16 (1991-1995).

Figure 5 and Table A9 show that the occupational choice of highly educated individuals is mainly uninfluenced by the neighborhood characteristics experienced during adolescence. Hence, higher education is an important means to mitigate the disadvantages that growing up in a socioeconomically weaker neighborhood brings. Being highly educated does however not help to fully overcome the impact of socioeconomic disadvantage at the family level. Our results (Table A9) show that also among highly educated individuals the likelihood of gaining an occupation that requires advanced higher education is higher if their father is also highly educated.

Neighborhood socioeconomic disadvantage is however still highly significant for non-highly educated individuals (Table A10), where the negative effect can be seen not only for occupations requiring advanced higher education (spec 2ivb), but also for manager positions (spec 2iva) and occupations requiring higher education or equivalent (2ivc).

4.4. The role of geography

Table A2, showing the results for the control variables of the baseline estimations, display that individuals residing in metropolitan regions at age 16 are less likely to have a high-skill occupation as an adult. This result goes against theory and previous literature pointing to increased labor market opportunities, due to, for example, more job diversity, better matching, and knowledge spillovers in larger regions (Duranton and Puga, 2004). Our somewhat counterintuitive result may be a function of our selected study population, which consists of individuals not residing in the same municipality in 2019 as at age 16. This is likely to exclude skilled individuals in metropolitan regions who opt for staying in their home municipality, while skilled individuals growing up in non-metropolitan regions tend to move towards metropolitan regions and are thus included in our population of study. We therefore re-estimate the long-term neighborhood effects on the probability of having a high-skilled occupation for individuals moving to metropolitan regions (from non-metropolitan regions), individuals staying in metropolitan regions, and individuals staying in non-metropolitan regions, presented in Table 3.

Table 3. Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019, Movers vs Stayers.

		(1v) Logit	
	(a) Movers to metro	(b) Stayers in metro	(c) Stayers in non-metro
Low education (base=5%)			
10%	-.0077	-.0036	-.0125
25%	.0072	-.0369***	-.0176
50%	-.0280	-.0357***	-.0383***
75%	-.0248	-.0661***	-.0562***
90%	-.0295	-.0454**	-.0555***
95%	-.0117	-.0476	-.0556***
100%	-.0323	.0018	-.0661***
Poverty (base=5%)			
10%	-.0128	-.0486*	.0053
25%	-.0085	-.0189	-.0031
50%	-.0169*	-.0232	-.0088
75%	-.0150	-.0293	-.0309***
90%	-.0218*	-.0274	-.0334***
95%	-.0078	-.0112	-.0465***
100%	-.0232	-.0463	-.0749***
Ethnic (base=5%)			
10%	.0130	.0717	.0311***
25%	.0077	.2364	.0102
50%	.0122	.2324	.0272***
75%	.01645	.1846	.0225**
90%	.0199	.1612	.0135
95%	-.0176	.1451	.0207
100%	-.0062	.1446	.0048
Parental controls			
Father's education	.0620***	.0950***	.1154***
Father's income	.0058***	.0048***	.0095***
Father's ethnic background	.0444***	.0550***	.0739***
Region type (age 16)	YES	YES	YES
Parental controls	YES	YES	YES
Individual controls	YES	YES	YES
Region FE	YES	YES	YES
Pseudo R2	0.1652	0.1653	0.1762
Observations	26,828	15,819	56,642
Predicted probability	0.8066	0.7561	0.6107

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

Table 3 shows that long-run neighborhood effects are virtually non-existent for individuals who move to metropolitan municipalities. Also stayers in metropolitan regions tend to be somewhat less affected by their neighborhood of adolescence, even though there seems to be a u-shaped effect of low-education neighborhoods. On the other hand, stayers in non-metropolitan regions are significantly influenced in their occupational choices by socio-economic disadvantage at neighborhood level, both in terms of low education and poverty. These results can be interpreted as if socioeconomic disadvantage resulting from the adolescent neighborhood can be overcome by moving to metropolitan municipalities, which is consistent with the literature on agglomeration economies (Duranton and Puga, 2004). What cannot be (fully) overcome by spatial mobility is the socioeconomic heritage from the parents. No matter whether individuals stay or move between region types, the father's education, income, and background matter for occupational outcomes. In line with previous studies, we find overall strong intergenerational persistence in socioeconomic outcomes (Lo Bello and Morchio, 2022; Björklund and Jäntti, 2012; García-Mainar and Montuenga, 2020; Chetty et al., 2020; Chetty et al., 2014; Case and Katz, 1991; Nicardo et al., 2024; Corcoran et al., 1990). The average marginal effects are however smaller in magnitude for movers than for stayers.

We further show in Figure 6 and Table A11 that individuals residing in neighborhoods with a higher share of low educated are less likely to move to metropolitan municipalities (as opposed to non-metropolitan municipalities, considering that all studied individuals do move), *and* are less likely to stay in metropolitan municipalities if they resided in such a municipality at age 16, which thus creates an additional barrier to obtaining high-skilled jobs. The predicted probability to move to a metropolitan municipality is approximately 50 percent for an individual who resided in the 5 percent of neighborhoods with the lowest shares of low educated (least disadvantaged), while the probability decreases by almost half, to 26 percent, for individuals who resided in the 5 percent of neighborhoods with the highest shares of low educated (most disadvantaged). An ambiguity is however that individuals residing in poorer neighborhoods are more likely to move to metropolitan neighborhoods, with a marginal effect of 10 percentage points going from the least to the most poor neighborhoods. These results further emphasize the central role of education, both of the individual himself and of the neighbors surrounding the individual during adolescence, for securing high-skilled occupations.

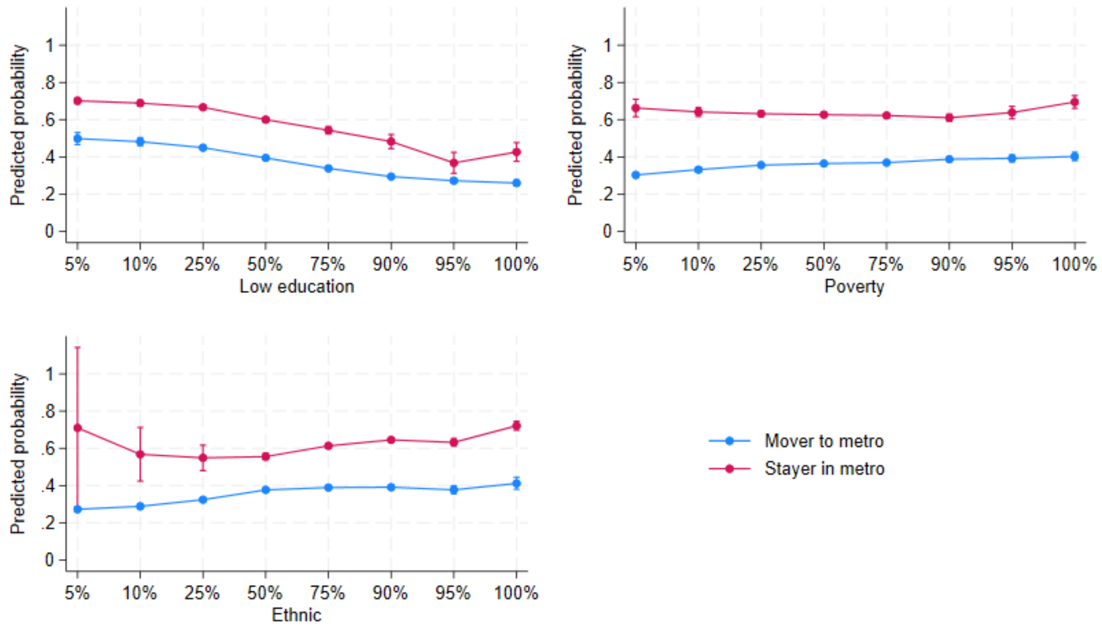

Figure 6. Predicted Probability of Moving to a Metropolitan Region vs Staying in a Non-Metropolitan Region (blue line), and Staying in a Metropolitan Region vs Moving to a Non-Metropolitan Region (red line) for Individuals Residing in Various Types of Neighborhoods at Age 16 (1991-1995).

5. Conclusions

In this paper we ask if there are enduring long-term effects of living in disadvantaged neighborhoods during adolescence on occupational choices in mid-prime working years. We specifically examine how socioeconomic and ethnic segregation experienced at age 16 (year 1991-1995) impact the likelihood of Swedish males getting high-skilled jobs at age 40-44 (year 2019). Males are in focus since for this group we can control for cognitive abilities and behavioral traits by matching military enlistment data to our register data. To avoid spatial correlation across time, our baseline estimations exclude individuals residing in the same municipality in 2019 as at age 16. The results indicate that neighborhood characteristics during adolescence notably influence the probability of obtaining high-skilled well-paid jobs later in life. Despite the significance of an individual's own cognitive ability and his parents' socioeconomic background, growing up in marginalized neighborhoods—specifically marked by low education and poverty—diminishes the likelihood of securing occupations that require advanced higher education in adulthood. These results are in line with previous studies in the Swedish context regarding long-term neighborhood effects on various educational and labor market outcomes (Andersson, 2004; Andersson and Subramanian, 2006; Andersson and Malmberg, 2015; Wixe, 2020). Our study is, however, the first to investigate the influence of socioeconomic background on occupational outcomes in particular.

We extend the analysis and show that the negative influence of socioeconomic deprivation at neighborhood level can be explained by both a lower probability to engage in higher education and a lower probability to move to metropolitan municipalities. While spatial mobility and educational achievements mitigate the disadvantages stemming from the neighborhood of residence, they cannot fully overcome the socioeconomic heritage stemming from the parents. The intergenerational persistence in socioeconomic outcomes (Lo Bello and Morchio, 2022; García-Mainar and Montuenga, 2020; Chetty et al., 2020; Chetty et al., 2014; Case and Katz, 1991; Nicardo et al., 2024; Corcoran et al., 1990) is thus strong also in Sweden (cf. Björklund and Jäntti (2012)), a country with relatively few formal barriers for socioeconomic mobility due to its institutional settings.

Interestingly, individuals appear to be less influenced by ethnic segregation, except for those entering certain occupations requiring an advanced level of higher education, as they show a positive correlation with experiencing a higher share of non-Nordic/EU15 populations in their neighborhoods during adolescence. However, it's crucial to note that contemporary segregation patterns differ significantly from those of the early 1990s. The stronger correlations observed today between socioeconomic and ethnic segregation make it more challenging to disentangle these neighborhood effects. Consequently, our results suggest that the negative aspects of residential segregation primarily stem from a socioeconomic perspective rather than ethnicity, which is in line with the conclusions of Wixe and Pettersson (2020).

These findings highlight several policy implications. If residing in disadvantaged neighborhoods during adolescence negatively impacts future occupational prospects, there's a crucial need for targeted intervention programs. These programs should concentrate on enriching educational opportunities and creating job prospects, as well as enhancing spatial mobility, particularly towards metropolitan areas, to enhance the chances of obtaining high-skilled occupations later in life. Moreover, mentorship programs and extracurricular activities could significantly enhance individuals' capabilities and ambitions. Supporting parents in disadvantaged neighborhoods might also positively influence their children's development and future prospects. Nicardo et al. (2024) provide evidence that the effects of policy initiatives targeting poverty in disadvantaged communities spill over to coming generations.

Additionally, community development initiatives focusing on overall well-being could potentially enhance occupational opportunities for residents. In summary, our results emphasize the necessity for policy interventions that target the young generation, community development, and economic opportunities within disadvantaged neighborhoods. Such interventions can collectively contribute to improving the long-term occupational outcomes for individuals growing up in these areas.

Having said this, occupational outcomes later in life is clearly also a function of educational choices along the way and our results show the strongest relationship between socioeconomic neighborhood environment and precisely those occupations requiring advanced higher education. Thus, it could be argued that our entire career paths and life journeys, including higher education, job choices, income, spatial mobility, and socioeconomic status, are shaped by our experiences in the neighborhood during adolescence.

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Appendix

Table A1. List of Independent Variables.

Variable	Definition
Neighborhood characteristics (age 16)	
Low education	Categorical variable indicating which percentile the neighborhood belongs to regarding share of working age population with elementary school or less (see below for percentiles).
Poverty	Categorical variable indicating which percentile the neighborhood belongs to regarding share of working age population in risk of poverty (see below for percentiles).
Ethnic	Categorical variable indicating which percentile the neighborhood belongs to regarding share of population born in non-Nordic/EU15 countries. - 5% (1^{st}-5^{th} percentile) (base) - 10% (6^{th} -10^{th} per.) - 25% (11^{th} -25^{th} per.) - 50% (26^{th} -50^{th} per.) - 75% (51^{st} -75^{th} per.) - 90% (76^{th} -90^{th} per.) - 95% (91^{st} -95^{th} per.) - 100% (96^{th} -100^{th} per.)
Region type (age 16)	Categorical variable indicating what type of region the municipality is part of: - Remote rural (base) - Near rural - Remote urban - Near urban - Metropolitan
Parental controls	
Father's education	Dummy variable equal to one if the father has three or more years of higher education.
Father's income	Father's wage income (ln).
Father's ethnic background	Dummy variable equal to one if the father is born in a non-Nordic/EU15 country.
Individual controls	
Age	Categorical variable indicating age of the individual in 2019: - 40 (base) - 41 - 42 - 43 - 44
Ethnic background	Dummy variable equal to one if the individual himself is born in a non-Nordic/EU15 country.
Civil status	Categorical variable indicating family status in 2019: - Single without children (base) - Single with child(ren) - Married without children - Married with child(ren)
IQ	Evaluation of verbal, spatial, logical, and technical abilities at age 18-19, summarized on a scale from 1 to 9 (continuous variable).
Region FE	Categorical variable indicating which local labor market region the individual resides in in 2019 (94 regions).

Notes. Married includes co-habitants.

Table A2. Average Marginal Effects for Control Variables, Continuation of Table 2.

	(1 cont.) Logit Group 1-3	(a) Group 1	(2 cont.) Mlogit (b) Group 2	(c) Group 3
Neighborhood characteristics (age 16)	See Table 2	See Table 2	See Table 2	See Table 2
Region type (age 16)				
Near rural	-.0094*	.0052	-.0119*	-.0027
	(.0053)	(.0049)	(.0063)	(.0056)
Remote urban	.0228***	.0120**	.0151**	-.0042
	(.0060)	(.0056)	(.0072)	(.0063)
Near urban	-.0007	.0077*	-.0030	-.0056
	(.0049)	(.0044)	(.0058)	(.0051)
Metropolitan	-.0532***	.0024	-.0603***	.0054
	(.0062)	(.0052)	(.0068)	(.0063)
Parental controls				
Father's education	.0991***	.0193***	.0948***	-.0184***
	(.0038)	(.0030)	(.0040)	(.0035)
Father's income	.0077***	.0031***	.0041***	.0007
	(.0006)	(.0006)	(.0008)	(.0007)
Father's ethnic background	.0671***	.0185***	.0524***	-.0035
	(.0064)	(.0064)	(.0080)	(.0070)
Individual controls				
Age				
41	.0125***	.0053	.0092**	-.0019
	(.0041)	(.0034)	(.0045)	(.0041)
42	.0031	.0110***	.0029	-.0107***
	(.0041)	(.0034)	(.0044)	(.0041)
43	.0052	.0168***	-.0050	-.0066
	(.0042)	(.0034)	(.0044)	(.0041)
44	.0172***	.0256***	-.0003	-.0079*
	(.0041)	(.0035)	(.0044)	(.0040)
Ethnic background	.0043	-.0001	.0106	-.0056
	(.0073)	(.0066)	(.0085)	(.0074)
Civil status				
Single with child	.0833***	.0590***	.0062	.0181***
	(.0066)	(.0055)	(.0071)	(.0064)
Married	.0424***	.0239***	.0104	.0079
	(.0076)	(.0055)	(.0077)	(.0070)
Married with child	.1411***	.0790***	.0379***	.0244***
	(.0032)	(.0023)	(.0033)	(.0030)
IQ	.0763***	.0100***	.0679***	-.0015**
	(.0007)	(.0006)	(.0008)	(.0007)
Region FE	YES	YES	YES	YES
Pseudo R2	0.1937	0.1098	0.1098	0.1098
Predicted probability	0.6868	0.1432	0.3367	0.2069

Notes. The number of observations is 99,289. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

Table A3. AMEs of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a Certain 2-digit High-Skill (level 3-4) Occupation vs a Low-Skill (level 1-2) Occupation in 2019, Managers.

				(3) Mlogit			
	(a) G11 CEO	(b) G12 Administration	(c) G13 Production	(d) G14 Education	(e) G15 Health	(f) G16 Finance	(g) G17 Services
Low education (base=5%)							
10%	-.0032	.0003	.0006	.0022*	.0031	-.0025*	-.0010
25%	-.0020	-.0036	.0008	.0015*	.0010	-.0040***	-.0003
50%	-.0038*	-.0075**	.0038	.0020**	.0001	-.0046***	-.0013
75%	-.0051**	-.0047	.0016	.0018**	.0006	-.0047***	-.0018
90%	-.0053**	-.0108***	.0031	.0030***	.0000	-.0049***	-.0001
95%	-.0042	-.0084*	.0109**	.0027*	-.0008	-.0047***	-.0011
100%	-.0071***	-.0107**	.0062	.0026*	.0009	-.0046***	.0022
Poverty (base=5%)							
10%	.0015	-.0005	-.0012	-.0010	.0026	.0014	.0001
25%	.0005	.0023	-.0008	-.0004	.0031**	.0006	.0010
50%	.0018	.0018	-.0029	-.0005	.0025*	.0009	.0020
75%	.0013	.0028	-.0018	-.0006	.0030**	.0009	.0026
90%	.0016	.0001	.0018	-.0012	.0033*	.0004	.0003
95%	.0029	.0037	-.0021	-.0005	.0042*	-.0004	-.0018
100%	-.0005	.0022	.0010	.0001	.0012	.0011	.0026
Ethnic (base=5%)							
10%	.0007	-.0009	.0032	.0002	.0039	.0002	.0012
25%	-.0021	.0015	.0006	-.0003	.0029	-.0007	.0020
50%	-.0004	.0052	.0003	.0002	.0014	-.0003	.0011
75%	-.0011	.0033	-.0002	.0008	.0032*	-.0008	.0004
90%	-.0021	.0015	-.0007	.0006	.0026	-.0014	-.0003
95%	-.0026	-.0052	-.0018	.0003	.0017	.0002	-.0042*
100%	-.0050*	-.0049	-.0059	-.0002	.0021	-.0007	-.0022
Region type (age 16)	YES	YES	YES	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES	YES	YES	YES
Region type	YES	YES	YES	YES	YES	YES	YES
Predicted probability	0.0121	0.0491	0.0513	0.0040	0.0121	0.0033	0.0113

Notes. The pseudo R2 is 0.0725 and the number of observations is 99,289. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

Table A4. AMEs of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a Certain 2-digit High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019, Occupations Requiring Advanced Level of Higher Education.

	(3) Mlogit					
	(h) G21 Science	(i) G22 Health	(j) G23 Education	(k) G24 Finance	(l) G25 ICT	(m) G26 Other
Low education (base=5%)						
10%	-.0002	-.0066*	.0021	-.0128**	.0042	-.0052
25%	.0040	-.0108***	.0007	-.0198***	.0050	-.0049*
50%	.0021	-.0138***	.0030	-.0232***	.0046	-.0115***
75%	.0019	-.0172***	.0049	-.0284***	.0048	-.0131***
90%	.0032	-.0194***	.0045	-.0348***	.0059	-.0128***
95%	.0080	-.0211***	.0025	-.0306***	.0030	-.0146***
100%	.0026	-.0210***	-.0000	-.0371***	.0046	-.0059
Poverty (base=5%)						
10%	.0011	-.0041	-.0007	.0045	-.0020	-.0017
25%	-.0013	-.0035	-.0018	.0040	-.0072	-.0002
50%	-.0016	-.0014	-.0035	.0031	-.0101**	-.0019
75%	-.0037	-.0005	-.0038	.0015	-.0182***	-.0014
90%	-.0037	-.0015	-.0074**	.0016	-.0184***	-.0003
95%	-.0062	-.0018	-.0005	.0038	-.0276***	-.0015
100%	.0045	-.0026	-.0022	.0009	-.0334***	-.0060
Ethnic (base=5%)						
10%	-.0052	.0026	.0060	.0097	-.0001	.0065*
25%	.0013	-.0001	.0065*	.0037	.0023	.0035
50%	.0029	.0008	.0110***	.0102**	-.0014	.0077***
75%	.0005	.0025	.0118***	.0107**	-.0011	.0075***
90%	-.0061	.0021	.0076**	.0116**	-.0005	.0105***
95%	-.0016	.0060	.0074	.0125**	.0094	.0072*
100%	-.0144**	.0018	.0060	.0089	.0238	.0051
Region type (age 16)	YES	YES	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES	YES	YES
Region type	YES	YES	YES	YES	YES	YES
Predicted probability	0.0770	0.0261	0.0471	0.0681	0.0917	0.0268

Notes. The pseudo R2 is 0.0725 and the number of observations is 99,289. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

Table A5. AMEs of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a Certain 2-digit High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019, Occupations Requiring Higher Education Qualifications or Equivalent.

			(3) Mlogit		
	(n) G31 Technology	(o) G32 Health	(p) G33 Finance	(q) G34 Other	(r) G35 ICT
Low education (base=5%)					
10%	.0058	-.0007	.0026	-.0061**	.0068**
25%	.0131***	.0002	-.0043	-.0021	.0017
50%	.0143***	.0008	-.0115**	-.0027	.0033
75%	.0168***	.0002	-.0167***	-.0035	.0009
90%	.0206***	.0005	-.0141**	-.0035	.0007
95%	.0216***	-.0004	-.0161**	-.0059*	-.0010
100%	.0221***	-.0011	-.0141*	-.0052	-.0016
Poverty (base=5%)					
10%	-.0046	-.0004	.0003	-.0008	.0011
25%	.0001	.0012	-.0013	-.0030	.0030
50%	-.0030	.0002	.0027	-.0026	.0019
75%	-.0003	.0001	-.0045	-.0012	-.0008
90%	.0010	-.0012	-.0030	-.0020	.0014
95%	.0007	-.0002	.0028	-.0029	-.0034
100%	-.0017	-.0007	-.0088	-.0001	-.0042
Ethnic (base=5%)					
10%	-.0021	-.0011	.0100	.0024	-.0082**
25%	-.0041	.0000	.0051	.0015	-.0063*
50%	-.0082*	-.0006	.0107**	.0031	-.0103***
75%	-.0125***	.0003	.0106*	.0038*	-.0084**
90%	-.0134***	-.0003	.0114*	.0055**	-.0064*
95%	-.0158***	.0001	.0053	.0016	-.0059
100%	-.0175***	.0032	.0142*	.0039	-.0012
Region type (age 16)	YES	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES	YES
Region type	YES	YES	YES	YES	YES
Predicted probability	0.0611	0.0052	0.0992	0.0160	0.0254

Notes: The pseudo R2 is 0.0725 and the number of observations is 99,289. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019, Excluding Individuals Residing in Rural Parts of Municipalities at Age 16.

	(1i) Logit Group 1-3	(a) Group 1	(2i) Mlogit (b) Group 2	(c) Group 3
Low education (base=5%)				
10%	-.0066	.0015	-.0183**	.0106
25%	-.0160**	-.0018	-.0256***	.0117
50%	-.0329***	-.0036	-.0372***	.0081
75%	-.0458***	-.0021	-.0455***	.0021
90%	-.0534***	-.0069	-.0540***	.0075
95%	-.0510***	.0042	-.0610***	.0057
100%	-.0524***	-.0039	-.0541***	.0054
Poverty (base=5%)				
10%	-.0114	.0001	-.0060	-.0054
25%	-.0099	.0044	-.0129*	-.0013
50%	-.0138**	.0056	-.0171**	-.0021
75%	-.0198***	.0117**	-.0229***	-.0085
90%	-.0198**	.0076	-.0260***	-.0013
95%	-.0048	.0164	-.0207	-.0007
100%	-.0365***	.0180	-.0349**	-.0194
Ethnic (base=5%)				
10%	.0130	.0083	.0026	.0022
25%	-.0031	.0062	.0031	-.0124
50%	.0129	.0102	.0235*	-.0211*
75%	.0049	.0045	.0214*	-.0213*
90%	-.0095	-.0038	.0132	-.0194
95%	-.0242*	-.0193*	.0258**	-.0309**
100%	-.0284**	-.0023*	.0103	-.0169
Region type (age 16)	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Pseudo R2	0.1907	0.1070	0.1070	0.1070
Predicted probability	0.7012	0.1461	0.3470	0.2081

Notes: The number of observations is 82,444. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

Table A7. Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019, Including Non-Movers.

	(1ii) Logit Group 1-3	(a) Group 1	(2ii) Mlogit (b) Group 2	(c) Group 3
Low education (base=5%)				
10%	-.0184**	-.0051	-.0164***	.0046
25%	-.0472***	-.0127***	-.0307***	-.0019
50%	-.0725***	-.0194***	-.0446***	-.0065
75%	-.0954***	-.0220***	-.0535***	-.0181***
90%	-.1007***	-.0280***	-.0571***	-.0142**
95%	-.1087***	-.0221***	-.0569***	-.0279***
100%	-.1162***	-.0235***	-.0641***	-.0273***
Poverty (base=5%)				
10%	-.0113*	.0012	-.0038	-.0086
25%	-.0142***	.0001	-.0091*	-.0051
50%	-.0196***	.0006	-.0138***	-.0064
75%	-.0330***	.0029	-.0216***	-.0144***
90%	-.0486***	-.0012	-.0300***	-.0176***
95%	-.0543***	-.0009	-.0343***	-.0192***
100%	-.0672***	-.0052	-.0330***	-.0290***
Ethnic (base=5%)				
10%	.0151**	.0028	.0103	.0020
25%	.0056	.0030	.0069	-.0043
50%	.0221***	.0050	.0240***	-.0069
75%	.0185***	.0017	.0267***	-.0101*
90%	.0157**	-.0043	.0263***	-.0065
95%	.0091	-.0075	.0392***	-.0225***
100%	.0254***	-.0088	.0315***	.0024
Region type (age 16)	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES
Region FE	YES	YES	YES	YES
Pseudo R2	0.1942	0.1214	0.1214	0.1214
Predicted probability	0.5867	0.1260	0.2612	0.1995

Notes: The number of observations is 188,356. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

Table A8. Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having at least Three Years of Higher Education.

	(4) Logit Highly educated	(5) Mlogit (a) Short higher education	(b) Bachelor	(c) Master	(d) PhD
Low education (base=5%)					
10%	-.0361***	-.0061	-.0346***	-.0038	.0017
25%	-.0530***	-.0083	-.0446***	-.0081***	-.0004
50%	-.0787***	-.0029	-.0653***	-.0125***	-.0010
75%	-.0819***	-.0107	-.0654***	-.0143***	-.0022
90%	-.0906***	-.0131*	-.0689***	-.0170***	-.0046
95%	-.0957***	-.0166**	-.0747***	-.0123***	-.0087**
100%	-.0921***	-.0158*	-.0837***	-.0127***	.0052
Poverty (base=5%)					
10%	-.0052	-.0047	-.0043	.0009	-.0017
25%	-.0043	-.0038	-.0039	.0007	-.0013
50%	-.0135**	.0015	-.0132*	.0014	-.0018
75%	-.0225***	-.0013	-.0256***	.0037*	-.0009
90%	-.0227***	-.0009	-.0252***	.0040*	-.0018
95%	-.0375***	.0091	-.0443***	.0033	.0034
100%	-.0256**	.0065	-.0346***	.0059	.0028
Ethnic (base=5%)					
10%	.0178*	.0000	.0211**	-.0032	-.0004
25%	.0170**	.0008	.0154*	.0001	.0011
50%	.0344***	.0000	.0284***	.0022	.0033
75%	.0368***	.0023	.0275***	.0040	.0051*
90%	.0332***	-.0054	.0272***	.0010	.0052*
95%	.0228**	.0036	.0140	.0029	.0066
100%	.0216*	-.0033	.0259**	-.0028	.0023
Parental controls					
Father's education	.1656***	-.0061*	.1314***	.0208***	.0189***
Father's income	.0090***	.0095	.0093***	-.0003	-.0003
Father's ethnic background	.0904***	.0004	.0586***	.0169***	.0130***
Region type (age 16)	YES	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES
Pseudo R2	0.2174				
Predicted probability	0.4249	14.69	37.71	2.04	2.74

Notes: The number of observations is 99,239[8] in specification 3 and 99,264 in specification 4. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

[8] 25 individuals are omitted due to unknown education, these are also omitted in specification 4. 25 individuals are omitted due their outcome being perfectly predicted by their region.

Table A9. Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019, Highly Educated Individuals.

	(1iii) Logit Group 1-3	(a) Group 1	(2iii) Mlogit (b) Group 2	(c) Group 3
Low education (base=5%)				
10%	.0082	.0035	-.0060	.0108
25%	.0103*	.0023	-.0084	.0148*
50%	.0080	-.0043	-.0023	.0125
75%	-.0008	-.0038	-.0078	.0093
90%	.0093	.0002	-.0082	.0152
95%	.0058	.0072	-.0124	.0087
100%	.0067	-.0015	-.0079	.0130
Poverty (base=5%)				
10%	.0031	.0062	.0027	-.0051
25%	.0117**	.0160*	-.0080	.0039
50%	.0046	.0139*	-.0097	-.0000
75%	.0081	.0277***	-.0237**	.0038
90%	.0057	.0174*	-.0229*	.0109
95%	.0090	.0298**	-.0231	.00212
100%	-.0007	.0250	-.0598***	.0351**
Ethnic (base=5%)				
10%	.0007	.0023	.0244	-.0252*
25%	-.0055	-.0001	.0189	-.0223*
50%	-.0056	-.0077	.0257*	-.0225**
75%	-.0030	-.0063	.0315**	-.0260**
90%	-.0122*	-.0115	.0169	-.0153
95%	-.0198**	-.0323**	.0594***	-.0433***
100%	-.0096	-.0259	.0470**	-.0279
Parental controls				
Father's education	.0113***	.0004	.0343***	-.0234***
Father's income	.0017***	.0050***	-.0036**	.0005
Father's ethnic background	.0154***	.0038	-.0008	.0124
Region type (age 16)	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES
Region FE/type[9]	YES	YES	YES	YES
Pseudo R2	0.0595	0.0191	0.0191	0.0191
Predicted probability	0.9398	0.1670	0.5898	0.1831

Notes: The number of observations is 42,137 in specification 1iii (41 observations are omitted due to perfect prediction by region), and 42,178 in specification 2iii. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

[9] In specification 2iii (and 2iv), region fixed effects are replaced by region type (defined as above), due to non-convergence of multinomial logit estimations with region FE included.

Table A10. Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of having a High-Skill (Level 3-4) Occupation vs a Low-Skill (Level 1-2) Occupation in 2019, Non-Highly Educated Individuals.

	(1iv) Logit Group 1-3	(a) Group 1	(2iv) Mlogit (b) Group 2	(c) Group 3
Low education (base=5%)				
10%	-.0209	-.0066	-.0130	-.0022
25%	-.0306**	-.0152*	-.0120	-.0098
50%	-.0501***	-.0172**	-.0249***	-.0196*
75%	-.0658***	-.0190**	-.0326***	-.0282**
90%	-.0670***	-.0243***	-.0360***	-.0229*
95%	-.0534***	-.0143	-.0266**	-.0272**
100%	-.0695***	-.0157	-.0410***	-.0268*
Poverty (base=5%)				
10%	-.0111	.0037	-.0035	-.0048
25%	-.0164	-.0003	-.0070	-.0032
50%	-.0174*	.0023	-.0099	-.0034
75%	-.0353***	-.0007	-.0103	-.0172*
90%	-.0396***	.0040	-.0166**	-.0162
95%	-.0404***	-.0058	-.0138	-.0116
100%	-.0741***	-.0011	-.0114	-.0474***
Ethnic (base=5%)				
10%	.0322**	.0106	.0078	.0195
25%	.0114	.0052	.0088	.0076
50%	.0286***	.0151**	.0180**	.0060
75%	.0176	.0091	.0143*	.0073
90%	.0058	.0026	.0168*	.0034
95%	-.0036	-.0044	.0194*	-.0011
100%	-.0037	-.0129	.0127	.0140
Parental controls				
Father's education	.0697***	.0160***	.0425***	.0107*
Father's income	.0079***	.0021***	.0034***	.0024***
Father's ethnic background	.0596***	.0235***	.0287***	.0032
Region type (age 16)	YES	YES	YES	YES
Parental controls	YES	YES	YES	YES
Individual controls	YES	YES	YES	YES
Region FE/type	YES	YES	YES	YES
Pseudo R2	0.1171	0.0746	0.0746	0.0746
Predicted probability	0.5000	0.2363	0.1498	0.1138

Notes: The number of observations is 57,082 in specification 1iv (4 observations are omitted due to perfect prediction by region) and 57,086 in specification 2iv. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.

Table A11 Average Marginal Effects of Residing in Different Types of Neighborhoods at Age 16 on the Probability of a) Moving to a Metropolitan Region vs Staying in a Non-Metropolitan Region (blue line), and b) Staying in a Metropolitan Region vs Moving to a Non-Metropolitan Region.

	(1vi) Logit	
	(a) Mover to metro	(b) Stayer in metro
Low education (base=5%)		
10%	-.0166	-.0136
25%	-.0487***	-.0370***
50%	-.1039***	-.1032***
75%	-.1602***	-.1571***
90%	-.2042***	-.2133***
95%	-.2260***	-.3226***
100%	-.2386***	-.2659***
Poverty (base=5%)		
10%	.0286***	-.0218
25%	.0528***	-.0314
50%	.0615***	-.0363
75%	.0663***	-.0407
90%	.0844***	-.0525*
95%	.0890***	-.0249
100%	.0998***	.0343
Ethnic (base=5%)		
10%	.0157	-.1455
25%	.0515***	-.1636
50%	.1042***	-.1572
75%	.1167***	-.1015
90%	.1183***	-.0691
95%	.1046***	-.0828
100%	.1393***	.0129
Parental controls		
Father’s education	.1020***	.0658***
Father’s income	.0038***	.0066***
Father’s ethnic background	.1680***	.1332***
Region type (age 16)	YES	YES
Parental controls	YES	YES
Individual controls	YES	YES
Region FE	YES	YES
Pseudo R2	0.0653	0.0353
Observations	74,190	25,099
Predicted probability	0.3616	0.6303

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parenthesis.