Studies in Educational Attainment and Returns to Education

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Chapter 1

Introduction

1.1 Background

Education is probably the main feature when it comes to explaining the individual's socio-economic outcome. The individual's education level is not only an important predictor of labour market outcomes, the education level is also an important factor for explaining a wide variety of other types of socio-economic outcomes, such as for instance, a person's health or marriage market outcome.

Knowing the importance of education the investment decision preceding an education ought to be carefully investigated. From a microeconomic perspective the fundamental questions to be raised are, why does anyone decide to invest in an education, and which individuals do actually invest in an education? The contribution of this thesis lies in its effort to study and to answer two aspects of these questions. In the first study "Ethnic Segregation and Educational Attainment in Sweden" the main question to be answered is whether youths brought up in ethnically segregated neighbourhoods differ in educational attainment from youths brought up in more affluent neighbourhoods. And furthermore, can this difference in educational attainment between the groups be associated with the ethnically segregated neighbourhood.

The main reason for investing in an education is to increase lifetime earnings, and given the expected education premium the investment decision is made. Therefore it is of great interest to investigate if the estimated return to education depends on the individual's ability level. In the second study, "Ability and Rates of Return to Schooling - making use of the Swedish Enlistment Battery Test" we try to answer this question, i.e. whether low respectively high ability individuals differ in their return from investing in an education.

Both studies use the same data from Statistics Sweden (SCB 2003). The data is a full sample of every individual in the age group 22-36 living in Sweden in the year 2001. In the econometric analyzes each paper then restricts the sample differently.

1.2 Summary of the first study

The metropolitan areas of Sweden have developed and continue to develop an ethnic and socio-economic segregation. The well educated and relatively socio-economically advantaged tend to leave the segregated areas and are replaced by newly arrived immigrants. In the presence of neighbourhood effects the perhaps major problem with a segregated society is that the disadvantaged influence the disadvantaged in a cumulative way. A negative neighbourhood effect therefore risks increasing the already established socio-economic segregation in the metropolitan areas of Sweden.

Against this background, the study "Ethnic Segregation and Educational Attainment in Sweden", tries to answer whether neighbourhood effects exist in Stockholm (and some of its suburbs), Göteborg and Malmö. The *Commission on Metropolitan Areas in Sweden* argues that these metropolitan areas contain the most socially disadvantaged areas in Sweden. The more precise purpose is to find out whether youths brought up in ethnically segregated neighbourhoods differ in educational attainment from youths brought up in more affluent neighbourhoods, after controlling for family characteristics.

To locate the socially disadvantaged areas in the metropolitan areas we assume that the ethnic segregation rate in an area is an indicator of the social status of the area. Moreover, within the attendance area of a school, we assume that the concentration of first and second generation immigrants attending a school is a mirror image of the ethnic segregation rate in an area. Thus, by using school attendance information, and the concentration rate of first and second generation immigrants attending a particular school, the ethnically segregated neighbourhoods are located. The schools selected with this strategy are to a large extent located in the areas which the *Commission on Metropolitan Areas in Sweden* has separated out as socially disadvantaged.

To explain the existence of neighbourhood effects three different types of models are often found in the literature (Jencks & Mayer, 1990). The epidemic, or contagious, model proposes peer influences as the main explanation for neighbourhood effects. In the second model, the collective socialization model, it is adults within the community who are assumed to influence the child through role modelling. In the last model, the institutional model, it is adults working in institutions within the community, who influence the child.

Besides an ordered probit model the paper uses propensity score matching to analyze the issues raised in the paper.

The study reports that there exists an association between educational attainment and attending an ethnically segregated school in the metropolitan areas of Sweden. The association does not seem to be large, but it is significant and seems to increase with the ethnic segregation rate. However, because of the problem of selection, i.e. unobserved family factors affecting both residential location and educational attainment, the estimated effect of growing up in a disadvantaged area should not be considered a causal effect. A causal neighbourhood effect is not attainable without controlling for some exogenous variation affecting residential location. With our dataset this is not feasible.

1.3 Summary of the second study

Most research on returns to education studies the average return to education. However, the return to investments in education might differ considerably between individuals from different parts of the ability distribution.

Research has found that the rising earnings inequality in the U.S. since 1970 primarily can be attributed to an increase in the demand for unobservable skills (Juhn, Murphy & Pierce, 1993). Moreover, research has recently more systematically started to explore the unobservable skills and found that the rising earnings inequality in the U.S. might be associated with an increase in the return to ability (Taber, 2001).

Are unobservable skills and ability also in Sweden becoming more important when it comes to determining determining the wage of the individual. If so the difference in the return to education between high respectively low ability individuals might increase. The objective of the study "Ability and Rates of Return to Schooling - making use of the Swedish Enlistment Battery Test" is therefore to estimate and compare the return to investments in education for men belonging to different parts of the ability distribution. The estimate will be referred to as an ability specific return to education.

The Swedish Military Enlistment Battery will be used for locating individuals in different parts of the ability distribution. The intention with the test result from the Enlistment Battery is to try to represent and numerically measure cognitive ability. The Enlistment Battery has been used for the assessment of intelligence in the Swedish military since the middle of the 1940s and has been taken by virtually every male Swedish citizen the year when the individual turns eighteen. As a measure of latent cognitive ability, the test result from the Enlistment Battery is probably a reliable measure. The measure is however likely to be increased or revealed by schooling and learning, and one has to be aware of the joint causality between the variable years of schooling and the test score (Hansen, Heckman & Mullen, 2003).

Besides estimating the ability specific return to education the study explores the measurement error in the test score from the Swedish Military Enlistment Battery. The measurement error in the test score is assumed to be the deviation from the individual true latent cognitive ability level. We also produce estimates of the return to education for different education levels when controlling for ability and assess whether log earnings is a linear function of years of schooling or whether "sheepskin effects" exist in Sweden.

We find that a higher score on the Swedish Enlistment test is associated with a higher return to schooling. The relationship between the return to schooling and the test score does however seem to be decreasing in the test score. Thus, it is primarily the ability specific returns to schooling for the lower test groups that divert from the average return to schooling. An average return to schooling is therefore a quite unsatisfactory measure to describe the return to schooling for individuals from the upper respectively the lower part of the ability distribution. Particularly the lowest test score groups have a problem completing a three-year upper-secondary education programme. The study also shows that individuals belonging to the four lowest test score groups do not seem to receive any significant return from a higher education, besides the earning premium from beginning the higher education. Furthermore, in general, the measurement errors in the test score do not seem to bring about any major biases in the ability specific returns to schooling.

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Chapter 2

Ethnic Segregation and Educational Attainment in Sweden

2.1 Introduction

The scientific literature on an individual's origin and intergenerational transmission has mostly been concerned with family background factors. A growing literature does, however, raise the question whether the neighbourhood or community that a child is brought up in affects the child's socio-economic performance, as measured e.g. by educational attainment and future earnings. However, neighbourhood and family effects overlap and are hard to distinguish from each other. But even if the research in the area of neighbourhood effects is relatively scarce and the task of separating neighbourhood effects from other background effects is a difficult one, there has been some successful attempts. Although the empirical evidence shows no general pattern there are studies that have documented different types of neighbourhood effects on social and economic outcomes (Borjas, 1995, Case & Katz, 1991, Corcoran et al. 1992, Cutler & Gleaser, 1997, Page & Solon, 2003, Solon et al. 2000).

The research on neighbourhood and community effects has primarily focused on disadvantaged neighbourhoods. Therefore, the discussion of whether the neighbourhood affects social and economic outcomes, has been closely connected to the problem of segregation and the forces that drive an individual to a particular location. In Sweden substantial evidence shows that the three Swedish metropolitan areas, greater Stockholm, Göteborg and Malmö, have developed and continue to develop an ethnic and socio-economic segregation. The well educated and relatively socio-economically advantaged leave the segregated areas and are replaced by newly arrived immigrants (Integrationsverkets stencilserie 2003:4).

In a segregated society different groups inhabit different parts of a region or a city. A particular group, for instance an ethnic enclave or a specific socio-economic class, concentrated in a certain area may have interests or needs that do not coincide with those of the rest of the population. This could cause problems and have policy implications both for the particular segregated area and for society at large. Even a small, segregated and disadvantaged minority could cause social tensions and insecurity for the majority of the people living in the region or city. However, if there also exist neighbourhood effects, the perhaps major problem with a segregated society is that the disadvantaged influence the disadvantaged in a cumulative way. Neighbourhood effects therefore risk increasing already established socio-economic segregation.

Contrary to the the American case where neighbourhoods often can be classified as either white, black or hispanic etc. the socioeconomic segregated neighbourhoods in Sweden are very ethnically mixed. Only in our sample of second-generation immigrants there is a mixture of 127 nationalities.

The purpose of this paper is to study the possible existence of neighbourhood effects in Sweden, more exactly in the metropolitan areas of Stockholm (and some of its suburbs), Göteborg and Malmö. The choice of areas is based on the targeted municipalities of the *Commission on Metropolitan Areas in Sweden*. The *Commission on Metropolitan Areas in Sweden* argues that these metropolitan areas contain the most socially disadvantaged areas in Sweden. The *Commission on Metropolitan Areas in Sweden* has further identified 24 areas in these municipalities as the most socially disadvantaged areas.

We assume that the ethnic segregation rate in a neighbourhood is an indicator of the social status of the neighbourhood, i.e. in the targeted municipalities we assume that there is a strong correlation between the ethnic segregation rate in an area and the socio-economic status of the area. Furthermore, we also assume that the concentration of first and second generation immigrants attending a school is a mirror image of the ethnic segregation rate in the school's attendance area. So to locate the ethnically segregated neighbourhoods we use school attendance information. The share of first and second generation immigrants among pupils attending a particular school is therefore used for locating schools situated in ethnically segregated neighbourhoods. The method of using the concentration rate of first and second generation immigrants attending a school as an indicator of the social status of the school's attendance area, captures to a large extent the areas which the *Commission on Metropolitan Areas in Sweden* has separated out as the most socially disadvantaged.

The objective is thus to find out whether youths brought up in ethnically segregated neighbourhoods, i.e. attending a school situated in an ethnically segregated area, differ in educational attainment from youths brought up in more affluent neighbourhoods, after controlling for family characteristics. Moreover, if the potential neighbourhood effect increases with the rate of ethnic segregation, an association between the ethnic segregation rate and the size of the potential neighbourhood effect can be established. The aim is also to study if an ethnically segregated neighbourhood affects second-generation immigrants differently from native Swedes. But because of the problem of disentangling a family effect from a neighbourhood effect we are not able to speak in terms of a causal neighbourhood effect. Our estimates might be biased due to selection, and therefore we are merely able to speak in terms of a potential neighbourhood effect.

An ordered probit model is the primary econometric model for the analysis in the paper. But the paper also uses an alternative method for studying if children brought up in segregated neighbourhoods differ in educational attainment from children brought up outside the segregated neighbourhoods, namely, propensity score matching.[1] The method of matching is used to create counterfactuals to which the individuals brought up in the segregated neighbourhoods can be compared. The main advantage with the matching technique is that it is non-parametric and that it extrapolates information only where there exists both treated and controls. Probit estimates are made with the intention to compare the marginal effects from the probit model with the results obtained from the matching estimator.

The paper is structured in the following way. It starts by a review of the literature regarding neighbourhood effects and intergenerational transmission. This is followed, in section 2.3, by a more thorough discussion of neighbourhood effects and the theories developed to explain the existence of neighbourhood effects. The next section summarizes the important features from the intergenerational mobility and neighbourhood literature and develops an analytic and theoretical framework for analyzing neighbourhood effects. The data and descriptive statistics are presented in section 2.5. Section 2.6 describes the econometric model and the methods used for answering the questions raised in the paper. The results are presented in section 2.7. Section 2.8 concludes the study.

2.2 Neighbourhood effects and intergenerational transmission

An intergenerational transmission setting gives a theoretical framework for analyzing a wide variety of questions concerning individual background factors and neighbourhood effects. In an intergenerational transmission model the utility function of the parents is assumed to depend on the child's future utility or earnings. The preferences of the parents therefore result in an "altruistic" behavior towards the child (Behrman & Taubman, 1976). Hence, the theory suggests that the child's future earnings are linked to the income and wealth of the parents. Wealthier parents are able to invest more in the child's human capital (Solon, 1999). But the total family background effect depends not only on the parents' "altruistic" preferences but also on the child's inherited endowments of ability and the parents' influence in terms of norms and culture.[2]

A method often applied in this context for measuring and studying the role of background factors is sibling correlations in earnings. The researcher tries to measure the proportion of the variation in earnings that comes from factors shared by siblings, i.e. common family background and neighbourhood effects. The empirical evidence indicates that the variation in the permanent component of log earnings that depends on background

[1] The matching estimator gives an unbiased estimate of the neighbourhood effect if all relevant differences between the group brought up in the segregated neighbourhoods and the group brought up outside the segregated neighbourhoods that affect location and educational attainment are captured by the observed covariates.

[2] Parents with an academic degree are for example often assumed to provide a family-environment that influences the child in a positive direction.

factors shared by siblings in the US is around 0.4.[3] However, only a minor part, 40%, of that variation tends to be related to parental wealth and income (Solon, 1999). Cameron & Heckman (2001) argue, and present empirical evidence, that long-term levels of family income determine college attendance and college achievements.[4]

After eliminating the variation in log earnings not coming from parental income and wealth, the genetic constitutions inherited from the parents are likely to contribute heavily to the variation in the permanent component of log earnings shared by siblings. To some extent neighbourhood effects may also contribute to explain the variation in correlation between siblings. A study conducted by Solon et al. (2000) tries to bound the proportion of inequality in educational attainment that depends on differences in neighbourhood characteristics. They find that, after controlling for family background characteristics, the correlation in educational attainment between unrelated neighbours is approximately 0.1.[5] Page & Solon (2003) extend the analysis to also study earnings. After controlling for family background characteristics they end up with an estimated neighbourhood correlation of 0.16, which is about half of their estimated brother correlation, 0.31.[6] Moreover, Raaum, Salvanes & Sörensen (2003) find that the schoolmate/neighbourhood correlation in years of schooling, for children born in the 1960s in Norway, is negligible.

The literature on neighbourhood effects is relatively scarce and the empirical findings show no general pattern. Corcoran et al. (1992) use a wide range of community background characteristics in their study of the relationship between men's economic status and the family and community they grew up in. Their study shows that a high rate of welfare programme participation in the community is correlated with a disadvantage in economic status for men. Borjas (1995) argues that there exists an ethnic externality, which affects the intergenerational income mobility. The ethnic externality implies that there is a skill spillover from the mean skill of the ethnic group in the parents' generation on the child's skill. Moreover, Borjas finds that much of the ethnic spillover effect depends on the neighbourhood the child is brought up in. Thus, because low-income ethnic groups in the US gather together in low-income neighbourhoods, there is an ethnic externality that influences the intergenerational income mobility for the ethnic child. Edin et al. (2004) study the economic consequences of living in ethnic "enclaves" for immigrants in Sweden. They

[3]For same-sex siblings in the US the variation that is due to background factors shared by siblings is about 0.5 for brothers and 0.4-0.5 for sisters. Studies performed for Sweden by Björklund & Jantti (1997) and Gustafsson (1994) report numbers that are smaller which indicates that the intergenerational mobility in Sweden is greater than in the US.

[4]They also point out that long-term family income first of all explains earlier grades and the ability to benefit from college.

[5]However, they underline that this is an upper bound of the neighbourhood correlation and it might be inflated by unobserved family background factors.

[6]They claim that a substantial part of the correlation between brothers and of the correlation between neighbours can be attributed to the " importance of being urban". The variation in earnings is more connected to whether an individual is brought up in a city or not, than with which part of a city the individual is brought up in. This stems from the fact that earnings differ considerably between individuals living in cities and individuals living in small cities or non-cities, and that childhood location largely determines adult location.

find that living in enclaves improves the labour market outcome for less skilled immigrants, and that the gain from living in an enclave is largest for immigrants belonging to a high-income ethnic group. Cutler & Gleaser (1997) examine the outcomes for blacks in terms of employment, schooling and single parenthood. They show that the quantitative effects of segregation are large, and the outcomes for blacks in ethnically segregated cities are significantly worse compared to those of blacks living in less segregated cities. The results of their study also suggest that segregation gives rise to "bad" outcomes, and not that "bad" outcomes give rise to segregation. However, in a recent study by Oreopoulos (2003) that examines the long-run labour market outcomes for individuals growing up in different public housing projects in Toronto no significant neighbourhood effects are detected. Oreopoulos finds that average education and annual earnings among youths from low-income families are unaffected by the low-income concentration in their neighbourhood. Instead, family differences between the low-income families do matter.

Even if the empirical evidence supports the existence of some kind of neighbourhood effect, at least in the case of ethnically segregated neighbourhoods, the neighbourhood variable could serve as a proxy for some unobserved aspects of family background. If there are some unobserved factors that affect both socio-economic performance and location, the neighbourhood effect may be overestimated (Borjas, 1997). Unobserved factors that influence the residential location can never be ruled out. That rich people live in an affluent area does not mean that it is the neighbourhood that makes them rich, and poor people are not necessarily poor as a result of living in a poor neighbourhood. The question is whether a child brought up in a poor family that lives in a disadvantaged community could do better (keeping everything else constant), if the family moved to an affluent neighbourhood. Or the opposite, whether children in a family in the upper part of the income distribution, that lives in an affluent neighbourhood, would lose in future socio-economic status if the family was relocated to a disadvantaged community. Thus, it is important not to misinterpret correlation for causality. It should also be noted that neighbourhood effects do not have to work in both directions. Poor families could very well improve their socio-economic status by moving to a better community, even if families from the upper part of the income distribution would not worsen their status by relocating to a disadvantaged community.

2.3 Why neighbourhood effects?

In standard economic theory individuals optimize behavior given their own preferences and constraints. Social interaction and influences from friends, neighbours etc. are assumed not to affect the individuals' optimizing behavior. Many sociologists and psychologists stress the fact that social interactions are important when individual preferences are determined (Jencks & Mayer, 1990). But even if we believe that the individual's preferences are partly determined in the interaction with friends and neighbours, it is difficult to model and empirically investigate the interaction. However, the difficulties in theoretically modelling and empirically measuring social interaction are not an adequate reason for ignoring the existence of social interaction.

To understand reasons for the existence of neighbourhood effects, different social interaction models within a community have been explored. The literature mentions three different types of models for explaining neighbourhood effects, epidemic models, collective socialization models and institutional models (Jencks & Mayer, 1990). Epidemic, or contagious, models propose peer influences. Collective socialization models propose adults within the community as influencing the children through role modelling. In institutional models it is adults working in institutions within the community, who influence the children.

There has been a growing research concerning peer influences. According to the epidemic model youth behavior depends highly on the behavior of the school friends and the prevailing teenage norms in the neighbourhood. Hence, to live in an area where most high school graduates continue to university influences the teenager to also continue to university. Hanushek et al. (2001) emphasize that the major problem with peer studies is to separate the peer effect from other school characteristics. The simultaneous character of peer influences, i.e. peers affect each other simultaneously, and the risk of omitted variables can easily result in biases. To address these problems they use a fixed effect framework and lagged measures of peer achievement. Their study shows that peer achievement has a positive effect on achievement. Zimmerman (1999) analyses if a student's academic outcomes in college are affected by his/her roommate's ability. Because Zimmerman assumes that the roommates are randomly assigned with respect to ability he categorizes his study as a "natural experiment". The conclusion of his study is that a student in the middle of the SAT-distribution[7] achieves a lower academic outcome if he/she shares a room with a student from the bottom of the SAT-distribution than if he/she shares a room with a student from the middle or top of the SAT-distribution.[8] A similar study carried out by Sacerdote (2001) strengthens the probability that there does exist an interaction effect between roommates in college.[9] A study performed by Case & Katz (1991) reports that a high youth criminal activity in a neighbourhood increases a child's probability of being involved in crime. Alcohol use and teenage pregnancy are other self-destructive behaviors that could be contagious. Crane (1991) argues that the peer effect in "bad" neighbourhoods in large cities is non-linear, i.e. the probability that an individual will develop a social problem increases sharply as neighbourhood quality decreases.[10] Crane claims that he finds empirical evidence supporting the "contagious" assumption. His study shows sharp jumps in dropout probabilities and childbearing in the worst neighbourhoods of the largest cities. Hence, a review of the literature regarding peer effects tends to support the epidemic theory.

A second possible reason for the existence of neighbourhood effects is through influences from adults in the community to the children. Collective socialization transfers norms and

[7]SAT stands for Scholastic Assessment Test.

[8]Zimmerman also notes that the peer effect seems to be stronger for verbal SAT scores than for math SAT scores.

[9]Sacerdote also mentions that earlier peer effects (i.e. in high school or junior college) may be more critical and long lasting for the child's future.

[10]And therefore the use of the term "contagious".

values from the older generations to the younger. Parents may also collectively look after the children growing up in the community and keep them out of trouble. To get a positive collective socialization effect there has to be good role models living in the community. A high degree of unemployment or a high degree of social assistance beneficiaries in the community may work negatively on the child's own opinion concerning his/her own labour market possibilities. Especially if the unemployed in the community are relatively well-educated the child's investments in human capital may be negatively affected.[11] The ethnic externality that Borjas (1995) refers to (see earlier section) is in fact a collective socialization effect within the ethnic group. In the Cutler and Gleaser (1997) study some of the effect of segregation on socio-economic outcomes can be attributed to less exposure to well-educated adults.

Finally, the institutional model assumes that it is adults working in institutions within the community who influence the child's behavior and academic performance. The institution that the child has the closest contact with is obviously the school, another possible institution is for example the police force. The argument motivating a positive or a negative school effect is the assumption that the school's capacity to attract teachers is connected to the neighbourhood and the neighbourhood's reputation. Therefore a more affluent school district may be able to attract the best teachers, while the schools in the "bad" neighbourhoods have to settle with the less talented teachers. In a Californian class size reduction program that led to a larger demand for teachers, a teacher quality deterioration emerged in schools where a substantial percentage of the students were black (Jepsen & Rivkin, 2002). Given that teacher quality has an effect on student learning, a school effect will exist. The reason for a police effect may not seem as straightforward. However, children in communities where criminal rates are high more often face policemen who treat violations of the law more strictly than would be the case in other communities, which increases the probability that the child will get a criminal record.

Thus, to get a negative (or a positive, in affluent neighbourhoods) school effect in the ethnically or socio-economically segregated neighbourhood two conditions have to be fulfilled. First, school quality has to be lower in the ethnically or socio-economically segregated neighbourhood and secondly, school quality must influence student learning and performance. The empirical evidence gives no straight answer to the question if student learning is related to school quality. A survey carried out by Hanushek (1986) reports no significant evidence that school quality affects student performance. Card & Krueger (1992), who instead studied the impact of school quality on earnings, find that school quality matters. A study made by Jepsen & Rivkin (2002) shows that teacher quality, measured as teacher education level or the share of teachers with a certificate, appears not to be correlated with student performance. However, they believe that unobserved differences in teacher quality may affect student performance.

A fourth type of model emphasizes relative deprivation as a source of neighbourhood

[11] However, Wilson (1987) mentions that segregation, and typically racial segregation, could have some benefits. He suggests that diminishing racial segregation in the US primarily pushes the black middle-class out of the ghettos. The ghetto then looses successful, and maybe well educated, role models inspiring the children in the community.

effects. Relative deprivation models assume that individuals compare themselves with the people in their community. From this perspective the neighbourhood effect could work in the opposite direction. To grow up in an affluent neighbourhood with low-income parents might result in a feeling of alienation. If the child compares his/her own family's socio-economic position with that of families of more advantaged children in the neighbourhood, the behavior of the child may be self-destructive because of a bad self-esteem. The probability of dropping out of school may increase if the mean difference between the education level of the adults in the community and the education level of the child's parents is large (Jencks & Mayer, 1990).[12]

A problem with all these models is that they do not consider that the neighbourhood effect may affect the parents' earnings. Some parental characteristics could be endogenous and dependent on the neighbourhood (Jencks & Mayer 1990). Assuming that the number of job opportunities, and the wage offers connected with these opportunities, are lower in a disadvantaged community, the parents in a "bad" neighbourhood are more likely to have low earnings. The spatial mismatch hypothesis (Kain, 1968) states that the segregated have a disadvantage on the labour market because they are far from the jobs, resulting in a lack of information and costly commuting. Following this argument, and the intergenerational transmission hypothesis, relating the parental income and wealth to the child's future earnings, gives rise to an indirect neighbourhood effect for the child. Therefore, to capture the full neighbourhood effect one cannot ignore this indirect neighbourhood effect, which affects the child via his/her parents' income and wealth. Even if we have to be aware of the fact that there might exist an indirect neighbourhood effect, this paper does not address the issue any further.[13]

2.4 Theoretical framework

In this section the theoretical literature on intergenerational transmission and neighbourhood effects is summarized. The important features found in the theories are highlighted, and an analytic and theoretical model is developed for analyzing whether youths brought up in ethnically segregated neighbourhoods in the Swedish big cities differ in educational attainment from youths brought up in more affluent neighbourhoods. The theoretical

[12]To consider the relative deprivation model as a model for explaining neighbourhood effects is in some sense problematic. There are reasons for not characterizing the deprivation effect as a neighbourhood effect but instead as an interaction effect between family income and neighbourhood. In fact, it is not the neighbourhood-specific characteristics that affect the child but instead the parents' relative socio-economic status in the specific community, i.e. a community specific family background effect.

[13]Besides that the spatial mismatch hypothesis might give rise to an indirect neighbourhood effect, spatial mismatch may obviously also explain the grown-up child's future labour market outcome. In contrast to the other theories explaining neighbourhood effects, the spatial mismatch hypothesis is only an adequate theory for describing the labour market outcome for persons who decide, as grown-ups, to stay in the segregated community. The effects from growing up in a segregated community on socio-economic outcomes are according to the social interaction models, independent of whether the person decides to move to another less segregated area or not.

model is based on Solon's (1999) simplified version of Becker and Tomes' (1979) model of intergenerational mobility.

The theory of intergenerational transmission assumes that the utility function of the parents depends on the child's future utility or earnings. By investing in the child's future socio-economic outcome, the parents increase their utility. A relationship between the parents lifetime earnings, y_{t-1}, and the child's future socio-economic outcome, SE_i is therefore established. This gives us:

$$SE_i = \alpha y_{t-1} + \beta E_i \tag{2.1}$$

where E_i is all other factors beside the parents' earnings that affect the child's future socio-economic outcome. The notation *t-1* indicates that it is the family *t-1* which invests in the child i. By separating E_i into three parts, the child's individual characteristics X_i (e.g. gender, age and ethnicity), other family background factors than the parents' economic investments in the child, F_{t-1}, and the neighbourhood factors, N_k, for the neighbourhood k, we get the following expression:

$$SE_i = \alpha y_{t-1} + \beta[X_i + F_{t-1} + N_k] \tag{2.2}$$

For a regular intergenerational mobility[14] study a serious problem arises. The estimation of the income mobility effect α will be biased because both y_{t-1} and F_{t-1} depend on the parents' ability. While this is a problem for an intergenerational mobility study, the bias does not entail any major drawbacks for a neighbourhood effects study, although we have to be aware of the fact that the intergenerational mobility parameter may be biased.

Our earlier exploration of the neighbourhood literature provides us with the potential sources for neighbourhood factors, namely peers, P_k, adults and role models in the neighbourhood, R_k, and the institutions in the neighbourhood and their staff, I_k. Taking all these factors into consideration gives us the model which our econometric specification rests upon:

$$SE_i = \alpha y_{t-1} + \beta[X_i + F_{t-1} + N_k(P_k, R_k, I_k)] \tag{2.3}$$

It should be recalled that the neighbourhood effect might be overestimated if there are unobserved family factors affecting both the child's educational attainment and the residential area. Residential location is not random and selection[15] is known to take place. Observed family factors, such as education level and earnings, obviously affect the residential decision. But if there is selection which we cannot control for we run the risk of overestimating the neighbourhood effect.[16] However, it is not sufficient that there are unobserved family factors affecting the residential decision, the unobserved family factors

[14] A regular intergenerational mobility study tries to estimate the causal income mobility parameter, i.e. the causal effect that the parents' income has on the child's future income.

[15] That individuals with specific characteristics inhabit different parts of a city.

[16] Selection could obviously also result in an underestimated neighbourhood effect. But when studying neighbourhood effects in segregated neighbourhoods it is commonly assumed that the bias coming from selection results in an overestimation of the neighbourhood effect.

do also have to affect the educational attainment of the child. In the case of our theoretical model we assume that some part of the family background factor, F_{t-1}, which we cannot control for, determines the choice of neighbourhood, N_k. For instance, the ability of the parents which the child inherits is likely to be correlated with the residential area and also the educational attainment of the child. Parents with low ability and therefore low earnings have to settle with a habitation where residential prices are low, say a disadvantaged area. However, for groups of people ending up in disadvantaged areas because of family characteristics not passed on to the children, selection is not biasing the neighbourhood effect. For immigrants with preferences of living close to other individuals of their own ethnic group this might be the case. Whereas factors related to the ethnic background are determining location for these groups, the ethnicity does not necessarily have to affect the individual's choice of education level.

2.5 Data and descriptive statistics

The empirical analysis uses data from Statistics Sweden (SCB 2003). The data is a full sample of every individual in the age group 25-29, living in Sweden in the year 2001. The sample used in the analysis is however only Swedish-born persons. Because the sample is restricted to Swedish-born persons, the sample includes only second-generation immigrants and natives.[17] The data is further restricted to individuals graduating from comprehensive school in either Stockholm (or some of its suburbs), Göteborg or Malmö. The sample then includes 62,766 individuals.

The exclusion of first-generation immigrants implies that the analysis escapes possible problems with immigration effects. The socio-economic outcome of every person in the sample is therefore not dependent on circumstances affecting the person before entering Sweden or in connection with entering Sweden. Of course, this fact does not mean that natives and second-generation immigrants are two identical groups, but instead that the differences in characteristics between the groups can be attributed to differences in observed or unobserved family background factors. Swedish-specific knowledge and language proficiency in Swedish for the parents of the second-generation immigrants are, according to this reasoning, categorized as family background characteristics.

The choice of municipalities is based on the targeted municipalities of the *Commission on Metropolitan Areas in Sweden*, which are Stockholm and its suburbs (Haninge, Huddinge, Botkyrka and Södertälje), Göteborg and Malmö. The *Commission on Metropolitan Areas in Sweden* argues that these 7 municipalities contain the most socially disadvantaged metropolitan areas in Sweden. The aim of the commission is among other things to prevent further social and ethnical segregation in the metropolitan areas. The *Commission on Metropolitan Areas in Sweden* has further identified 24 areas in the 7 municipalities as the most socially disadvantaged areas.

To locate the disadvantaged areas in these municipalities we assume that the ethnic segregation rate in an area is an indicator of the social status of the area. Thus, within a

[17] I.e. Swedish-born persons with Swedish-born parents.

neighbourhood we assume that there is a strong correlation between the ethnic segregation rate and the socio-economic status of the neighbourhood. Furthermore, we also suppose that the concentration of first and second generation immigrants attending a school is a mirror image of the ethnic segregation rate in the school's attendance area. By using the concentration rate of first and second generation immigrants attending a school as an indicator of the socio-economic status of the school's attendance area, the areas which the *Commission on Metropolitan Areas in Sweden* has identified as the most socially disadvantaged are to a large extent located.

The data provides information on which compulsory school the individual has graduated from. This attendance information is then our proxy for categorizing the individuals into different neighbourhoods.[18] If the individual has moved from the local school district, but within the municipality, either before or after the graduation from compulsory school, this is unknown to us. However, the decision to move after compulsory school does not imply any drawback for the study, because the effect from growing up in the specific neighbourhood has then already affected the child.

Obviously, this method will misplace some individuals, i.e. individuals attending a school outside of the area where he/she lives. From the academic year 1992/93 every Swedish pupil has a right to choose to attend a school outside of the local school district. But because our sample is restricted to the age groups 25-29 the sample does not contain individuals who have enjoyed this right to choose a school outside of the local school district.

However, it is still probable that some individuals living in a segregated area attend a school in a more affluent area. The opposite case, that individuals prefer a segregated school to a less segregated school, is not as likely. Given that the skills of the misplaced individuals are above average, the neighbourhood effect may be overestimated because some high-skill students living in a segregated area are included in the analysis as individuals living in a less segregated area. It is likely that a student who has decided to attend a school outside of the local school district has chosen a private school. By excluding the individuals attending a private school we therefore minimize the potential overestimation.[19] By excluding individuals attending a private school the sample is reduced to 62,367 individuals. For 11 cases there is missing information regarding the educational variable. Furthermore, 991 individuals have for some time of their childhood been living abroad.[20] Excluding these individuals reduces the sample to 61,365 individuals.

After categorizing the individuals into different neighbourhoods using the school atten-

[18]Another method for constructing neighbourhoods could be one based on postcodes. This is however not a possibility because the data does not contain information on postcodes. To use the postcode as a proxy for neighbourhood may also not be the best method. Postcode areas may be more socio-economically and ethnically heterogeneous than neighbourhoods based on school districts. Also, the peers whom the child encounters are most frequently his/her school and class friends.

[19]Furthermore, by excluding individuals attending private schools as possible extreme cases, the reference group, i.e. individuals growing up outside the segregated neighbourhood, is more comparable to the individuals brought up in the segregated neighbourhoods.

[20]Because these children have partly been brought up outside of Sweden they are not comparable to children who have been living in Sweden for their entire childhood.

dance information, the socio-economically and ethnically segregated neighbourhoods have to be located. Our strategy for selecting the schools located in a socio-economically and ethnically segregated area is based on the concentration of first- and second-generation immigrants attending the school. According to our assumptions, the concentration of first and second generation immigrants attending a school is an indicator of the social status of the school's attendance area, i.e. the quality of the neighbourhood.

If the concentration of first- and second-generation immigrants attending the school is more than 40%, the school is classified as a school located in a socio-economically and ethnically segregated area.[21] Or, more precisely, the concentration rate is the share of first- and second-generation immigrants graduating from the particular school during the time period 1988-1995.[22] The 40% concentration rate of first- and second-generation immigrants is in some sense arbitrarily chosen. As already mentioned, the schools selected with this strategy are to a large extent located in the areas which the *Commission on Metropolitan Areas in Sweden* has separated out as socially disadvantaged. Thus, even if the concentration rate of 40% is arbitrarily chosen it is effectively identifying schools situated in socially disadvantaged neighbourhoods. The reason for favoring this strategy compared to any other strategy is the fact that we want the neighbourhood not only to be socio-economically segregated but also ethnically segregated. Another practical reason for this strategy for selecting schools is that there are schools located at the borderline between areas. To decide if the students attending a borderline school mainly inhabit the ethnically segregated area or not, something else than geographical location has to be taken into account, namely the concentration of first- and second-generation immigrants attending the school.

To establish if there exists an association between the ethnic segregation rate and the size of the neighbourhood effect, neighbourhoods with higher concentration rates of first- and second-generation immigrants than 40% are also identified. Schools with 50-60% respectively 60% or more first- and second-generation immigrants attending the school are therefore identified. We thus get neighbourhoods where the ethnic segregation rate is 40-50%, 50-60% respectively over 60%.[23]

Table 2.1 provides information about sample sizes in each municipality, the fraction growing up in a segregated neighbourhood, the fraction of second-generation immigrants,

[21] For 8% of the first-generation immigrants information regarding home municipality and school attendance is missing. By excluding these individuals the actual concentration rate of first- and second-generation immigrants is in fact higher than that observed, particularly because most first-generation immigrants decide to live in the metropolitan areas.

[22] This means that we use school attendance information for all aged between 22 and 29 years of age. Separate concentration rates for the different age groups are not used because this will not give as good a picture of the overall ethnic segregation rate in the school attendance area as well as of the average concentration rate for the whole time period. By adding the age groups 22-24 when calculating the average ethnic concentration rate for a particular school the overall ethnic segregation rate in the area is probably closer to the true ethnic segregation rate in the school attendance area, compared to what would be the case if we used only the age groups 25-29.

[23] In Haninge a lower concentration rate is used, due to the fact that there exists no schools with a concentration rate of first- and second-generation immigrants above 40%.

Table 2.1: Summary Statistics for the Municipalities

Municipality:	*No. of Observations*	*% in Segregated Neighbourhoods*	*% Second-generation Immigrants*	*% Second-gen. Im. in Seg. Neighbourhoods[a]*
Stockholm	20,621	18	22	40
Göteborg	16,337	28	23	42
Malmö	8,544	34	23	38
Botkyrka	4,052	54	28	35
Haninge	4,010	15	20	32
Huddinge	3,365	29	22	30
Södertälje	4,149	30	27	40
Total	61,365	26	23	38

Note: [a] The fraction of second-generation immigrants in the segregated neighbourhoods.

and the fraction of second-generation immigrants in the segregated neighbourhoods, for each municipality.[24] 20,621 individuals (or 34% of the sample) are brought up in Stockholm, 16,337 individuals (or 27%) are brought up in Göteborg. The third largest city in Sweden, Malmö, contributes with 8,554 individuals (or 14% of the sample). Each of the four suburbs to Stockholm, Haninge, Huddinge, Södertälje and Botkyrka contribute roughly 6.5% of the sample. Botkyrka and Malmö have the highest fractions of individuals growing up in a segregated neighbourhood, 54% respectively 34%. Haninge has the smallest fraction, only 15%. In Stockholm respectively Göteborg the fraction of individuals brought up in a segregated neighbourhood are 18% and 28%. Botkyrka is not only the municipality with the highest fraction of individuals growing up in a segregated neighbourhood, it is also the municipality with the highest fraction of second-generation immigrants growing up in the municipality, 28%. About 40% of the sample brought up in a segregated neighbourhood in Stockholm, Botkyrka, Södertälje, Malmö and Göteborg are second-generation immigrants. Haninge and Huddinge are the municipalities with the smallest fraction of second-generation immigrants, 20% respectively 22%, and with the smallest fraction of second-generations immigrants growing up in segregated neighbourhoods, 32% respectively 30%.

2.5.1 Measures of educational attainment

The objective of our study is to investigate whether youths brought up in ethnically segregated neighbourhoods differ in educational attainment from youths brought up in more affluent neighbourhoods. Our educational attainment measure, SUN 2000, is for the year 2001 and describes both the level of education achieved and the type of study programme attended. The measure is a revision of the former SUN classification adjusted to fit the International Standard Classification of Education (ISCED97). Our construction of the variable educational attainment intends to capture the highest education level completed

[24] A more accurate segregation measure would include the first-generation immigrants, but the total sample of first-generation immigrants is not available.

before or during the year 2001. To construct it we use information both on the level of education achieved and on the study programme attended. From the SUN 2000 measure we can either construct a years of schooling variable or an education variable that is ordered but where the distances between the levels is unknown. We prefer the ordered education variable to the years of schooling variable for three reasons. First, one year of extra schooling is qualitatively not valued the same irrespectively of where the individual is in the education system. For example, for a three year upper secondary study programme, finishing the last year, i.e. getting an exam, is qualitatively valued more than finishing the second year. Secondly, for different study programmes the same years of schooling might produce different levels of education. A theoretical education is often thought of as providing a higher education level than a vocational education even if the study programme is for the same number of years. And third, the Swedish system of education has changed during the time period. Some upper secondary study programmes have during the time period gone from being two years to three years. Even if this might result in a higher formal education level for the individual the decision to study for three years instead of two years is not made by the individual. Most individuals who before attended the two year upper secondary study programme would probably attend the three year study programme if this was the only possible length of upper secondary study programmes. The constructed variable is ranked in 6 discrete education levels, where the first level is compulsory education. The second level is classified as dropouts from upper secondary education, both from vocational education and theoretical education. The third and fourth levels are vocational upper secondary education respectively upper secondary theoretical education. The fifth level contains both post secondary education outside the colleges and universities, and college or university education, which neither results in a degree nor in 80 academic points.[25] The sixth education level is college or university education either resulting in a degree or in achieving more than 80 academic points.

Moreover, with the ordered education variable we construct two binary education variables. In the education system there are two choices that play an important part in determining the individual's attained educational level. The first choice is whether to continue to an upper secondary education. We assume that the decision to finish upper secondary education is a part of the decision, meaning that a dropout who fails to finish upper secondary education decides to do so. Because having completed an upper secondary education is a requirement for continuing to a post-secondary education, the decision whether to choose a vocational or a theoretical upper secondary education is not vital for the final education level attained. Irrespective of which study programme one takes at the upper-secondary level, the individual is able to continue his/her studies and complete an academic degree. The second important decision is whether to continue to study after upper secondary school. Hence, the two decisions, completing an upper secondary education respectively continuing to an academic education[26] are therefore modelled as two separate binary events.

[25] 80 academic points correspond to two years of full time studies or 120 ECTS credits.

[26] This variable is modelled as given the fact that the individual has finished upper-secondary school.

Table 2.2: Educational Attainment Statistics for the Municipalities.

Municipality:	*Education level(%):*					
	Comp.	Dropout	Voc. Upp-sec.	Theo. Upp-sec.	Low ac.	High ac.
Stockholm	9.9	4.3	21.9	23.0	10.6	30.3
Göteborg	9.3	5.2	26.4	20.5	9.9	28.6
Malmö	10.5	5.0	27.8	21.6	9.4	25.6
Botkyrka	11.4	4.9	31.4	20.1	8.8	23.4
Haninge	11.9	6.3	30.0	23.2	8.8	19.7
Huddinge	11.2	6.3	29.7	18.2	10.4	24.2
Södertälje	13.0	4.4	31.1	18.0	9.4	24.1
Total	10.4	4.9	26.2	21.3	9.9	27.3

Summary statistics for the ordered educational attainment variable are given separately for the municipalities in tables 2.2 - 2.4. The tables are constructed in the following way. The first table, table 2.2, describes the distribution of individuals between the six levels of education for each municipality. In tables 2.3 - 2.4, differences in the distribution of individuals between the education levels, between sub-populations within the municipalities, are described. Table 2.3 shows the difference in the distribution of individuals between the education levels, between individuals brought up in the segregated neighbourhoods and individuals brought up outside the segregated neighbourhoods. Differences in the distribution of individuals between the education levels, between second-generation immigrants and natives are documented in table 2.4, both for the entire municipality and separate for the sample of individuals brought up within the segregated neighbourhoods.

Taking a closer look at table 2.2 reveals that achieving 80 academic points or completing a degree at the colleges or the universities is the most common education level for the individuals in the sample. About 26% of the sample has taken a vocational upper-secondary education. Furthermore, 10.4% has only a compulsory education and 4.9% of the sample are dropouts from an upper-secondary education. 21,3% of the individuals in the sample have a theoretical upper-secondary education as their highest education. Almost 10% of the sample has at this point in time continued to study either outside the colleges and universities, or at a college or a university, but not yet reached a degree or 80 academic points. The share of individuals with a post-secondary education is higher in Stockholm than in the other municipalities. Stockholm and Haninge have the highest share of individuals with a theoretical upper-secondary education as their highest education level. Furthermore, Stockholm is also the municipality with the smallest share of individuals choosing a vocational upper-secondary education as their highest education. However, although youth in Stockholm tends to achieve a higher education level than youth in the other big cities, the share of individuals with only a compulsory education is higher in Stockholm than in Göteborg. The education level is generally higher in the big cities, where over one third of the individuals choose to continue studying after upper-secondary school, than in the suburbs of Stockholm. Haninge is the municipality with the smallest share of individuals, only 28.5%, continuing to study after upper-secondary education. Moreover, the share of

Table 2.3: Differences in Educational Attainment Between Segregated Neighbourhoods and the Rest of the Municipality.

Municipality:			*Education level:*			
	Comp.	Dropout	Voc. Upp-sec.	Theo. Upp-sec.	Low ac.	High ac.
Stockholm	+2.6	+2.2	+6.1	+1.5	-1.4	-11.1
Göteborg	+8.1	+1.5	+10.0	+1.3	-3.3	-17.6
Malmö	+6.2	+1.7	+5.5	+2.1	-1.9	-11.2
Botkyrka	+4.1	+2.3	+7.2	-3.2	-5.3	-13.1
Haninge	+3.8	+1.9	-2.9	+8.0	-7.5	-2.9
Huddinge	+4.1	+0.1	+6.7	+0.8	-2.4	-9.3
Södertälje	+6.8	+2.1	+2.6	+1.3	-1.5	-8.2
Total	+5.3	+1.6	+7.4	+3.4	-2.1	-12.5

Note: The table describes, for each education level, the percentage point difference in educational attainment between the individuals brought up in the segregated neighbourhoods and the individuals brought up outside the segregated neighbourhoods.

individuals with only a compulsory education is very high in Södertälje, 13,0%, even in comparison with the other suburbs of Stockholm. Haninge and Huddinge have the highest dropout rate from upper-secondary education, whereas the probability to be a dropout from upper-secondary education is smallest in Stockholm and Södertälje.

Table 2.3 describes the difference in educational attainment between the individuals brought up in the segregated neighbourhoods and the individuals brought up outside the segregated neighbourhoods. The table shows that the share of individuals with only a compulsory education is dramatically higher in the segregated neighbourhoods, for all municipalities. The dropout rate from upper-secondary education and the share of individuals with a vocational secondary education as their highest education, are also higher in the segregated neighbourhoods. Studying the higher education levels shows that youths brought up in the segregated neighbourhoods especially have a problem reaching 80 academic points or finishing a degree. Göteborg is the municipality with the largest differences in educational attainment between the segregated neighbourhoods and the rest of the municipality, whereas the smallest differences can be found in Haninge. Among the big cities, the smallest differences in educational attainment between the segregated neighbourhoods and the rest of the municipality are found in Stockholm.

Table 2.4 describes the differences in the distribution of individuals between the education levels between second-generation immigrants and natives. The (a) columns are for the entire municipality and the (b) columns are for the sample of individuals brought up within the segregated neighbourhoods. The table shows that the largest differences between the groups exist for the highest education level. Differences in educational attainment between the groups for the other education levels are generally small. The pattern is that second-generation immigrants do not as often as natives reach the highest education level and, further, that second-generation immigrants are overrepresented in all the non-academic education levels. When studying the lowest education level, compulsory education, the table reveals that the largest differences between second-generation immigrants and na-

Table 2.4: Differences in Educational Attainment Between Second-Generation Immigrants and Natives.

Municipality:	*Education level:*											
	Comp.		Dropout		Voc. Upp-sec.		Theo. Upp-sec.		Low ac.		High ac.	
	a	*b*	*a*	*b*	*a*	*b*	*a*	*b*	*a*	*b*	*a*	*b*
Stockholm	+1.6	+1.4	+0.6	-0.7	+1.8	+0.2	+2.3	+4.2	-0.4	-1.2	-5.9	-4.0
Göteborg	+2.8	-1.8	+1.6	+0.3	+5.4	+1.3	+1.6	+1.9	-0.3	+0.6	-11.1	-2.2
Malmö	+1.1	-2.8	+1.4	+1.4	+0.9	+0.1	+3.0	+6.9	-1.3	-1.5	-5.1	-4.1
Botkyrka	+4.9	+4.7	+0.9	+0.3	+0.5	-1.8	+2.2	+2.1	-1.1	-0.8	-7.3	-4.5
Haninge	+3.2	+4.7	+0.7	-0.2	+0.0	-4.3	+1.3	-2.8	+0.1	+4.2	-2.7	-1.5
Huddinge	+1.5	+1.2	+0.2	-1.0	+3.4	+0.1	+0.4	-0.4	-0.5	-0.5	-5.3	+0.5
Södertälje	+5.1	+5.3	+0.9	+1.3	+3.2	+1.9	+0.7	+2.3	-1.4	-0.4	-8.5	-10.3
Total	+2.5	+0.6	+1.0	+0.2	+2.8	+0.2	+1.6	+3.1	-0.6	-0.4	-7.3	-3.7

Note: The (a) columns describe, for each education level, the percentage point difference in educational attainment between second-generation immigrants and natives, the (b) columns describe the percentage point difference between second-generation immigrants and natives brought up within the segregated neighbourhoods.

tives are to be found in Botkyrka and Södertälje. In Göteborg a relatively large share of second-generation immigrants are choosing a vocational upper-secondary education as their highest education. Moreover, for the highest education level, the largest differences between second-generation immigrants and natives are found in Södertälje and Göteborg. In Haninge the difference in educational attainment for the highest education level between second-generation immigrants and natives is considerably smaller than in the other municipalities.

When studying the differences in educational attainment between second-generation immigrants and natives brought up within the segregated neighbourhoods we find some deviations from the general pattern. In Göteborg and Malmö, the share of second-generation immigrants with only a compulsory education is smaller than the share for natives. Furthermore, within the segregated neigbourhoods in Botkyrka and Haninge natives more often than second-generation immigrants have a vocational upper-secondary education. The second-generation immigrants brought up within the segregated neigbourhoods of Haninge reach in comparison to natives more often the fifth education level, whereas they less frequently choose a theoretical upper-secondary education level. By comparing column (a) and column (b) we also see that the difference in educational attainment for the highest academic education level between second-generation immigrants and natives, is smaller within the segregated neighbourhoods than outside for all of the municipalities except Södertälje.

2.5.2 Explanatory variables

Expression (2.3) formulates the theoretical model and describes the determinants of variation in educational attainment. The corresponding empirical variables used in the empirical application are listed and discussed below.

As to the individual characteristics, age and gender are used together with a set of dummy variables describing which part of the world the parent/parents are born in. If one, or both, of the parents originate from a specific part of the world the individual is classified as a second-generation immigrant from this part of the world. The variables indicating which part of the world the parent/parents originate from are the Nordic countries, Europe[27], the Middle East, Africa, Asia and Latin America.

Following the theory of intergenerational transmission the wealth and income of the parents have to be controlled for. An estimate of average earnings, based on more than one year, is a less "noisy" measure than one based on a single year and therefore the mother's and father's average earnings for the years 1970, 1975 and 1980 [28] are computed. If any of the earnings for the three years is zero, an average of the remaining positive earnings is computed. We then add the mother's and father's average incomes and obtain a measure for the family income. Using family income instead of each parent's separate earnings has two reasons. The first reason is that using the mother's earnings separately may capture labour supply effects rather than earnings effects.[29] The second reason is a statistical one. In some cases there is missing information or zeros for all three earning years, and this fact is especially common for the mothers. By adding the parents' earnings we minimize the number of observations where there are zeros. Because a family cannot live on nothing, there is something strange with the cases where family earnings are zero (175 observations), and therefore we exclude them.

The parents' education levels will serve as proxies for the endowment of ability inherited from the parents and also for the culture and norms transferred from the parents to the child.[30] The reported education level is the highest education attained by the parent. In the econometric analysis, four dummy variables are used to measure each of the parents education level. For each of the variables, a 1 indicates a upper secondary, a short university, a long university or a doctor's degree respectively. The reference group has completed compulsory school for the mother's, respectively the father's, education level. Missing values for the father's and the mother's education level are reported in 10% respectively 4% of the cases. These observations are in the first stage of the econometric analysis excluded. To determine if we get sample selection problems when excluding these individuals we add them in a second stage. Including two dummy variables into the model, indicating if either the mother or the father has missing information for the variable education level, answers the question if sample selection is a problem. If the model is not affected, by including these individuals into the model, sample selection is not believed to be a severe problem.

Table 2.5 gives the mean values of the explanatory variables for the sample brought up within the segregated neighbourhoods respectively the sample brought up outside the segregated neighbourhoods and for natives respectively second-generation immigrants. For the individual characteristics, age and gender, there are no differences between the different

[27]In Europe we also include North America, Australia and New Zealand.

[28]All earnings are in 1980-years prices.

[29]A labour supply effect is primarily a cultural influence rather than an actual monetary investment in the child's socio-economic outcome. Furthermore, the direction of the labour supply effect on educational attainment is uncertain and may vary with the child's personal characteristics.

[30]Specific ethnic norms and values are also passed on to the child through the foreign origin variables.

Table 2.5: Summary Statistics for the Municipalities (means)

Variable	*Segregated Neighbourhoods*	*Rest of the sample*	*Second-generation Immigrants*	*Natives*
Men	.51	.52	.52	.51
Age	27.1	27.0	27.0	27.1
Family earnings(/1000)	89.3	102.8	91.8	101.5
Father's level of education:				
Compulsory	.33	.22	.30	.23
Upp. Secondary	.41	.40	.37	.41
Short university	.07	.09	.06	.09
Long university	.07	.17	.09	.16
Graduate	.01	.03	.01	.02
Missing information	.12	.09	.16	.08
Mother's level of education:				
Compulsory	.34	.20	.33	.21
Upp. Secondary	.43	.42	.40	.43
Short university	.10	.16	.12	.16
Long university	.07	.18	.11	.16
Graduate	.00	.01	.01	.01
Missing information	.05	.04	.05	.03

populations. The family income is, on average, about 13,000 Swedish crowns lower for individuals brought up within the segregated neighbourhoods than for individuals brought up outside the segregated neighbourhoods. The difference is almost as large between natives and second-generation immigrants. The parents of the children brought up outside the segregated neighbourhoods are also considerably more educated. 29% of the fathers and 35% of the mothers of children brought up outside the segregated neighbourhoods have a university education. For children brought up within the segregated neighbourhoods, 15% of the fathers and 17% of the mothers have a university education. On average 27% of the fathers and 33% of the mothers of natives are university educated, whereas among fathers and mothers of second-generation immigrants only 16% respectively 24% are university educated.

2.6 Econometric analysis

To understand what we actually estimate with our variables explaining the concentration of first and second generation immigrants attending a school, we have to look closer into what the variables capture. Our aim is to capture the total neighbourhood effect, that is, all the neighbourhood factors influencing the child, i.e. peers, adults and role models, and institutions within the neighbourhood. However, the most straightforward answer to the question what we actually estimate would be that we estimate the effect of attending an ethnically segregated school, and everything that is associated with attending these schools. The main factors influencing the children attending the ethnically segregated schools are the peers, which the children come across in school, and the school characteristics. If the school characteristics are different in schools situated in disadvantaged areas[31] than in schools situated in more affluent areas, and this affects the child, our variables will capture this effect. Besides the factors associated with attending an ethnically segregated school the variables will also capture neighbourhood characteristics in the school's attendance area. All existing neighbourhood characteristics, not controlled for, influencing the educational attainment of the group of students attending the school situated in the segregated neighbourhoods will be captured by our ethnic segregation variables. Hence, the influence from adults and role models living within the attendance area of the ethnically segregated schools will be included in our estimate. However, due to our method of constructing the neighbourhood variables, we are probably mainly estimating the effect on educational attainment from attending an ethnically segregated school, even if other neighbourhood characteristics also might affect the educational attainment of the individuals attending the segregated schools.

Our econometric tools for identifying a potential neighbourhood effect are an ordered probit model, a standard probit model and a non-parametric matching estimator. The ordered probit model is used to examine the six discrete, ranked education levels. The standard probit model is used to illuminate the determinants of the probability to complete an upper secondary education respectively the probability to continue to a post-secondary education, given that the individual has finished upper-secondary school. The effect from being brought up in a segregated neighbourhood on the probability of completing an upper secondary education or on the probability of continuing to a post-secondary education are the baseline results, to which the results from the alternative, matching technique are compared. The matching estimator gives an unbiased estimate of the neighbourhood effect if the conditional independence assumption (CIA) is fulfilled. The CIA property is fulfilled if all relevant differences between the group brought up in the segregated neighbourhoods and the group brought up outside the segregated neighbourhoods and that affect location and educational attainment are captured by the observed covariates. The main advantage with the matching technique is that it is non-parametric, which means that the researcher avoids having to define a specific form of the outcome equation. Heterogenous treatment effects will therefore not severely bias the estimated treatment effect.

2.6.1 The ordered probit model

A standard method for explaining an ordered discrete choice or outcome variable is the ordered probit model:

$$y_i^* = \beta X_i + \varepsilon_i \tag{2.4}$$

The index i denotes the individual, X_i is a vector of covariates, β is the coefficient vector and ε_i is the normally distributed error term, with mean 0 and variance 1. y_i^* is the

[31] Teacher quality and class size could be school characteristics that are different in the ethnically segregated schools.

unobserved outcome, i.e. the expected outcome. What we instead observe is:

$$y_i = j \qquad if \quad m_{j-1} < y_i^* \leq m_j \tag{2.5}$$

where j represents our J discrete outcomes. The m's are unknown cut-off points defining the ranges of the outcomes. For the first outcome, $j = 0$, we assume that m_{-1} = -∞ and for the last outcome we assume $m_J = \infty$. The cut-off points have to be estimated in conjunction with the coefficients, the β vector. The estimation is carried out by maximum likelihood. With Φ representing the cumulative normal distribution, the probabilities for the different outcomes are:

$$\begin{aligned} &Pr(y_i = j) = \Phi(m_j - \beta' X_i) - \Phi(m_{j-1} - \beta' X_i) \\ &where \quad \Phi(m_{-1} - \beta' X_i) = 0 \\ &and \quad \Phi(m_J - \beta' X_i) = 1. \end{aligned} \tag{2.6}$$

However, the estimated β does not describe the change in the probability of a given outcome dependent on a unit change in one of the regressors. The marginal effect of a continuous regressor on the probability for outcome j is instead given by the partial derivative of expression (2.6) with respect to X_j:

$$\frac{\partial Pr(y = j)}{\partial X_j} = [\phi(m_j - \beta' X) - \phi(m_{j-1} - \beta' X)]\beta_j \tag{2.7}$$

ϕ is the density function of a standard normal distribution. For a discreate regressor the marginal effect is:

$$\frac{\partial Pr(y = j)}{\partial X_j} = Pr(y = j, x_m = x_E) - Pr(y = j, x_m = x_S) \tag{2.8}$$

where the discrete regressor, x_m, changes from x_S to x_E.[32]

2.6.2 The method of matching

In an experimental environment the researcher is able to measure the effects from a treatment by drawing a random sample of individuals receiving treatment and comparing the outcome for this sample to that of a control group not receiving treatment. In a non-experimental study the treatment group and the control group are likely to differ substantially in characteristics. Comparing the treated group with the control group will then produce a seriously biased estimate of the treatment effect. What the researcher wants to do is to compare a treated individual with an untreated individual with similar characteristics. The construction of the control group has to be made with the intention to create a mirror image of the treatment group. The method of matching has the purpose

[32] For more information on ordered probit models, see Greene (1993).

of performing this task. Matching has in economics usually been used in labour market policy evaluations (see Deheijia & Wahaba, 2002 and Heckman, Ichimura & Todd, 1999). Laura Larsson (2000) has used the matching estimator for evaluating the direct effects of Swedish active labour market programmes for youth.

In our study the treatment variable is the variable indicating that the individual has been brought up in a segregated neighbourhood. The treatment is in this context the time the individual spends, growing up, in the segregated neighbourhood and the effect from the treatment is what is called the neighbourhood effect.

Define Y^t as the potential outcome for the individuals receiving treatment and Y^c as the potential outcome for the individuals not receiving treatment. For a particular individual only one outcome can be observed, either Y^t or Y^c, never both. Because one of the two outcomes is unobservable for any individual the average treatment effect cannot be measured. To get past this problem matching is the key.

The main property which has to be fulfilled for the matching method to produce an unbiased estimate is the conditional independence assumption (CIA). The CIA is formalized as follows: conditional on X, the outcome for the treated and the outcome for the controls, Y^t respectively Y^c, and the treatment, D, has to be independent (Rubin, 1977).

$$(Y^t, Y^c) \perp D \backslash X \tag{2.9}$$

where the sign $\perp$ describes independence. This means that all relevant differences between the treatment group and the control group affecting the selection into treatment and the potential outcome has to be captured by the observed X, otherwise the CIA is not fulfilled. If (2.9) is valid the untreated can be used as a measure of what the outcome of the treated would have been if they were untreated, and given the X's the average treatment effect will be same for the control group and the treatment group. Are there unobserved factors affecting both selection into treatment and potential outcome, the CIA is not fulfilled. In the case of treatment effects from active labour market programmes, more able and motivated persons might have a higher propensity to participate in the programme. Furthermore, if the average outcome of these individuals can be expected to be higher in both the untreated and treated state compared to the control group, the treatment effect will be overestimated.

However, for the CIA to be empirically valid there has to be treated and controls for each X for which comparison is to be made. This requirement can be expressed as:

$$0 < Pr(D = 1\ X) < 1 \tag{2.10}$$

The region of X where there exist both treated and controls is called the common support region. If condition (2.9) and (2.10) are met, together known as the "strong ignorability" condition, the average treatment effect can be computed (Rosenbaum & Rubin, 1983). However, matching can only be justified when performed within the common support region and the treatment effect has to be redefined as the treatment effect for those individuals within the region of support, **S**. Because there does not exist treated and controls for each X in a finite sample with many X's, a balancing score, b(x) is constructed. Rosenbaum

& Rubin (1983) have shown that if the CIA is valid for X, the CIA is also valid for a function of the X's, i.e. the balancing score, b(x). For the function b(x), the conditional distribution of X given b(X) is the same for the treatment group and the control group. Hence, the covariates X and the treatment D are conditional on b(x), independent. The construction of the balancing score reduces the dimensionality from the whole set of X to a function of X. The advantage of the balancing score is therefore that the matching can be conditioned on only one function instead of on the whole set of X. Besides X, which is in fact a balancing score, the propensity score, p(x) = Pr (D = 1 \ X), is a balancing score. Replacing X with p(x) the CIA can be expressed as:

$$(Y^t, Y^c) \perp D \backslash p(x) \tag{2.11}$$

When using the conditional probability that the individual is assigned to treatment, i.e. the propensity score, the method is often known as *propensity score matching.*

Besides the main advantage of being a non-parametric approach the matching estimator has one additional attractive property. Because the treatment effect is only estimated within the common support region, the method avoids extrapolation outside the common support.

Matching Estimators

The basic matching estimator takes the following form:

$$\hat{e}_M = \frac{1}{n^t} \sum_{i \in I^t \bigcap S_p} [Y_i^t - \hat{E}(Y_i^c \backslash D = 1, P_i)] \tag{2.12}$$

where P = Pr (D=1 \ X) and:

$$\hat{E}(Y^c \backslash D = 1, P_i) = \sum_{j \in I^c} W_{ij} Y_j^c \tag{2.13}$$

I_t is the set of treated and I^c is the set of controls. The common support region is S_p and n^t is the number of individuals belonging to the set $I^t \bigcap S_p$. The outcome of every treated individual, $i \in I^t \bigcap S_p$, is matched to a weighted average of the outcomes of the controls. The weights W_{ij} depends on the distance between P_i and P_j. To locate the individuals matched to i, a set A_i is constructed. A neighbourhood, C (P_i), is defined for every treated individual. The neighbours to i are then $j \in I_c$ such that $P_j \in C(P_i)$. This gives us then the set $A_i = \{j \in I_c \backslash P_j \in C(P_i)\}$. Depending on how the weights are constructed, and how the neighbourhood is defined, different types of matching estimators exist.

Nearest neighbour matching
The traditional matching estimator is the nearest neighbour estimator. The nearest neighbour estimator is a one-to-one matching where the control individual j with the P_j value closest to P_i is selected as the match to i. The neighbourhood C (P_i) is then:

$$C(P_i) = min \|P_i - P_j\|, j \in I_c \tag{2.14}$$

The weight used is $W_{ij} = 1$

Radius matching
In Radius matching all individuals within some tolerance level, δ are approximated to have the same propensity score. A treated individual is then matched to all controls within the δ-radius. In radius matching the weight is $W_{ij} = 1$, which implies that the outcome of the treated is compared to the mean outcome of the controls within the radius (Deheija & Wahaba, 1998).

Increasing the number of controls matched to a single treated unit means that the bias of the estimator increases whereas the precision of the estimate increases. The increased bias depends on the fact that on average poorer matches are used (Deheija & Wahaba, 1998). However, in a finite sample, using the nearest-neigbour matching technique, the matches might also be fairly poor, because the distance in propensity score between two neighbours could be large. The bias in the radius matching estimate might then, especially when the radius is very small, be less than in the nearest-neighbourhood estimate. Considering both the matching estimators often offers the best way to check the robustness of the estimates (Becker & Ichino, 2002).

2.7 Results

2.7.1 Results using the ordered probit model

In Table 2.6 different specifications of the ordered probit model are estimated for the full sample. The table reports the coefficients determining the six discrete, ranked education levels; comprehensive education, dropouts from upper secondary education, vocational respectively theoretical upper secondary education and the two levels of post secondary education, together with the cut off points. Column (1) in the table reports the coefficients of the different second-generation immigrant groups when controlling for age, gender and municipality. There seems to be a negative relationship between originating from a foreign country and educational attainment, for all second-generation immigrant groups except the one from Asia. Originating from Asia is instead significantly positive for educational attainment. The group originating from the Middle East is the group most negatively affected by having one or both parents born abroad. In column (2) we control for family background, i.e. family income and the parents' education levels.[33] When controlling for family background, the impact of being a second-generation immigrant decreases dramatically.[34] Except for the Nordic countries, the Middle East, and Latin America all second-generation immigrant coefficients turn positive. Österberg (2001) finds a similar result for young first-generation immigrants and second-generation immigrants from the

[33] All family background variables work in the expected manner.

[34] An exception is the group originating from Latin America. For this group the impact of being a second-generation immigrant is hardly affected when controlling for family background.

Table 2.6: Ordered Probit Estimates of the Determinants of Educational Attainment.

Variable:	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
Segregated neigh.			-.247 (.01)***	-.092 (.01)***	-.088 (.01)***
Ethnic conc.>50%			-.095 (.02)***	-.070 (.02)***	-.078 (.02)***
Ethnic conc.>60%			-.154 (.03)***	-.040 (.03)	-.050 (.02)**
Male	-.152 (.01)***	-.164 (.01)***	-.152 (.01)***	-.164 (.01)***	-.159 (.01)***
Origin:					
Nordic countries	-.224 (.02)***	-.056 (.02)***	-.162 (.02)***	-.035 (.02)**	-.052 (.02)***
Europe	-.090 (.02)***	.017 (.02)	-.011 (.02)	.047 (.02)***	.055 (.01)***
Asia	.174 (.07)**	.247 (.07)***	.231 (.07)***	.270 (.07)***	.306 (.06)***
Africa	-.105 (.06)	.096 (.06)	-.036 (.064)	.120 (.06)*	.060 (.05)
Middle East	-.438 (.04)***	-.023 (.04)	-.276 (.04)***	.034 (.04)	-.005 (.04)
Latin America	-.110 (.07)	-.108 (.07)	-.063 (.07)	-.088 (.07)	-.051 (.06)
Mixed Cat	-.065 (.05)	.036 (.05)	.020 (.05)	.069 (.05)	.075 (.04)*
Father's education:					
Upp.Secondary		.248 (.01)***		.241 (.01)***	.243 (.01)***
Short University		.473 (.02)***		.462 (.02)***	.462 (.02)***
Long University		.700 (.02)***		.685 (.02)***	.688 (.02)***
Graduate		.778 (.04)***		.763 (.04)***	.774 (.04)***
Missing					.050 (.02)***
Mother's education:					
Upp.Secondary		.201 (.01)***		.190 (.01)***	.191 (.01)***
Short University		.525 (.02)***		.508 (.02)***	.513 (.02)***
Long University		.671 (.02)***		.652 (.02)***	.668 (.02)***
Graduate		.819 (.07)***		.794 (.07)***	.841 (.07)***
Missing					.082 (.02)***
Family Income		.060 (.00)***		.059 (.00)***	.056 (.00)***

Notes: In all models age and municipality are controlled for.
The reference group is a Swedish woman of age 25 attending a school in the 9th grade outside of the segregated neighbourhoods. When adding the family background variables, the reference group has parents with a compulsory education level.
Standard errors in parenthesis.

Nordic countries and Southern Europe. But in comparison to her study the effect of controlling for family background on the coefficients indicating origin is considerably larger in our study.

The next step is to add our three dummy variables measuring the ethnic concentration ratio in the segregated neighbourhoods. The first dummy variable indicates that the school which the individual attended had a concentration of first- and second generation immigrants that was above 40%. The second and third variables indicate that the ethnic concentration ratio was above 50% respectively above 60%.[35] This way of categorizing the ethnic concentration ratio allows us to measure if an increase in the ethnic segregation gives rise to a significant rise in the neighbourhood effect. By measuring different levels of ethnic segregation we are also able to capture non-linear effects. In column (4) we estimate the neighbourhood effect when the family background factors are added to the model, and in column (3) the neighbourhood effect is estimated without controlling for family background. Model (4) is also the main model of the paper. The size of the effect from growing

[35]This means that an individual attending a school with an ethnic concentration ratio above 60% has a 1 for all three dummy variables.

up in a segregated neighbourhood decreases by about 60% when the family background factors are added, which shows that location is related to the socio-economic status of the family. The neighbourhood effect in column (4), is our best estimate of the true neighbourhood effect.[36] If the selection bias in the estimate is negligible this neighbourhood effect would be a causal effect. However, we are not able to conclude that our estimate of the neighbourhood effect is a causal effect, and accordingly it should be regarded merely as correlation. Moreover, the behavior of the three ethnic concentration coefficients does indicate that there exists an association between the ethnic segregation rate and the size of the neighbourhood effect. We can also establish that the effect seems to increase as segregation increases.[37] [38] Column (4) reveals that when adding the neighbourhood effect to the model that includes family background, the coefficients belonging to the variables describing origin exhibit a large change in a positive direction. Hence, having a foreign background is even more positive for educational attainment when the neighbourhood effect is controlled for. It is only for the Nordic countries the coefficient remains negative and significant.

In column(5) the individuals with missing information for the parents' education levels are included. The coefficients for the variables indicating that the mother's respectively the father's education levels are missing are rather small. This indicates that the variables do not capture family or individual characteristics that are restricted to the group of individuals with missing information for the parents' education level. Moreover, the other estimates do not seem to change much when we add these individuals to the sample. Worth mentioning is that the variable for the 60% ethnic concentration rate turns significant. But even if this is the case, the model does not change dramatically and therefore sample selection does not seem to be a severe problem.

We continue the analysis by studying each of the municipalities separately. The full model (model 4 in table 2.6), where we take all the independent variables into consideration are therefore reported for the 7 municipalities in tables 2.7 and 2.8. Table 2.7 reports the results for the big cities, Stockholm, Göteborg and Malmö. In table 2.8, the results are reported separately for each of the suburbs of Stockholm, i.e. Botkyrka, Haninge, Huddinge and Södertälje. The results for Stockholm show that it is first when the ethnic concentration reaches 50% that the neighbourhood effect becomes effective. The effect does not seem to increase at the 60% level either. In Göteborg and Malmö the neighbourhood effect is only significant at the 40% level. Moreover, the largest neighbourhood effect for all of the seven municipalities is found in Göteborg. Among the big cities the effects on educational attainment from having one or both parents born abroad are most positive in Stockholm. For some reason, the group originating from the Middle East in Malmö is, given the family background factors and the neighbourhood effect (and in contrast to the other municipalities) strikingly well educated.

[36]The effect of growing up in the most segregated neighbourhood on educational attainment, is almost as large as having a father with a short university education instead of a upper-secondary education.

[37]Remember that the 50% and 60% ethnic concentration variables measure the increase in the neighbourhood effect and not the absolute neighbourhood effect.

[38]The 60% ethnic concentration coefficient is significant on the 15%-level.

Table 2.7: Separate Ordered Probit Estimates of the Determinants of Educational Attainment for Stockholm, Göteborg and Malmö.

Variable:	*Stockholm*	*Göteborg*	*Malmö*
Segregated neigh.	-.004 (.03)	-.198 (.03)***	-.141 (.04)***
Ethnic conc.>50%	-.161 (.07)**	.011 (.04)	-.023 (.05)
Ethnic conc.>60%	.013 (.08)	-.072 (.04)	.009 (.07)
Origin:			
Nordic countries	.048 (.03)	-.123 (.04)***	-.097 (.06)
Europe	.064 (.03)**	.035 (.03)	.038 (.04)
Asia	.210 (.11)*	.231 (.13)*	.428 (.22)*
Africa	.129 (.10)	.059 (.14)	.085 (.19)
Middle East	.043 (.07)	-.122 (.10)	.495 (.15)***
Latin America	-.104 (.11)	-.154 (.14)	-.428 (.26)*
Mixed Cat	.043 (.08)	.014 (.10)	-.096 (.14)

Notes: In all models family background, gender, age and municipality are controlled for.
The reference group is a Swedish woman of age 25 attending a school in the 9th grade outside of the segregated neighbourhoods, and with parents having a compulsory education level.
Standard errors in parenthesis

Table 2.8: Separate Ordered Probit Estimates of the Determinants of Educational Attainment for Botkyrka, Haninge, Huddinge and Södertälje.

Variable:	*Botkyrka*	*Haninge*	*Huddinge*	*Södertälje*
Segregated neigh.	-.102 (.06)*	-.046 (.05)	-.088 (.05)*	-.146 (.05)***
Ethnic conc.>50%	-.054 (.06)		-.155 (.07)**	.083 (.08)
Ethnic conc.>60%	-.505 (.48)			-.082 (.09)
Origin:				
Nordic countries	.021 (.06)	.033 (.06)	-.015 (.06)	-.113 (.05)**
Europe	.016 (.07)	.168 (.08)**	-.014 (.07)	.089 (.08)
Asia	.248 (.30)	-.308 (.61)	.254 (.29)	1.552 (.62)**
Africa	-.265 (.25)	-.080 (.23)	.833 (.31)***	.427 (.45)
Middle East	.064 (.10)	-.123 (.15)	-.015 (.17)	.037 (.12)
Latin America	.361 (.29)	-.270 (.42)	.309 (.30)	-.112 (.42)
Mixed Cat	.448 (.17)***	.190 (.20)	.120 (.20)	-.042 (.24)

Notes: In all models family background, gender, age and municipality are controlled for.
The reference group is a Swedish woman of age 25 attending a school in the 9th grade outside of the segregated neighbourhoods, and with parents having a compulsory education level.
Standard errors in parenthesis

Table 2.9: Estimates of the Marginal Effects for the Entire sample.

Variable:	*1*	*2*	*3*	*4*	*5*	*6*
Segregated neigh.	1.3***	0.5***	1.7***	-0.1***	-0.5***	-2.9***
Ethnic conc.>50%	1.0***	0.4***	1.3***	-0.1*	-0.4***	-2.2***
Ethnic conc.>60%	0.5	0.2	0.7	-0.0	-0.2	-1.3
Origin:						
Nordic countries	0.5**	0.2**	0.7**	-0.0	-0.2**	-1.1**
Europe	-0.6***	-0.3***	-0.9***	-0.0	0.3***	1.5***
Asia	-3.0***	-1.3***	-5.4***	-0.8*	1.1***	9.4***
Africa	-1.5**	-0.6*	-2.4*	-0.2	0.6**	4.0*
Middle East	-0.4	-0.2	-0.7	-0.0	0.2	1.1
Latin America	1.3	0.5	1.6	-0.1	-0.5	-2.8
Mixed Cat	-0.9	-0.4	-1.3	-0.0	0.4	2.3

Notes: All numbers are in percentage points.

Studying the suburbs of Stockholm, we find that the neighbourhood effect increases as the segregation rate increases, which strengthens the assumption of an association between the ethnic segregation rate and the size of the neighbourhood effect. However, it is only in Huddinge that the increase is significant, and in the largest suburb of Stockholm, Södertälje, the neighbourhood effect seems to decrease at the 50% level. As mentioned in section 5, the ethnic segregation rate in Haninge does not quite reach the 40% level for any of the schools located in the municipality.[39] Hence, the small and insignificant neighbourhood effect in Haninge is in line with the results for the total sample and does not weaken the assumption of an association between the ethnic segregation rate and the size of the neighbourhood effect. The small neighbourhood effect in Haninge is in fact more of an evidence that supports the hypothesis.

By studying the marginal effects we can find out which education levels individuals brought up in segregated neighbourhoods are over- and underrepresented in, i.e. which education levels that drive the results found earlier. The marginal effects also give us estimates that can be interpreted in terms of the magnitude of the neighbourhood effect. Marginal effects are computed for the full sample. The marginal effects are reported for the ethnic segregation dummies and for the variables describing origin. In Table 2.9, the marginal effects of the ethnic segregation variables show a clear pattern. To be brought up in a segregated neighbourhood increases the probability to have only a compulsory education, to be a dropout from upper secondary education, and to have a vocational upper secondary education. The probabilities of completing a theoretical upper secondary education and of continuing to a post-secondary education are however smaller for the segregated group than for the group brought up outside an ethnically segregated neighbourhood. The neighbourhood primarily affects the probability of having a compulsory education, a vocational upper secondary education or the highest academic education level. Thus, attending

[39]The highest ethnical segregation rate for a school in Haninge is merely 38%. Furthermore, in Huddinge there exist no schools with an ethnic segregation rate above 60%.

a school with an ethnic segregation rate above 60% increases the probability of having a compulsory education by 2.8%, the probability of having a vocational upper secondary education by 3.7%, and decreases the probability of having an academic degree or 80 academic points by 6.4%. The probability of being a dropout from upper secondary education and the probability of having a theoretical upper secondary education are only marginally affected by the ethnical segregation rate. The differences in probabilities between natives and second-generation immigrants of different origins are also largest for the compulsory education level, vocational upper secondary education level, and the highest academic education level. For example, given the family background and the neighbourhood effect Asians have a 9.4% higher probability of reaching the highest education level, 5.4% lower probability of having a vocational upper secondary education and a 3.0% smaller probability of having only a compulsory education. The conclusion is that ethnic segregation and origin primarily affect whether an individual decides to settle with a compulsory education, chooses a vocational upper secondary education or achieves the highest level of academic education.

2.7.2 Results for the probit model and the matching estimator

The two decisions, finishing an upper-secondary education respectively continuing to an academic education are first estimated with our probit model. The neighbourhood effect we get, i.e. the marginal effect from growing up in a segregated neighbourhood on the probability to complete an upper secondary education respectively on the probability to continue to an academic education, are then compared to our results from the matching estimator.

In table 2.10 the probit model estimates for the two binary choices are reported. In the first two columns of table 2.10 the coefficients for the event "completing an upper secondary education" are reported. In Column (1) we estimate the model with only the dummy variable for the first segregation level, the 40% level, included. In column (2) we add the 50% and 60% segregation levels. Column (3) and (4) model the event "continue to study after upper-secondary school".[40] The sign and size of the estimated segregation coefficients are in line with the results found earlier. Columns (2) together with column (4) report that the total neighbourhood effect is larger for the event "continue study after upper-secondary school" than for the event "complete an upper-secondary education", in areas where the ethnic segregation rate is above 50%. This result indicates that the largest negative influence from growing up in an ethnically segregated neighbourhood is upon the decision whether to continue to an academic education or not, and that this is the case especially in the most ethnically segregated neighbourhoods. When studying the coefficients for the origin variables a reflection has to be made. The probability of continuing to an academic education is negatively related to originating from Latin America. However, for some reason, originating from Latin America does not decrease the probability of completing upper-secondary school. Moreover, except for individuals originating from

[40]This event is modelled given that the individual has completed upper-secondary school.

Table 2.10: Probit Estimates of the Determinants of Completing Upper Secondary Education respectively of Continuing to an Academic Education.

Variable:	*(1)*	*(2)*	*(3)*	*(4)*
Segregated neigh.	-.122 (.02)***	-.099 (.02)***	-.138 (.02)***	-.066 (.02)***
Ethnic conc.>50%.		-.047 (.03)		-.102 (.03)***
Ethnic conc.>60%.		-.001 (.04)		-.122 (.04)***
Origin:				
Nordic countries	-.045 (.02)*	-.043 (.02)*	-.033 (.02)	-.025 (.02)
Europe	.027 (.02)	.028 (.02)	.049 (.02)**	.053 (.02)**
Asia	.369 (.12)***	.370 (.12)***	.201 (.09)**	.208 (.09)**
Africa	.036 (.09)	.035 (.09)	.079 (.09)	.080 (.09)
Middle East	-.006 (.06)	-.001 (.06)	.077 (.06)	.103 (.06)*
Latin America	.037 (.12)	.038 (.12)	-.202 (.10)**	-.197 (.10)**
Mixed Cat	.020 (.07)	.021 (.07)	.105 (.07)	.109 (.07)*

Notes: In all models family background, gender, age and municipality are controlled for.
The reference group is a Swedish woman of age 25 attending a school in the 9th grade outside of the segregated neighbourhoods, and with parents having a compulsory education level.
Standard errors in parenthesis

Asia or Latin America the foreign background tends to have a larger positive impact on the probability of continuing to an academic education than on the probability of completing upper-secondary education.

Our next step is to calculate the marginal effect from growing up in a segregated neighbourhood on the probability to finish an upper secondary education respectively on the probability to continue to an academic education. The matching results will also be reported together with the marginal effects.[41] Because the outcome variable is binary, the matching estimator can be compared to the marginal effects from the probit model. The matching estimator is, more precisely, the average difference in the outcome variable (in this case the two events) between individuals brought up in the ethnically segregated neighbourhoods and the matched individuals brought up outside the ethnically segregated neighbourhoods.

Biases in the average neighbourhood effect caused by heterogeneous neighbourhood effects and incorrect parametric specifications are not a problem for the matching estimator. Moreover, for the matching estimator, the neighbourhood effect is only estimated within the common support region. This means that relevant information for estimating the neighbourhood effect is only extrapolated from individuals belonging to a subpopulation of the total population. The subpopulation, or the common support, is the sample of individuals where there exist, based on the balancing score, both an individual brought up in an ethnically segregated area and a comparable match brought up outside the ethnically segregated areas. Hence, the neighbourhood effect obtained with the matching estimator is redefined as the average neighbourhood effect for the individuals within the common support. For the matching estimator to be an unbiased estimator of the neighbourhood

[41] Appendix 2 contains information and statistics describing the construction of the matching estimates.

effect the conditional independence assumption (CIA) has to be fulfilled. The CIA is fulfilled if all relevant differences between the groups that affect both location and educational attainment are captured by the independent variables. Thus, unobserved family factors affecting both location and the educational outcome, i.e. selection on unobservables, is as much of a problem for the matching estimator as for the probit model.

Tables 2.11 and 2.12 report the probabilities for the total sample and for each of the municipalities separately. Separate probabilities are also reported for natives, second-generation immigrants, and each of the second-generation immigrant groups.[42] Besides the marginal effects the tables also contain our matching estimates. In table 2.11 the marginal effects and the matching estimates for the outcome "completing an upper secondary education", are reported. Column (1) shows the marginal effects for the probit model, column (2) shows the nearest neighbour estimates, and columns (3)-(5) show the radius matching estimates with different tolerance levels (0.1, 0.01, 0.001 and 0.0001).

For the total sample and for most of the 7 municipalities the marginal effects and the nearest neighbour matching estimates report a similar neighbourhood effect. However, when using the radius matching technique the neighbourhood effect is generally larger. When the tolerance level decreases the radius matching estimates tend to get smaller, but there is still a clear difference between the nearest neighbour estimator and the radius matching estimator for most of the estimates. Moreover, as the tolerance level decreases the radius matching estimator uses fewer matched controls. The number of matched controls used is nevertheless considerably larger for most of the radius matching estimates than for the nearest-neighbour matching estimates. The radius matching estimators, and especially the radius matching estimator with a tolerance level of 0.0001, do also match fewer treated than the nearest-neighbour matching estimator does. The radius matching estimator discards treated individuals if there are no controls within the given tolerance level from the propensity score of the individual. By discarding treated for whom there are no comparable controls we gain precision in the estimate. When we analyze our results we have to be aware of this fact, but we do also have to be aware that the radius matching estimator might give biased estimates when the tolerance level is high, because the matched controls might then be on average fairly poor matches. We therefore keep a sceptical attitude towards the radius matching estimates when the tolerance level is high. Contrary, in small samples the nearest-neighbour matching estimator is not reliable because of the high probability of using poor matches.

We begin by more thoroughly studying the results found in table 2.11. The marginal effect and the nearest-neigbour matching estimator report that individuals brought up in the ethnically segregated neighbourhoods have an approximately 3% lower probability of completing an upper secondary education. The radius matching estimator with the smallest tolerance level does however report a neighbourhood effect of 4.5%. The estimates do also indicate that the negative effect from growing up in a segregated neighbourhood on the probability of finishing an upper secondary education is largest in Göteborg, Malmö

[42]By adding interaction effects between the variable "growing up in an ethnically segregated neighbourhood" and municipality respectively origin we retrieve the separate probabilities.

Table 2.11: The Effect from Growing up in a Segregated Neighbourhood on the Probability of Completing an Upper Secondary Education.

Sample:	*Marg. eff:*	*Nearest-n:*	*Rad(0.1):*	*Rad(0.01):*	*Rad(0.001):*	*Rad(0.0001):*
Total	-.026***	-.027***	-.051***	-.049***	-.049***	-.045***
Municipality:						
Stockholm	-.005	-.009	-.035***	-.032***	-.029***	-.029***
Göteborg	-.042***	-.040***	-.070***	-.067***	-.065***	-.062***
Malmö	-.038***	-.035***	-.058***	-.056***	-.053***	-.049***
Botkyrka	-.032***	-.029**	-.054***	-.052***	-.048***	-.006
Haninge	-.027*	-.015	-.050***	-.056***	-.053***	-.046**
Huddinge	-.010	-.061***	-.028*	-.026*	-.026	-.015
Södertälje	-.032***	-.044**	-.057***	-.055***	-.052***	-.049**
Origin:						
Natives	-.032***	-.033***	-.055***	-.052***	-.052***	-.048***
Sec-gen. imm	-.011*	-.005	-.029***	-.027***	-.023***	-.013
Nordic con.	-.033***	-.021	-.054***	-.051***	-.041***	-.024
Europe	.011	.003	.000	.002	.005	.025*
Asia	.012	-.039	-.002	-.029	-.025	[a]
Africa	-.036	.055	-.034	-.027	-.091	[a]
Middle East	-.023	-.020	-.048	-.036	-.059	-.044
Latin America	-.062	-.164**	-.102*	-.078	-.119	[a]
Mixed Cat	-.012	-.014	-.043	-.049	-.029	[a]

Note: [a] To few treated for whom there exist controls within the radius to calculate a neighbourhood effect.

and Södertälje. The effect is 4-6% in Göteborg, 3.5-5% in Malmö and somewhere between 3% to 5% in Södertälje. It is only the radius matching estimators that show a significantly negative neighbourhood effect in Stockholm. Whereas the marginal effect and nearest-neighbour matching estimator report a negative and significant effect of attending an ethnically segregated school in Botkyrka, the radius(0,0001) matching estimator reports that the effect is zero.[43] Furthermore, the nearest-neighbour matching estimator reports a large and significant negative neighbourhood effect in Huddinge. But because the radius matching estimates are considerably smaller than the nearest-neigbour matching estimate, and closer to the marginal effect, it seems as if there is something peculiar with the nearest-neighbour matching estimator for Huddinge. The nearest-neighbour matching estimator is probably for part of the treated using poor matches. The marginal effect from the probit model, which indicates that the neighbourhood effect is insignificant in Huddinge, is therefore more reliable when it comes to Huddinge. The inconsistency in the estimates for Haninge does also seem to indicate that the nearest-neighbour matching estimator for Haninge uses poor matches.

The study continues by investigating the neighbourhood effects for natives and for the different second-generation groups. Natives brought up in ethnically segregated neighbourhoods have a 3 to 5% lower probability of completing an upper secondary education compared to natives brought up outside the ethnically segregated neighbourhoods. The

[43] However, the radius matching estimator with tolerance level 0.0001 for Botkyrka does only find comparable matches for 44% of the treated individuals, which is much less than for any other of the municipalities.

Table 2.12: The Effect from Growing up in a Segregated Neighbourhood on the Probability of Continuing to an Academic Education.

Sample:	*Marg. eff:*	*Nearest-n:*	*Rad(0.1):*	*Rad(0.01):*	*Rad(0.001):*	*Rad(0.0001):*
Total	-.054***	-.054***	-.105***	-.100***	-.099***	-.092***
Municipality:						
Stockholm	-.025**	-.027*	-.094***	-.077***	-.072***	-.052***
Göteborg	-.091***	-.080***	-.143***	-.130***	-.126***	-.116***
Malmö	-.049***	-.067**	-.065***	-.050***	-.053***	-.042***
Botkyrka	-.049***	-.063**	-.064***	-.057***	-.058**	-.026
Haninge	-.002	-.041	-.017	-.010	-.005	.004
Huddinge	-.086***	-.095***	-.109***	-.099***	-.093***	-.127***
Södertälje	-.041*	-.046	-.051**	-.038*	-.045**	-.026
Origin:						
Natives	-.061***	-.052***	-.100***	-.093***	-.092***	-.084***
Sec-gen. imm	-.037***	-.062***	-.082***	-.078***	-.074***	-.069***
Nordic con.	-.040**	-.044*	-.067***	-.062***	-.061***	-.069***
Europe	-.049***	-.076***	-.079***	-.071***	-.071***	-.066***
Asia	-.101	-.243**	-.195***	-.201**	-.321**	[a]
Africa	.041	.080	.004	.015	-.079	[a]
Middle East	-.070	-.143**	-.089**	-.090*	-.121**	-.115
Latin America	.203**	.204*	.143*	.181**	.505***	[a]
Mixed Cat	.038	-.006	-.022	-.055	-.099	[a]

Note: [a] To a few treated for whom there exist controls within the radius to calculate a neighbourhood effect.

estimates for the whole group of second-generation immigrants show that the probability of completing an upper secondary education for individuals with a foreign background is almost unaffected whether the individual has attended an ethnically segregated school or not. However, when studying the separate second-generation immigrant estimates it seems as if second-generation immigrants from Latin America and the Nordic countries are negatively affected by growing up in the ethnically segregated neighbourhoods. The nearest-neighbour matching estimator and the radius (0.0001) matching estimator do however not support the negative neighbourhood effect for individuals originating from the Nordic countries. For Latin Americans it is only the nearest-neighbour and the radius(0.1) matching estimator that report a negative and significant effect of growing up in the ethnically segregated neighbourhoods.

Let us now turn to table 2.12, where the probability to continue to an academic education (given that the individual has completed upper secondary school) is modelled. The first finding in table 2.12 is that the neighbourhood effect seems to be larger for this event compared to the former one. Attending a school in the ethnically segregated neighbourhoods results in a 5.5 to 9% lower probability of continuing to an academic education. In Göteborg the probability to continue to an academic education is approximately 8 to 11.5% lower if you are brought up in a segregated neighbourhood, in Malmö the probability is about 4 to 6.5% lower, and in Huddinge 8.5 to 12.5% lower. Moreover, for this educational attainment outcome there is a small neighbourhood effect in Stockholm. Except for the radius (0.0001) matching estimator our estimates indicate that there is a significant and relatively large association between attending an ethnically segregated school and the probability of continuing to an academic education in Botkyrka. In the case of Södertälje the marginal effect from the probit model, and the radius matching estimators with a tolerance level above 0.0001, report a negative and significant effect of attending an ethnically segregated school on the probability of continuing to an academic education.

Contrary to the former event, attending an ethnically segregated school seems to affect the probability of continuing to an academic education in the same way for natives and second-generation immigrants. Our findings do however indicate that individuals originating from Asia or the Middle East are more negatively affected by attending an ethnically segregated school than the other second-generation immigrant groups. Furthermore, for some reason Latin Americans growing up in the ethnically segregated neighbourhoods have a substantially higher probability of continuing to an academic education compared to Latin Americans brought up outside the ethnically segregated neighbourhoods.

2.8 Conclusions

Our study has shown that there exists an association between educational attainment and attending an ethnically segregated school in the metropolitan areas of Sweden. Thus, youth brought up in ethnically segregated neighbourhoods with similar observed family characteristics as youth brought up in more affluent areas attain a lower education level. The association is not large, but it is significant and seems to increase with the ethnic segregation rate. However, because of the problem of selection, i.e. unobserved family factors affecting both residential location and educational attainment, the effect of growing up in the disadvantaged areas (as measured here) is only a potential neighbourhood effect. A causal neighbourhood effect is not attainable without controlling for some exogenous variation affecting residential location. With our dataset this is not feasible. Nevertheless, our estimate of the potential neighbourhood effect is at least an upper bound of the true neighbourhood effect.[44] Hence, the negative influence of attending an ethnically segregated school will therefore not affect the individual's choice of education level to a larger extent than what is found in our study.

The neighbourhood effect primarily affects the probabilities to attain a compulsory education, a vocational upper secondary education, and the highest academic education level. Thus, attending a school with an ethnic segregation ratio above 60% increases the probability of having only a comprehensive education by 2.8%, the probability of having a vocational upper secondary education by 3.7%, and decreases the probability of having an academic degree or 80 academic points by 6.4%. Moreover, the largest neighbourhood effect is to be found in Göteborg. We have also found that second-generation immigrant youths, after controlling for family background and the neighbourhood effect, on average attain a higher education level than native youths. The group originating from the Nordic countries and the group originating from Latin America are exceptions and do seem to attain a lower education level than natives.

[44]Given that selection is not biasing the neighbourhood effect downwards, which is not very likely.

Finally, the probit model and the nearest neighbour matching estimator confirm the existence of a negative neighbourhood effect in the segregated neighbourhoods. Our conclusion is that the neighbourhood effect is significant for the event ”completing an upper-secondary education” in Göteborg, Malmö, Södertälje and Botkyrka. The neighbourhood effect seems to be larger for the event ”continue to an academic education” than for the event ”completing an upper-secondary education”, which is in line with the results found using the ordered probit model. Attending a school in the ethnically segregated neighbourhoods is associated with a 5.5 to 9% lower probability of continuing to an academic education whereas the probability of completing an upper-secondary education is about 3 to 4.5% lower. To grow up in an ethnically segregated neighbourhood affects the probability of continuing to an academic education in all of the municipalities except Haninge.

The study shows that attending an ethnically segregated school does not affect the probability of completing an upper-secondary education for second-generation immigrants. It is only second-generation immigrants from the Nordic countries and Latin America that are negatively affected by attending an ethnically segregated school. Furthermore, the probability of having an academic education is, strangely, substantially larger for Latin Americans brought up in the segregated neighbourhoods compared to Latin Americans brought up outside the ethnically segregated neighbourhoods. Why this is so is uncertain, but it could be that an ethnic externality might have a positive impact on educational attainment for second-generation immigrants living in ethnic enclaves. Assuming that it is positive to grow up in an ethnic enclave together with relatively well-educated and high-income fellow countrymen, segregation does not have to be negative for youths brought up in an ethnic enclave. If this is a correct assumption, it implies that positive role models and adults belonging to the same ethnic group as the child within the neighbourhood are more important for the child's educational attainment than peers, institutional factors and adults belonging to other ethnic groups. Another possible explanation of why second-generation immigrants brought up outside segregated neighbourhoods are choosing a lower education level than second-generation immigrants brought up within segregated neighbourhoods might be relative deprivation. Second-generation immigrants comparing themselves to native children in the neighbourhood may feel as outsiders, resulting in bad self-esteem, and finally in a low education level. However, this does not explain the fact that it is primarily only the probability of completing an upper-secondary education for second-generation immigrants that is unaffected by the neighbourhood effect.

When using a matching estimator to evaluate if individuals brought up in segregated neighbourhoods have a lower probability of finishing upper secondary school respectively of continuing to an academic education, one avoids biases because of incorrect parametric specifications. Another advantage with the matching estimator is that it only extrapolates information where there exist both treated and controls. Unobserved family factors affecting both location and the educational outcome are however, still a problem and may bias the matching estimates. The choice of matching estimator has been shown to affect the results. The nearest-neighbour matching estimator and the marginal effect from the probit model do in most of the cases, report a similar neighbourhood effect. However, in some cases the nearest-neighbour matching estimator seems to use poor matches, especially when the sample size is small. The radius matching estimators with a low tolerance level often discard a large number of treated individuals for whom there does not exist comparable controls. However, discarding treated for whom there do not exist comparable controls does not seem to change the estimates a great deal. Furthermore, the radius matching estimators generally report a larger neighbourhood effect than the probit model and the nearest-neighbour matching estimator and this is probably because we use more matched controls. If this primarily increases the precision in the estimates or biases the estimates is however uncertain.

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Appendix 2

The first step when constructing the matching estimates is to estimate the propensity score. The propensity score is in this context the propensity to be brought up in an ethnically segregated neighbourhood. The propensity score is estimated with a probit model. The probit model contains all factors determining location and educational attainment. In table A2.1 a list of the covariates is found. The predicted propensity score is saved and constitutes the basis for the matching. Before matching the groups, i.e. the group brought up within the segregated neighbourhoods and the group brought up outside the segregated neighbourhoods, the common support region is determined. In column (2) in table A2.2 the sample of individuals in the common support region is reported. We then control that the propensity score for the common support is balanced for the groups. This means that the distribution of the independent variables (the X's) is given the predicted propensity score, $\hat{p}(x)$, the same for the groups. We come to the conclusion that the balancing property is sufficiently fulfilled. However, a small note has to be made. For the balancing property to be fulfilled we have to split up the $\hat{p}(x)$ into quite small blocks, otherwise we find differences in the distribution of the X's. There is obviously nothing strange with this; in a large sample even very small differences in the distribution of the X's become significant. But one has to be aware of this, and if one performs the test of the balancing property in for instance Stata, the default test will report that the balancing property is not fulfilled.[45]

The next step is to match the individual brought up within the segregated neighbourhoods with the controls, i.e. the individuals brought up outside the segregated neighbourhoods. The matching is performed with nearest neighbour and radius matching. In Column 3 in A2.2, the common support of individuals brought up within the segregated neighbourhoods is reported. Column 4 in A2.2 reports the number of controls belonging to the common support. In column 1 in A2.3 the matched number of treated and controls belonging to the common support is reported for the nearest neighbourhood estimator. For the nearest neighbour estimate, the matching of the controls is made with replacement, meaning that a control can be used as a match more than once. This makes the nearest neighbour estimate more precise, but the standard error of the estimate larger.

Finally, the matching estimates are calculated in the manner described in section 2.6.2. The tolerance level, δ, used when calculating the radius matching estimates is 0.1, 0.01, 0,.001 respectively 0.0001. Choosing a larger tolerance level increases the number of controls matched to each of the individuals brought up in a segregated area. Columns 2 to 4 of table A2.3 reports the matched number of treated and controls belonging to the common support for the four radius matching estimators.

[45]However, even if the balancing property is performed with a large number of blocks the test in Stata reports that the balancing property is not fulfilled. But by taking into consideration that with a significance level of 1% every hundred test will be significant, one finds that the balancing property is fulfilled (see Becker & Ichino, 2002). Thus, with our 27 covariates we can expect that for every 4th block we will end up with a X that is significantly different between the treated and the controls.

Table A2.1: Covariates used for Estimating the Propensity Score.

Covariates:
Individual characteristics: Male, Age group 26, Age group 27, Age group 28 and Age group 29.
Municipality: Göteborg, Malmö, Botkyrka, Haninge, Huddinge and Södertälje.
Origin: Nordic countries, Europe, Asia, Africa, Middle East, Latin America and Mixed Cat
Father's education: Upp.Secondary, Short University, Long University and Graduate.
Mother's education: Upp.Secondary, Short University, Long University and Graduate.
and Family Income

Table A2.2: Statistics for the Matching Estimator.

Variable:	*Sample:*	*Common Support(CS):*	*Treated within CS:*	*Controls within CS:*
Total: Upper-sec.	53,417	53,416	13,662	39,754
Total: Ac. ed.	45,813	45,812	11,079	34,733
Municipality:				
Stockholm: Upper-sec.	17,714	17,654	3,153	14,501
Stockholm: Ac. ed.	15,395	15,338	2626	12,712
Göteborg: Upper-sec.	14,198	13,986	3,766	10,220
Göteborg: Ac. ed.	12,293	12,083	3,014	9,069
Malmö: Upper-sec.	7,466	7,462	2,413	5,049
Malmö: Ac. ed.	6,372	6,368	1,944	4,424
Botkyrka: Upper-sec.	3,578	3,571	1,887	1,684
Botkyrka: Ac. ed.	3,032	3,013	1,544	1,469
Haninge: Upper-sec.	3,592	3,575	531	3044
Haninge: Ac. ed.	2,971	2,955	418	2,537
Huddinge: Upper-sec.	3,238	3,226	886	2,340
Huddinge: Ac. ed.	2,699	2,687	716	1971
Södertälje: Upper-sec.	3,631	3,631	1,026	2,605
Södertälje: Ac. ed.	3,051	3,051	817	2,234
Origin:				
Natives: Upper-sec.	42,157	42,156	8,870	33,286
Natives: Ac. ed.	36,388	36,385	7,193	29,192
Sec-gen. imm.: Upper-sec.	11,260	11,240	4,792	6,448
Sec-gen. imm.: Ac. ed.	9,425	9,405	3,886	5,519
Nordic con.: Upper-sec.	4,320	4,314	1,629	2,685
Nordic con.: Ac. ed.	3,539	3,533	1,264	2,269
Europe: Upper-sec.	5,049	5,037	2,233	2,804
Europe: Ac. ed.	4,311	4,299	1,883	2,416
Asia: Upper-sec.	228	210	77	133
Asia: Ac. ed.	210	192	70	122
Africa: Upper-sec.	273	271	109	162
Africa: Ac. ed.	229	228	88	140
Middle East: Upper-sec.	719	717	461	256
Middle East: Ac. ed.	562	560	349	211
Latin America: Upper-sec.	202	190	67	123
Latin America: Ac. ed.	176	165	54	111
Mixed Cat: Upper-sec.	470	462	216	246
Mixed Cat: Ac. ed.	398	391	178	213

Table A2.3: Controls and treated for the Matching Estimators.

Variable:	*Nearest-n, Matched treated/contr:*	*Rad(0.1), Matched treated/contr:*	*Rad(0.01), Matched treated/contr:*	*Rad(0.001), Matched treated/contr:*	*Rad(0.0001), Matched treated/contr:*
Total: Upper-sec.	13,662/9478	13,662/39,754	13,662/39,754	13,541/39,617	12,755/37,479
Total: Ac. ed.	11,079/7,807	11,079/34,733	11,075/34,733	10,971/34,596	10,244/32,179
Municipality:					
Stockholm: Upper-sec.	3,153/2,521	3,153/14,501	3,146/14,501	3,089/14,322	2,754/10,844
Stockholm: Ac. ed.	2,626/2,118	2,626/12,712	2,622/12,712	2,571/12,531	2,254/8,924
Göteborg: Upper-sec.	3,766/2,520	3,766/10,220	3,760/10,220	3,710/10000	3,107/7,190
Göteborg: Ac. ed.	3,014/2046	3,014/9,069	3,009/9,068	2,966/8,852	2,424/5,794
Malmö: Upper-sec.	2,413/1,611	2,413/5,049	2,408/5,049	2,363/4,858	1,788/2,980
Malmö: Ac. ed.	1,944/1,339	1,944/4,424	1,941/4,424	1,901/4,227	1,361/2,316
Botkyrka: Upper-sec.	1,887/931	1,887/1,684	1,886/1,674	1,741/1,592	836/811
Botkyrka: Ac. ed.	1,544/794	1,544/1,469	1,540/1,469	1,406/1,389	644/632
Haninge: Upper-sec.	531/454	531/3044	530/3040	507/2,811	407/989
Haninge: Ac. ed.	418/353	418/2,537	4,17/2,531	396/2,252	308/723
Huddinge: Upper-sec.	886/665	886/2,340	879/2,340	833/2,200	545/814
Huddinge: Ac. ed.	716/542	716/1,971	710/1,971	666/1,806	419/593
Södertälje: Upper-sec.	1,026/734	1,026/2,605	1,000/2,605	957/2,489	617/936
Södertälje: Ac. ed.	817/597	817/2,234	801/2,232	766/2,075	482/690
Origin:					
Natives: Upper-sec.	8,870/6,845	8,870/33,286	8,868/33,286	8,854/33,154	8,412/30,825
Natives: Ac. ed.	7,193/5,608	7,193/29,192	7,193/29,192	7,164/29,063	6,778/26,392
Sec-gen. imm.: Upper-sec.	4,792/2,662	4,792/6,448	4,792/6,448	4,670/6,280	3,710/4,590
Sec-gen. imm.: Ac. ed.	3,886/2,194	3,886/5,519	3,882/5,519	3,777/5,326	2,865/3,600
Nordic con.: Upper-sec.	1,629/1,015	1,629/2,685	1,628/2,672	1,560/2,509	932/1,167
Nordic con.: Ac. ed.	1,264/802	1,264/2,269	1,263/2,257	1,197/2,064	652/838
Europe: Upper-sec.	2,233/1,193	2,233/2,804	2,232/2,781	2,139/2,574	1,349/1,407
Europe: Ac. ed.	1,883/1,029	1,883/2,416	1,882/2,393	1,802/2,185	1,065/1,075
Asia: Upper-sec.	77/53	75/133	69/127	34/38	4/4
Asia: Ac. ed.	70/50	68/122	62/112	28/31	3/3
Africa: Upper-sec.	109/67	103/162	93/156	51/62	12/12
Africa: Ac. ed.	88/58	81/140	77/134	37/44	9/9
Middle East: Upper-sec.	461/156	461/256	458/250	248/172	35/37
Middle East: Ac. ed.	349/118	349/211	342/205	170/119	26/25
Latin America: Upper-sec.	67/45	65/123	55/115	22/25	8/9
Latin America: Ac. ed.	54/38	52/111	45/103	17/21	7/8
Mixed Cat: Upper-sec.	216/117	216/246	208/246	109/116	15/17
Mixed Cat: Ac. ed.	178/104	178/213	170/213	85/96	11/13

Chapter 3

Ability and Rates of Return to Schooling - making use of the Swedish Enlistment Battery Test

3.1 Introduction

The return to investments in education might differ considerably between individuals from different parts of the ability distribution. The average return to investments in education is a quite unsatisfactory measure for explaining the individual's choice of utility maximizing education level. For a low ability person, investing in an academic education does not necessarily have to bring about any substantial increase in earnings, while an individual from the upper part of the ability distribution might get a return from investing in an academic education that is well above the average return. Furthermore, the well known ability bias in the schooling coefficient may also differ in magnitude between individuals of low respectively high ability.

For an individual to correctly maximize his/her expected lifetime earnings the individual has to be aware of his/her true return to investments in education. If a person does not consider his/her own ability, and ability influences the return to education, the maximizing decision might be made on false grounds. A study performed by Ingram & Neumann (forthcoming in Labour Economics) reports that in the US, for the past several decades the group that fared worst in the labour market was the group who did not invest in specific skills, but with a college education. Juhn, Murphy & Pierce (1993) has shown that the wage inequality in the US has increased since 1970. They assume that the increase is primarily due to an increase in the return to unobservable skills. A recent paper by Gould (2005) reports that the increased inequality can be attributed to an increase in the demand for mental ability and/or the general, unobserved skill within each occupation. Furthermore, Meghir & Palme (2003) has shown that the reform of the Swedish schooling system in the 1950s, which increased compulsory schooling, resulted in a significant and large rise in earnings for individuals above the median ability level but with unskilled fathers. Taking these findings as a starting point, we want to more thoroughly investigate the relationship between ability and the return to investments in education.

The main objective of this paper is to estimate and compare the return to investments in education for men belonging to different parts of the ability distribution. We name this estimate the ability specific return to education. The ability measure used for locating individuals in different parts of the ability distribution, is the achievement test score from the Swedish Military Enlistment Battery. The Swedish Military Enlistment Battery tries to measure cognitive ability and the test is used for allocating individuals into different branches of the military, and to select those who are capable of performing more qualified jobs. The Swedish Military Enlistment Battery is taken by virtually every male Swedish citizen the year when the individual turns 18.

The second aim of this paper is to explore the measurement error in the ability proxy, i.e. the test score from the Swedish Military Enlistment test, and the bias in the ability specific return to education coming from the measurement error in the test score.[1] The measurement error in the test score is assumed to be the deviation from the individual true latent cognitive ability level.

The final objective of the paper is to produce estimates of the return to education for different education levels when controlling for ability. We also assess the question whether log earnings is a linear function of years of schooling or whether "sheepskin effects" exist in Sweden.[2]

When estimating the relationship between earnings and schooling it is commonly assumed that the schooling coefficient is upward biased.[3] When ability is an omitted variable in the earnings equation three different approaches have been used with the intent to capture the true return to education.

In the first approach, and also in the approach used in this study, achievement test scores, measuring cognitive ability, work as indicators for ability. The main problem with this approach is that both schooling and the test score are generated by the same latent ability. This means that using test score as an indicator for ability one has to be aware of the joint causality between schooling and the test score (Hansen, Heckman & Mullen, 2003).

In a study performed by Kjellström (1999), using two separate Swedish data sets, IQ-tests and grades from the end of the sixth year of schooling serve as controls for ability. When controlling for ability, the earning premium for one more year of schooling fell from .052 to .043. Blackburn & Neumark (1995) uses the Armed Services Vocation Aptitude Battery (ASVAB) test as an indicator of ability. They show that the upward bias in the return to education is roughly 40% when ignoring ability. In a similar fashion, Murnane et al. (1995) study how the mathematical skills of graduating high school seniors affect their

[1]Because this is the first study actually using the test score result from the Swedish Military Enlistment Battery in a cross-sectional study we believe the test score has to be thoroughly explored.

[2]"A sheepskin effect" is assumed to exist if degrees or credentials are more important for explaining returns to education than the actual years of schooling completed.

[3]However, if potential high wage earners are induced to leave school early, the schooling coefficient could in fact be biased downward (Griliches, 1977).

wage at age 24.

The second approach uses institutional changes in the schooling system, and changes in compulsory schooling laws, as sources for exogenous variations in educational attainment. With these "natural variations" affecting the schooling decision, a causal return to education effect is estimated within an instrumental variable framework. Most of these IV-estimates of the return to education report a higher return to education than the OLS-estimated return to education (see e.g. Angrist & Krueger, 1991, Card, 1995, Harmon & Walker, 1995, Kane & Rouse, 1993). The results of a study performed on Swedish data by Meghir & Palme (1999), using a reform in the 1950s of the Swedish comprehensive school system as an instrument, are in line with these results.

An explanation for these puzzling results might be that the institutional changes in the school system affect the schooling decision of individuals who, otherwise, would choose a relatively low educational level. Furthermore, given that these individuals have a higher return to education than the average individual, the IV-estimate will give a return to education estimate that is higher than the OLS return to education.[4]

Controlling for family background tends to reduce the estimated return to education by approximately 5-10 percent (Ashenfelter & Zimmerman, 1997, Card, 1995). In an IV-framework, where family background is used as an instrument, the estimated return to education exceeds the OLS estimate. Ashenfelter & Zimmerman (1997) state that this result indicates that the OLS-estimate is upward biased due to omitted variables.

The third approach uses twins, with the intent of capturing the causal return to education parameter. By comparing the earnings of twins with different educational levels, unobserved family differences are eliminated within families. Studies performed on American data report a within-family difference estimate that is about 30 % smaller than the OLS estimated return to education (Ashenfelter & Rouse, 1998, Rouse, 1997).[5] Isacsson (1997) finds that the within-family estimate of the return to education for identical twins in Sweden is .023, or less than 50% of the OLS estimated return, .049.

In section 3.2 the Swedish Military Enlistment Battery is thoroughly explored. The theoretical model used for capturing the ability specific return to schooling is presented in section 3.3. In section 3.4 we analyze the measurement errors in the test result from the Swedish Military Enlistment test and the bias in the ability specific return to schooling coming from the measurement error. Section 5 gives a description of the sample data and presents some descriptive statistics. The econometric specification and the empirical results are presented in section 3.6. Section 3.7 summarizes the study and discusses the findings.

[4]For further explanations of the upward bias in the IV-estimate of the return to education, see Card (1999).

[5]When the within-family difference estimate is corrected for measurement errors in the schooling variable, the estimate is approximately 10-15% smaller than the OLS estimate.

3.2 The Swedish Military Enlistment Battery and cognitive ability

The intention with the test result from the Enlistment Battery is to try to represent and numerically measure cognitive ability. The Enlistment Battery has been used for the assessment of intelligence in the Swedish military since the middle of the 1940s. The test results from the Enlistment Battery principally measure a general ability. The information from the test is then used to allocate the individuals into different branches of the military, and to select those who are capable of performing more qualified jobs.

Tests trying to measure cognitive ability or an individual's mental capacity have been undertaken for over a century. The first test for measuring cognitive abilities constructed for practical purposes was produced by Binet & Simon between 1905 and 1911 (Ross, 1988). The method most often used today for measuring and calculating individuals' cognitive abilities is the factor model.[6] A general intelligence factor, G, that influences measures of cognitive performance was first identified by Spearman (1904). The general intelligence factor, G, explains the greater part of all variance in test scores, and is often strikingly similar across race and gender (Cawley, Conneely, Heckman & Vytlacil, 1997).[7] Thus, the variable used in this paper for measuring cognitive ability is in fact the general intelligence factor, G.

Scores in ability tests rise with age and education. Therefore it is evident that the tests principally measure knowledge. For example, the US AFQT (Armed Forces Qualification Test) test score rises with human capital and age (Hansen, Heckman & Mullen, 2003, Neal & Johnson, 1996, Winship & Korenman, 1997). Caroll's (1993) opinion is that differences in cognitive abilities depend on both learning experiences and genetic influences. General ability is closely connected to education and the environment of the individual, which means that the ability is not biologically independent of education and the individual's past experiences. However, even if the general ability is related to the education and environment of the individual, the measure seems to capture something that is closely connected to the cognitive ability of the individual. The general ability, i.e. the G factor, is therefore, probably, a reliable measure of latent cognitive ability, but a measure that is either increased or revealed by schooling and learning.

Herrnstein & Murray (1994) proposed that there exists a relationship between G and socio-economic outcomes such as education, occupational attainment, unemployment, and wages. They argue that there has been a rising return to ability in the US for the last decade and that wages are much closer connected to ability than to education. The general G-factor has also been attributed dominant in explaining job performance (Ree & Earles, 1991) and as the largest contributor to academic performance (Brodnick & Ree, 1995). In a discrimination context, Neal & Johnson (1995) has explained the entire black-white wage gap for young women, and much of the wage gap for young men using the AFQT score. Cawley et al. (1997) consents to the view that G explains socio-economic outcomes.

[6] For more information on the factor model, see Johnson & Wichern (2002).

[7] For more information about the G factor, and the other group factors, see Caroll (1993).

However, they maintain that the contribution is modest and that more variables are needed to explain wages and occupational choice. They also find that whether using G or the AFQT as a cognitive ability measure makes little difference in explanatory power in wage regressions. Cawley, Heckman & Vyctlacil (1998) concluded that the rising return to schooling in the US is not driven by a rising return to ability. In 1999 the Ministry of Defence completed a validation of the enlistment results against verdicts from the basic military education. The conclusion was that job performance in the military seems to be connected to a high G-factor (Carlstedt, 1999).

The Enlistment Battery 80, which is the test our sample of individuals has taken, includes four tests, Instructions, Synonyms, Metal Folding and Technical Comprehension. The aim of the Instructions test is to measure the individual's ability to make inductions, while the test Synonyms captures verbal ability. Verbal skills are however also needed for performing well on the Instructions test. Metal Folding is a spatial test, and the fourth test measures technical comprehension. Each test is normalized into a nine-point scale. The values are then, in accordance with the method of factor analysis, summed up and transformed into a new nine-point scale labelled "test score group" (Carlstedt & Mårdberg, 1993).[8]

3.3 The ability specific return to schooling

In the basic human-capital model, the relationship between schooling and earnings is independent of ability (Mincer, 1975). The model assumes that all individuals have the same opportunity for investments in human-capital and that the return from the investment is equal for all individuals. However, it is unlikely that the return to schooling is constant for all ability levels. An average return to schooling will probably exaggerate the return for low ability groups and underestimate the return to schooling for high ability groups. We therefore follow Becker's (1975) human-capital model, and allow ability to affect the rate of return to investments in education.

Moreover, Griliches (1977) explores the bias in the return to education coefficient when ignoring ability in the earnings equation. In this study, and in most other studies that try to capture the true return to education, the estimated return to education is the average return to education for all ability levels. Thus, even if the average return to education estimate does not suffer from any severe ability bias the estimate does not have to be an accurate measure for explaining the return to education for individuals with different ability levels.

A model that intends to capture the return to education for individuals in different parts of the ability distribution is therefore constructed. The construction of the model is made in a fashion that corresponds to using an achievement test score as a proxy for ability. With the model in mind we also discuss the potential biases in the ability specific return to education when using the Swedish Military Enlistment test.

[8]For more information about the "test score groups" and the separate test results see Appendix 3.

From the following expression of the earnings function the average and unbiased return to education, β, can be determined (Griliches, 1977):

$$y = \alpha + \beta S + \gamma_A A + \varepsilon \quad (3.1)$$

where A is ability and S is schooling. Letting the return to schooling, in some functional form, depend on ability level we generalize the expression to:

$$y = \alpha + \beta(f(A))S + \gamma_A A + \varepsilon \quad (3.2)$$

where *f(A)* determines the size of the ability specific return to education for different ability levels.

3.3.1 Using a test score as a proxy for ability

Since we lack information about the true ability levels of the individuals we use an achievement test score as a proxy for ability, [9] and get the expression:

$$y = \alpha + \beta(f(T))S + \gamma_T T + \varepsilon \quad (3.3)$$

Unlike true ability that reasonably is a continuous variable a test score will always be a discrete variable. But besides from not being a continuous variable, we assume at this stage that the test score, T, is perfectly measuring ability. An elementary [10] specification of *f(T)* could be to let the test score affect the ability specific return to education linearly:

$$f(T) = 1 + T \quad (3.4)$$

Which gives the earnings equation:

$$y = \alpha + \beta_0 S + \beta_1 TS + \gamma_T T + \varepsilon \quad (3.5)$$

A more flexible specification of the relationship between the test score and the ability specific return to education could be to divide the test score results into M[11] test score groups, where $m \in$ *[1,...,M]*, and write *f(T)* in the following form:

$$f(T) = \delta_1 + \delta_2 + ... + \delta_m + ... + \delta_M \quad (3.6)$$

where δ_m is M indicator variables, indicating which test score group the individuals belong to. The true ability specific returns to education, β_1 to β_M, could then be estimated from the expression:

$$y = \alpha + \beta_1\delta_1 S + \beta_2\delta_2 S + ... + \beta_m\delta_m S + ... + \beta_M\delta_M S + \gamma_T T + \varepsilon \quad (3.7)$$

[9]Ignoring ability in the earnings equation results in a biased estimate of β. Assuming that schooling and ability are positively related and that the return to ability, γ, is positive, the return to schooling will be upward biased.

[10]And also a traditional way of specifying an interaction effect.

[11]When using the Swedish Military Enlistment test we end up with 9 test score groups.

However, even if we have an achievement test score that predicts the true ability, we have to be aware of the fact that such test scores are only proxies for the true ability. And even if the test score is very highly correlated with the true ability level, the relationship can never be perfect. Because of different types of measurement errors in the test score, biases in the ability specific returns to education could arise. The magnitude of the biases for different test scores may also be of different sizes.

3.4 Measurement errors in the Military Enlistment test

Addressing the issue of measurement errors in the test score, we have to start by exploring the test score, T, and the probable reasons why T should differ from A. If we assume that the test score from the Military Enlistment test is correctly measuring ability, the only reason for T to differ from A is measurement errors in the test score. Principally, measurement errors in the test score result in a downward bias in the return to ability, γ.[12] Besides that the measurement errors in the test score biases the return to ability, the measurement errors will also bias the ability specific return to education, because this is an interaction effect between both education and ability. If we denote μ to be the deviation between the true latent ability level of the individual and the test score, the Military Enlistment Battery test might contain two [13] different types of measurement errors.

There are reasons to believe that μ and T might be correlated, i.e. that $Cov(T,\mu)\neq 0$. The first measurement errors that could cause $Cov(T,\mu)$ to differ from zero is that the individuals have different education levels when they take the test. The second problem that might result in a measurement error, and a nonzero covariance between μ and T, is that there might be individuals underachieving on the test with intent. Both these problems will therefore be discussed in detail.

The score on ability tests is known to increase with age and schooling (Cawley, Connely, Heckman & Vytlacil, 1996). Schooling can be seen as a mechanism for both increasing and revealing latent ability. And, in accordance with this view, studies show that schooling increases measured ability by 2 to 4 test score points (Hansen, Heckman & Mullen, 2003, Neal & Johnson, 1996, Winship & Korenman, 1997).

The Swedish Military Enlistment Battery is taken by virtually every male Swedish citizen the year when the individual turns 18.[14] Hence, the measured test score level will therefore depend on the upper-secondary school choice. That schooling affects the test

[12] Because the paper aims at capturing the ability specific return to education, and not the return to ability, the bias in the return to ability is not investigated any further.

[13] We ignore the measurement error that distinguishes all proxies, i.e. that $V(\mu) \neq 0$. Instead we focus on the measurement errors that are specific for the Swedish Military Enlistment test.

[14] A small number of individuals takes the test at an older age, primarily because they study abroad during the particular year. But this is probably a minor problem for two reasons. First, the group missing out on the test because of their studying abroad is not a very large group, and secondly, there are no legitimate reasons for believing that $Cov(T,\mu)$ for this particular group should be of any specific sign.

score, means that both the decision to study after compulsory education and the choice whether to study at a vocational respectively a theoretical study programme, creates test score differentials between individuals.[15]

For two persons having different schooling levels, the achieved test scores for the two persons are not fully comparable. Thinking of the test score as a measure of latent ability, the measure is enhanced if the individual chooses to continue studying after compulsory school. The measured ability will therefore, irrespective of the true latent ability level, be higher for individuals continuing to upper secondary school. But even if the measured ability is higher the true latent ability level does not have to be higher for individuals continuing to upper secondary school. On the contrary, for a given achieved test score level, one can assume, given that the test score rises with schooling, that individuals either choosing not to continue to upper-secondary school or studying at a vocational upper secondary study programme have a "true" latent ability level that is on average higher than for the group that decides to continue studying at a theoretical upper-secondary study programme. Thus, if $E[\mu]$ is larger than zero for the lower test score levels, $Cov(T,\mu)$ will be negative.

If this is the case, the heterogeneity in schooling level when the test is taken, might bias the ability specific returns to investment in education. A downward bias in the ability specific returns to education arises if individuals with either a compulsory or a vocational upper-secondary education, for a given test score level, are more likely to earn a higher salary than individuals continuing to a theoretical upper-secondary education, because of their assumed higher latent ability level.[16] For the highest test score levels a significant downward bias in the return to education is however not as likely. This comes from the fact that there is not a large group of individuals with only a compulsory education level achieving a high test score.

The second reason for a measurement error in the test score is individuals intentionally under-performing on the test. It is obvious that some individuals will not do their best at a military enlistment test for various reasons. If this occurs frequently we can expect the return to education for the lower test score groups to be seriously biased upward. This is because the expected latent ability for the lowest test score groups then is, on average, higher than what the test score tells, i.e. that $E[A|T = m] > m$ for small m.

In table 3.1 the expected sign of the bias in the ability specific return to education is reported separately for low, medium respectively high achievers on the test. The table reports that the return to education for the higher test score levels is unbiased. The problem with heterogeneity in schooling level probably results in a small downward bias in the

[15] The type of theoretical study programme may also affect the test score differently. Natural science study programmes, where math, physics and other technical subjects are important subjects on the schedule, are often believed to increase cognitive ability more than social science study programmes.

[16] As Griliches (1977) points out, when controlling for ability using a test score, schooling might be negatively correlated with the wage equation residual. For a high ability individual it is not always, from a utility maximizing perspective, preferable to invest in a higher education level, because of different types of investments costs. Forgone earnings for high ability individuals might be considerable and exceed the discounted total gains from education.

Table 3.1: The Bias in the Ability Specific Return to Education for Low, Medium respectively High Achievers on the Test.

Test score group	Low:	Medium:	High:
Problem:		(Sign of the Bias)	
Heterogeneity in schooling	-	(-)	0
Individuals underachieving	+[a]	0	0

Note: [a] Primarily a problem for the lowest test score level.

return to education for the medium test score levels. For the lowest test score levels it is uncertain whether the bias is positive or negative. The problem with individuals intentionally underachieving on the test may very well outweigh the heterogeneity in schooling problem. In the data description, in section 3.5, we come back to the problem with measurement errors, and by studying the test score distribution and the schooling variable we can with higher accuracy discuss the potential biases.

3.5 Data description

In this section we describe the sample data, list the covariates and present some descriptive statistics.

The data is a cross-sectional register data from Statistics Sweden (SCB2003). The data is a full sample, containing every individual in the age group 22-36 living in Sweden in the year 2001. Since we intend to capture the ability specific return to education, we have to restrict the sample to men who have taken the Military Enlistment test.[17] We also restrict the sample to Swedish born individuals, with Swedish born parents. By excluding first- and second generation immigrants and adopted, we escape problems with ethnic discrimination in the labour market. Furthermore, since we are going to estimate an earnings equation, only men that meet the following conditions are included in our analysis: [i] individuals who are employed, and who have not been studying during any part of the year 2001; [ii] those aged 30 or above; [iii] those with an income from work above 80,000 Swedish crowns. Conditional on these restrictions, the sample is reduced to 228,840 individuals.

Our earnings variable is a measure of annual income from work for the year 2001.

The educational attainment variable, SUN 2000, used in this study is a revision of the former SUN classification adjusted to fit the International Standard Classification of Education (ISCED97). The new revised education measure allows us to compute a years of schooling variable that is qualitatively closer to the correct number of years of schooling an

[17] There is only a small number of women who have taken the Military Enlistment test, and this group of women can hardly be considered a representative sample.

individual has completed, than the years of schooling variable constructed from the former SUN measure. Furthermore, the SUN 2000 education variable is for the year 2001 and describes both the highest level of education achieved and the type of study programme attended. The constructed years of schooling variable goes from nine years of schooling, i.e. completing compulsory school, to twenty years of schooling, i.e. getting a doctor's degree.[18] From the schooling variable eleven indicator variables are constructed, where each of the indicator variables corresponds to a certain number of years of schooling attained. More years of schooling are assumed to correspond to a higher education level. The former SUN years of schooling variable does only contain six different education levels.[19]

Four indicator variables indicating whether the individual has received a degree or not, are also constructed. The first variable indicates whether the individual has obtained a final upper-secondary degree or not. The second indicator variable indicates that the individual has studied at a university or college for at least six months, receiving at least 20 academic points[20] in one subject, but not for two years, which corresponds to 80 academic points, and has not yet received a degree. The third variable indicates that the individual has studied for more than two years (80 academic points) but not for three years (120 academic points) and has not completed a degree. And finally, the fourth indicator variable indicates that the individual has studied at a university or college for at least three years, and has received at least 120 academic points, but not achieved a degree. To indicate which type of study programme the individual has attended, thirteen indicator variables are used in the analysis.

Tables A3.1 and A3.2 report descriptive statistics for the educational attainment variables. Table A3.1 shows that the average schooling level is higher for the former schooling variable in comparison to the newer and revised schooling variable. This is primarily because the revised schooling variable separates out the individuals who reach thirteen years of schooling, a group that formerly was categorized as reaching fourteen years of schooling. This group constitutes about 11.2% of the sample. Another important schooling level that is included in the revised schooling variable is fifteen years of schooling (an education level that earlier was classified as sixteen years of schooling), which 7.5% of the sample reach. Moreover, from table A3.1 it can also be seen that 8.4% of the sample does not reach a degree. A considerable share, 53% of the individuals, has a technical education, which is because we are only studying men. About 14% of the sample has a general education, which in this case corresponds to having a compulsory education as the highest education.

Table 3.2 reports the distribution of individuals reaching the different education levels for each of the test score groups. The information from table 3.2 together with our earlier exploration of the measurement error in the ability proxy, i.e. the test score from the Swedish Military Enlistment test, determine the expected biases in the ability specific return for each of the different test score groups. The relative number of individuals, for

[18]Except for nineteen years of schooling, all potential years of schooling between nine and twenty are contained in our schooling variable.

[19]The former SUN classification system contains the following number of years of schooling; 9, 11, 12, 14, 16 respectively 18 years of schooling.

[20]40 academic points correspond to one year of full time studies or 60 ECTS credits.

each of the test score groups, reaching less than twelve years of schooling, indicates how large the problem with heterogeneity in schooling might be. By studying the lower test score groups we might also get an insight into whether people intentionally underachieving on the test, constitutes a problem for the analysis.

Table 3.2: The Distribution of Individuals Reaching the Different Education Levels for Each of the Test Score Levels.

Test score group:		*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
Years of schooling:										
9	n	707	2,881	4,511	4,583	3,416	1,575	499	120	13
	(%)	(39,7)	(28,9)	(19,1)	(11,2)	(6,3)	(3,3)	(1,5)	(0,8)	(0,5)
10	n	119	538	936	1,025	831	404	138	29	4
	(%)	(6,7)	(5,4)	(4,0)	(2,5)	(1,5)	(0,8)	(0,4)	(0,2)	(0,1)
11	n	871	6,043	15,889	26,906	29,140	16,303	5,093	751	36
	(%)	(49,0)	(60,6)	(67,2)	(65,9)	(53,8)	(33,8)	(15,7)	(5,0)	(1,3)
12	n	53	357	1,476	4,441	8,583	8,660	4,693	1,428	171
	(%)	(3,0)	(3,6)	(6,2)	(10,9)	(15,8)	(17,9)	(14,5)	(9,5)	(6,3)
13	n	9	46	271	1,305	4,222	7,822	7,778	3,762	583
	(%)	(0,5)	(0,5)	(1,1)	(3,2)	(7,8)	(16,2)	(24,0)	(25,1)	(21,4)
14	n	7	75	315	1,197	2,982	4,048	3,282	1,440	223
	(%)	(0,4)	(0,8)	(1,3)	(2,9)	(5,5)	(8,4)	(10,1)	(9,6)	(8,2)
15	n	8	30	202	993	3,340	5,402	4,612	2,124	319
	(%)	(0,4)	(0,3)	(0,9)	(2,4)	(6,2)	(11,2)	(14,2)	(14,2)	(11,7)
16	n	4	9	56	376	1,472	3,562	5,288	4,220	1,043
	(%)	(0,2)	(0,1)	(0,2)	(0,9)	(2,7)	(7,4)	(16,3)	(28,1)	(38,3)
17	n	1	-	2	19	99	251	468	471	100
	(%)	(0,1)	-	(0,0)	(0,0)	(0,2)	(0,5)	(1,4)	(3,1)	(3,7)
18	n	-	-	2	4	16	53	112	126	47
	(%)	-	-	(0,0)	(0,0)	(0,0)	(0,1)	(0,3)	(0,8)	(1,7)
20	n	-	-	1	5	52	198	448	529	186
	(%)	-	-	(0,0)	(0,0)	(0,1)	(0,4)	(1,4)	(3,5)	(6,8)

Note: Percentages are column percentages.

When studying the distribution of individuals reaching the different education levels, for the lowest test score group, it does not seem as if there is a large group of persons underachieving on the test with intent. Only 1.6% of the individuals, belonging to the lowest test score group, choose to study at a post upper-secondary education. However, among the individuals with an upper-secondary education there might exist some persons underachieving on the test with intent, which could result in an overestimated ability specific return to education for this test score group. For the second test score group there might also be some individuals underachieving on the test with intent. For test score groups higher than the second we do not believe underachieving on the test with intent is a major problem.

That individuals have different education levels when the test is taken might bias the ability specific returns downward. Table 3.2 shows that the share of individuals, with only nine years of schooling, is small for the test score groups five to nine. Furthermore, for all test score groups, except the two highest, there is a considerable number of individuals with only eleven years of schooling. Having eleven years of schooling implies in most of the cases that the individual has studied at a vocational upper-secondary study programme.[21] Whether a vocational upper-secondary education has a positive or a negative effect on the test result is however uncertain.[22]

The test is taken sometime during the second half of the eleventh year of schooling or during the first half of the twelfth year of schooling. This implies that a person with a theoretical upper-secondary education, who takes the test during the second half of the year, has on average received about two more months of schooling than a person with only eleven years of schooling. Taking into account that one year of schooling might increase measured ability by 2 to 4 test score points,[23] the extra two months of education, for the group of individuals taking the test during the second half of the year, is not likely to significantly bias the ability specific return to education. The conclusion reached from studying table 2 is therefore that the heterogeneity in schooling problem primarily is expected to bias the ability specific return to education downward for the four lowest ability groups. And further, for the two highest test score groups the heterogeneity in schooling level problem can be assumed not to bias the ability specific return to education. A sensitivity analysis will be performed to test if our estimates are heavily biased.

3.6 Econometric specification and empirical findings

In this section we discuss the choice of econometric specification and present and analyze the empirical findings.

The usual equation to be estimated when trying to capture the return to education is the Mincer equation. A common formulation of the Mincer equation states that the log of hourly wages should be regressed on years of schooling, work experience and work experience squared, where experience often is replaced by age.[24] Antelius & Björklund (2000) shows that when excluding observations with low incomes hourly wages can be replaced by annual earnings.[25] There has, however, been a controversy as to whether the years of schooling variable is the proper educational attainment variable for measuring returns to education (Card, 1999). Relaxing the linearity assumption, by introducing dummy variables for each year of schooling, tends to reveal that degrees or credentials

[21] 89% of the individuals with eleven years of schooling have a vocational upper-secondary education.

[22] A vocational study programme is often thought of as providing a lower education level than a theoretical study programme. However, Technical comprehension and Metal Folding constitute half of the military enlistment test, and many vocational study programmes are in engineering or other technical fields (as much as 79% of the individuals with a vocational study programme in our study have it in a technical field of education). The technical study programmes might give an advantage on the Technical comprehension and Metal Folding tests. Therefore, in comparison to a theoretical study programme, it is uncertain if a vocational study programme affects the test score positively or negatively.

[23] See section 3.4

[24] When experience is replaced by age, it is often the case that the estimated return to education is smaller than if experience is used (Mincer, 1974).

[25] When using register data from Statistics Sweden.

are more important for explaining returns to education than actual years of schooling completed.[26] This is generally known as "sheepskin effects" or the screening hypothesis.

Accordingly, in the econometric analysis we estimate models with different educational attainment variables with the intent of answering the question if there is such a thing as "sheepskin effects" in Sweden.

3.6.1 Baseline earnings equation

The baseline econometric model, where we use years of schooling, S, as the educational attainment variable, will therefore take the following form:

$$lny = \alpha + bS + \varphi_1 exp + \varphi_2 exp^2 + \rho X + \varepsilon \tag{3.8}$$

where b is the ability biased return to education. Furthermore, exp and $\exp^2$ are experience and experience squared[27] and X is a set of covariates.[28] We then add ability, i.e. the test score from the Military Enlistment test, to the earnings equation, and get a measure of the return to education, β, that is, at its best, cleansed from the ability bias. However, if the schooling variable suffers from severe measurement errors, we have to be aware of the fact that the estimated return to education might be biased downward.

In model 1 in table 3.3 the Mincer equation is estimated with the new revised schooling variable, i.e. the SUN2000 schooling variable, and in model 2 the former SUN schooling variable is used. The schooling estimates show that the estimated return to education is larger when using the revised schooling variable. Thus, with the finer schooling variable with better precision the downward bias in the return to education estimate is reduced. Moreover, using the finer schooling variable also increases the precision in experience which consequently increases the estimated return to experience. When adding the test score from the Military Enlistment test to the model (model 3) the schooling estimate decreases from .080 to .061.[29] Controlling for ability therefore reduces the earnings premium for one more year of schooling by approximately 23%. In comparison to the results found in Kjellström (1999), where the return to schooling estimate decreased from .052 to .043 when controlling for ability, our estimated return to schooling is larger,[30] but the relative decrease in the schooling estimate when controlling for ability is about the same. Björklund, Edin, Fredriksson & Krueger (2004) reports that the return to schooling has increased during

[26] See, for instance, Hungerford & Solon (1987).

[27] Lacking an actual experience measure we use the standard method of constructing experience, i.e. exp = age - 7 - years of schooling.

[28] We will control for labour market region and family income. If one assumes that individuals from affluent homes have a higher probability of finding well-paid jobs, and family background is correlated with ability, family background has to be controlled for. The ability measure might otherwise, partly, capture the family background effect. The appendix describes the family income measure and explains the construction of the variable.

[29] Using indicator variables for each of the test score groups, instead of the discrete and ordered test score variable, does not change the results in this table or in table 3.4.

[30] The specification of the model in Kjellström (1999) is however not in every aspect the same as in our model.

Table 3.3: OLS Earnings Equation Estimates.

Independent: variables	(1)	(2)	(3)	(4)	(5)
Schooling(SUN2000)	.080 (.001)***		.061 (.001)***	.074 (.001)***	.056 (.001)***
Schooling(SUN)		.075 (.001)***			
Test Score			.040 (.001)***		.039 (.001)***
Experience	.061 (.002)***	.051 (.002)***	.051 (.002)***	.060 (.002)***	.050 (.002)***
Experience^2	-.002 (.000)***	-.001 (.000)***	-.001 (.000)***	-.002 (.000)***	-.001 (.000)***
Family income	no	no	no	yes	yes
R^2	.189	.190	.210	.196	.215

Notes: In all models we control for labour market region.
Standard errors in parenthesis.

the 1990s in Sweden, and that the average wage premium seems to be around .060 in 2000. Our estimate of the average wage premium therefore indicates that the return to schooling has increased even more since 2000.[31] The average return to increasing the test score by one level is .04. In columns (4) and (5) of table 3.3 family income is controlled for. In column (4) family income is added to the model and in column (5) both the test score and family income are included in the model. Irrespective of whether ability is controlled for or not, the schooling estimate decreases by about 8% when family income is taken into consideration, which is in accordance with results found elsewhere (Ashenfelter & Zimmerman, 1997, Card, 1995).

To assess if there are "sheepskin effects", the years of schooling variable, S, is replaced with our set of indicator variables for education levels. Thus, all models estimated in table 3.4 contain the set of indicator variables for education level. In the first two columns of table 3.4 the model is estimated without, respectively with, the score from the Military Enlistment test. In the third model (column 3) we add the variables indicating whether the individual has received a degree or not. The individual's choice of study programme is included in the fourth model (column 4). The fifth model estimated (column 5) contains all of our educational attainment variables.

From columns 1 and 2 we can see that the relationship between years of schooling and the return to education is not perfectly linear. Figure 3.1 pictures the relationship between years of schooling and the return to education for the second, fourth and fifth models of table 3.4. Studying the results from model 2 we see that for the tenth, fourteenth and twentieth (a Ph.D. degree) year of extra schooling the relationship seems to be decreasing.

Model 3 reports that achieving a credential or degree is important if one wants to

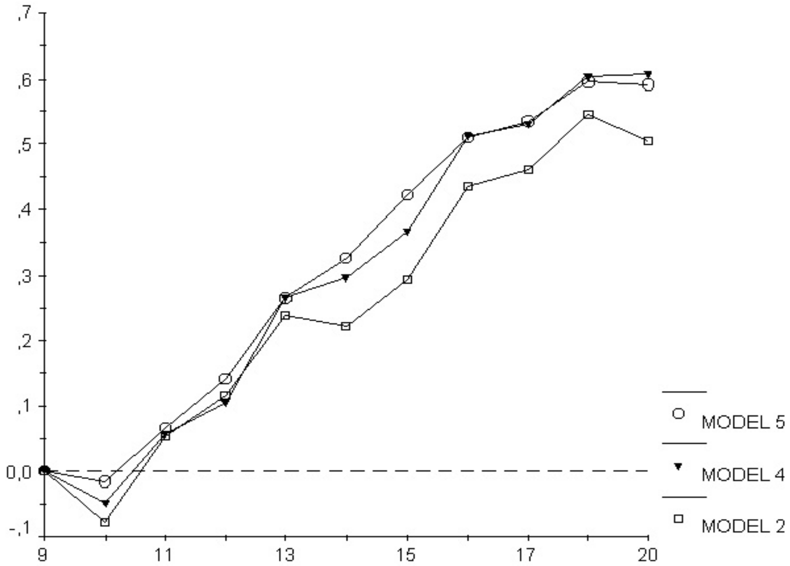
[31] The new SUN2000 schooling variable does however partly explain our comparatively high estimate.

Table 3.4: Estimates of the Return to Schooling Using Indicator Variables for Each Schooling Level.

Independent: variables	(1)	(2)	(3)	(4)	(5)
Years of schooling:					
10	-.070 (.006)***	-.077 (.006)***	-.051 (.006)***	-.049 (.006)***	-.016 (.006)***
11	.080 (.003)***	.053 (.003)***	.055 (.003)***	.058 (.004)***	.067 (.004)***
12	.178 (.003)***	.116 (.004)***	.144 (.004)***	.105 (.004)***	.141 (.004)***
13	.333 (.004)***	.239 (.004)***	.254 (.004)***	.264 (.005)***	.264 (.005)***
14	.304 (.004)***	.222 (.004)***	.233 (.005)***	.298 (.005)***	.326 (.005)***
15	.382 (.004)***	.294 (.004)***	.342 (.005)***	.365 (.005)***	.422 (.006)***
16	.548 (.004)***	.435 (.005)***	.425 (.005)***	.511 (.006)***	.510 (.006)***
17	.582 (.010)***	.460 (.010)***	.447 (.010)***	.530 (.013)***	.535 (.013)***
18	.672 (.018)***	.544 (.018)***	.527 (.018)***	.603 (.018)***	.595 (.018)***
20	.635 (.010)***	.504 (.011)***	.477 (.010)***	.607 (.011)***	.591 (.011)***
No upper-sec. degree			-.168 (.005)***		-.158 (.005)***
20-79p			-.060 (.005)***		.033 (.005)***
80-119p			-.068 (.007)***		-.090 (.007)***
At least 120p			-.234 (.006)***		-.210 (.006)***
Study programme	no	no	no	yes	yes
Test Score		.037 (.001)***	.035 (.001)***	.032 (.001)***	.031 (.001)***
Experience	.062 (.002)***	.062 (.002)***	.050 (.002)***	.061 (.002)***	.051 (.002)***
$Experience^2$	-.002 (.000)***	-.002 (.000)***	-.001 (.000)***	-.002 (.000)***	-.001 (.000)***
R^2	.202	.218	.228	.261	.269

Notes: In all models we control for labour market region.
The reference group has a compulsory education, i.e. nine years of schooling.
Standard errors in parenthesis.

Figure 3.1: Returns to schooling



Years of schooling

Note: The earnings premium for a specific years of schooling level, in comparison to a compulsory education, is on the vertical axis.

profit from the full return of an education. To undertake higher education for a relatively long period of time, for more than three years, without reaching a degree is particulary negative, and associated with a 23.4% lower annual income. Also, not completing an upper-secondary education is associated with significantly lower earnings. Hence, the result is a clear indication that sheepskin effects exist in the Swedish education system. What is worth emphasizing is that investments in long higher educations are not economically rewarding if one does not make the effort to reach a degree. The expected income level of a person who has completed three years of academic education, but without completing a degree, is in parity with the expected income of a person who has completed three years of upper-secondary education. Not attaining a degree after many years of studies may be a signal to the employer of a lack of discipline or talent.

Adding study programme dummies to the model tends to make the relationship between schooling and the return to education more linear. From model 4 in figure 3.1 it can be seen that an extra year of schooling results in a larger earning premium when study programme is controlled for. Furthermore, except for the tenth year of education more years of schooling now increases earnings. However, when the effect from not achieving a degree is controlled for, the negative coefficient for attaining the tenth year of schooling almost disappears. Thus the graph for the full model, i.e. model 5, reveals that the relationship between schooling and the return to education is very close to linear. In the tail of the relationship there is however still some nonlinearities. A licentiate degree is for instance rewarded more or less the same as a Ph.D. degree. This is maybe not surprising, knowing that the salaries in the academic sector, where many of the Ph.D.s are employed, are lower than those outside academics.

3.6.2 Estimating the ability specific return to education

The next step of our empirical investigation is to specify the model used for estimating the ability specific return to education. From expression (3.7) we specify:

$$lny = \alpha_m + \sum_{m=1}^{9} \delta_m \beta_m S + \varphi_1 exp + \varphi_2 exp^2 + \rho X + \varepsilon \qquad (3.9)$$

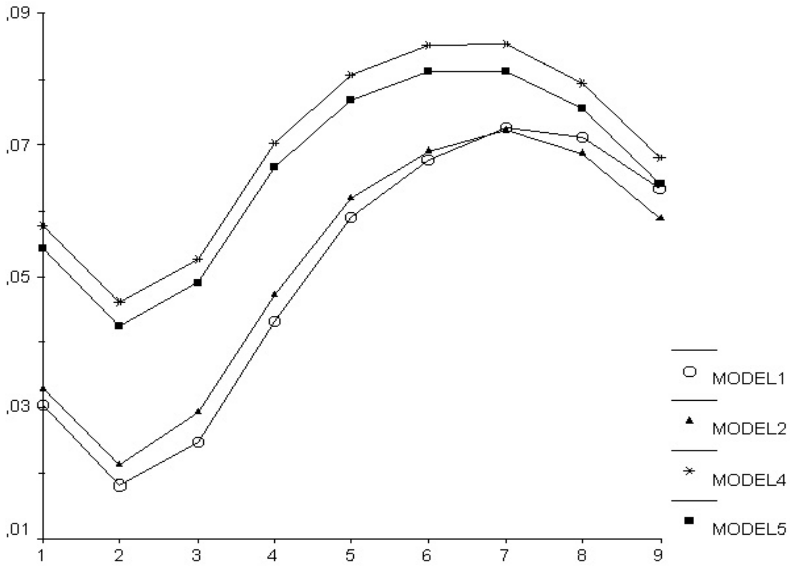
where β_m is the ability specific return to education for each of the nine test score groups and δ_m is nine dummy variables indicating which test score group the individual belongs to. However, when analyzing, β_m, the return to education for the different test score groups, we have to take the ability specific biases, reported in table 3.1, into consideration. We also let the intercept, α_m, vary with test score group. Different specifications of expression 3.9 are estimated and presented in table 3.5. The ability specific returns to schooling for the nine test score groups are also pictured in figure 3.2. The figure shows that there seems to be a hump-shaped relation between the return to schooling and the score on the Military Enlistment test. It is only the lowest test score group that diverts from the pattern, i.e. the return to schooling is higher for the lowest test score group than for the second and third test score groups.[32] The reason behind the relatively high return to education for the lowest test score group is probably that some otherwise relatively high-achieving persons underachieve on the test with intent. The problem with people intentionally underachieving on the test probably biases the return to education estimates for the lowest test score level more than does the heterogeneity in schooling level problem. The return to education for the second test score group might also be slightly overestimated due to persons underachieving on the test with intent.

The hump-shaped relationship between the return to schooling and the score on the Military Enlistment test is surprising and has to be more thoroughly investigated. From a human capital perspective it is strange that the most talented people should have a lower return to schooling than the groups just below them in ability. The sensitivity analysis to be found in the next section tries to question this result. However, the finding does not mean that the highest test score groups on average earn less than individuals belonging to test score group seven. It only implies that the return to one extra year of schooling is higher for the seventh test score group than for the two highest test score groups.

The curve furthest down in figure 3.2 illustrates the first model of table 3.5, where we only control for experience and labour market region. Model 2, in figure 3.2, shows the ability specific returns to schooling, when the variables indicating whether the individual

[32]The difference in the ability specific return to education between the first and the second, and also between the first and the third, test score groups is however not statistically significant.

Figure 3.2: Ability Specific Returns to Education



Test Score Group

Note: The return to schooling is on the vertical axis.

has received a degree or not have been added. In model 4 we add study programme, and in model 5 also family income is included. One can easily see that the ability specific return to schooling increases for all test score groups when study programme and information on whether the individual has attained a degree or not, are taken into account. Merely taking into account whether the individual has attained a degree or not does, however, decrease the ability specific returns to schooling for the two highest test score groups. When adding family income to the model, which is done in model 5, it is obvious that the ability specific returns to schooling for all test score levels decrease. The decrease is however small and does not seem to change the relationship between the return to schooling and the score on the Military Enlistment test.

The first model of table 3.5 shows that for the three lowest test score groups the return to schooling is below .025.[33] For the group of individuals achieving at least six on the Military Enlistment test the ability specific return to education lies around .07. However, the largest increase in the ability specific return to education exists when going from the third to the fourth test score group. The sharp increase in the ability specific return to education when going from the third to the fourth test score group, and also when going from the fourth to the fifth test score group, might partly depend on the heterogeneity in schooling level problem. We have earlier found that it is primarily the ability specific return to education for the four lowest test score groups that might be biased downward.

[33] If we assume that the return to schooling for the lowest test score group is overestimated.

Table 3.5: Estimates of the Ability Specific Returns to Education.

Independent: variables	(1)	(2)	(3)	(4)	(5)
Ability Specific Ret. to Ed:					
Test score group 1	.030 (.007)***	.033 (.007)***	.050 (.007)***	.058 (.007)***	.054 (.007)***
Test score group 2	.018 (.003)***	.021 (.003)***	.038 (.003)***	.046 (.003)***	.042 (.003)***
Test score group 3	.025 (.002)***	.029 (.002)***	.045 (.002)***	.053 (.002)***	.049 (.002)***
Test score group 4	.043 (.001)***	.047 (.001)***	.065 (.001)***	.070 (.001)***	.066 (.001)***
Test score group 5	.059 (.001)***	.062 (.001)***	.077 (.001)***	.080 (.001)***	.077 (.001)***
Test score group 6	.068 (.001)***	.069 (.001)***	.083 (.001)***	.085 (.001)***	.081 (.001)***
Test score group 7	.073 (.001)***	.072 (.001)***	.084 (.001)***	.085 (.001)***	.081 (.001)***
Test score group 8	.071 (.001)***	.069 (.001)***	.079 (.001)***	.079 (.001)***	.075 (.001)***
Test score group 9	.064 (.003)***	.059 (.003)***	.069 (.003)***	.068 (.003)***	.064 (.003)***
No upper-sec. degree		-.160 (.004)***		-.175 (.004)***	-.173 (.004)***
20-79p		-.008 (.004)*		.061 (.004)***	.057 (.004)***
80-119p		-.102 (.006)***		-.082 (.006)***	-.082 (.006)***
At least 120p		-.222 (.005)***		-.189 (.005)***	-.187 (.005)***
Experience	.071 (.002)***	.063 (.002)***	.060 (.002)***	.054 (.002)***	.052 (.002)***
Experience^2	-.002 (.000)***	-.002 (.000)***	-.002 (.000)***	-.001 (.000)***	-.001 (.000)***
Study programme	no	no	yes	yes	yes
Family income	no	no	no	no	yes
R^2	.213	.224	.255	.266	.269

Notes: In all models we control for labour market region.
Standard errors in parenthesis.

Thus, given this assumption, the sharp increase in the ability specific return to education would probably partly be smoothed out if the downward bias could be eliminated.

Again, to assess whether the relationship between schooling and the return to education is linear for the different test score groups we replace the years of schooling variable with our eleven years of schooling indicator variables. By categorizing the nine test score groups into three test score levels, low, medium and high [34] and combining these with the years of schooling indicators we receive 33 test score/years of schooling variables, each variable corresponding to a certain test score level/years of schooling combination. In figures A3.1, A3.2 and A3.3 the returns to schooling are pictured for the different test score groups. Figure A3.1 illustrates the relationship when controlling for experience and labour market region. In figure A3.2 the type of study programme is added, and in figure A3.3 both study programme and information on whether the individual has received a degree or not, is included. Figure A3.3 shows that the result found earlier, that the relationship between earnings and years of schooling becomes almost linear when study programme and "sheepskin" effects are controlled for, is true for all test score groups.[35] Another interesting result found in the figures, is that it is merely individuals belonging to the highest test score group that seem not to gain an earnings premium from a Ph.D. degree. Figure A3.1 and figure A3.2, where we do not control for "sheepskin" effects, report that low achievers on the military enlistment test, i.e. those with a test score below four, have a lower earnings premium for twelve years of schooling than for eleven years of schooling. But taking into account, in figure A3.3, whether the individuals achieve a degree or not changes this result. Hence, individuals with a low result on the Military Enlistment test seem to have some problems finishing an upper-secondary education of three years.

3.6.3 Sensitivity analysis

By estimating the ability specific returns to schooling for sub-samples of the total sample we can check the stability of the results, and test whether the non-random measurement errors are heavily biasing our results. The sub-samples of individuals are restricted to groups of individuals within different parts of the education system. Estimating the relationship between the test result on the Military Enlistment test and the return to eduction, for smaller parts of the education system, principally exposes whether the estimates are stable and can be applied all over the education system. Non-random measurement errors might be one source of unstable results.

The relationship is therefore estimated for the following years of schooling intervals; 9-12, 9-17, 12-17, and 13-17 years of schooling.[36] When studying the pre-academic education

[34] The low test score level includes the test score groups one to three, the medium test score level the test score groups four to six, and finally the high test score level includes the test score groups seven to nine.

[35] We disregard the right-hand side of the relationship for the lowest test score group, because of the small number of individuals with a test score of three or below, who reach more than 16 years of schooling (see table 3.2).

[36] In the estimates that follow we do not control for either the type of study programme or for whether

levels, i.e. 9 to 12 years of schooling, besides from checking the stability in the results, we try to investigate the problem with persons intentionally underachieving on the test. By excluding individuals with either a licentiate or a Ph.D degree, i.e. those with more than 17 years of schooling, we test the accuracy in the hump-shaped relationship between the result on the enlistment test and the return to schooling. Restricting the sample, to individuals with 12 to 17 years of schooling, the return to schooling for the different test score groups should not be biased because people have different education levels when they take the test. Also excluding the individuals with 12 years of schooling, the relationship is estimated separately for the sample of individuals with an undergraduate education level.

Figure A3.4 illustrates the ability specific returns to schooling for the whole sample, i.e. for all of the years of schooling levels, and for the sample of individuals attaining 9 to 12 years of schooling. On the whole, the relationship between the test score result and the return to schooling, seems to be stable when the sample is restricted to the compulsory and the upper-secondary education levels. The upward bias in the ability specific return to schooling for the lowest test score group seems to be somewhat smaller, when we exclude the individuals reaching an academic education. However, the estimates are probably still biased upward because of the problem with people intentionally underachieving on the test. In figure A3.5, where we exclude the graduate education levels, the hump-shaped relationship completely disappears. Thus, also for the highest test score levels the relationship between the score on the enlistment test and the return to schooling is positive. But even if the earnings premium for one extra year of education increases with the result on the enlistment test the increase seems to be diminishing.

In figure A3.6, where we test the heterogeneity in schooling level problem, we have to be aware that the ability specific return to schooling estimates are heavily overestimated for the lowest test score groups because people intentionally underachieve on the test. The graph shows that the returns to schooling are about the same, or somewhat lower, for the test score groups four to nine when we exclude the education levels 9 to 11. This result indicates that the ability specific return to education for the test score groups four to nine are not underestimated because individuals have different education levels when they take the test. If the ability specific returns to schooling estimates were underestimated, the estimates for the test score groups in the middle of the ability distribution would be higher when excluding the education levels nine to eleven, in comparison to the estimates for the whole sample. For the three lowest test score groups the heterogeneity in schooling level problem might of course, partly, explain the high return to schooling for these groups, found in figure A3.6. But because the return to schooling does not seem to be underestimated for the fourth test score group we do not believe that the returns to schooling are underestimated for the three lowest test score groups either.

Illustrating, in figure A3.7, the relationship separately for the undergraduate education levels (13-17), reveals two interesting features. First, the returns to schooling decreases substantially (as compared to the 12-17 education levels in figure A3.6) for most of the test score groups. Since beginning an academic education is rewarded with a relatively

a person has achieved a degree or not.

large earnings premium, [37] the estimated return to schooling is reduced when leaving this earnings premium out. Secondly, for the test score groups one to four the return to one extra academic year of education is not significantly different from zero.[38]

3.7 Conclusions

The results of our study indicate that a higher score on the Swedish Military Enlistment test is associated with a higher return to schooling. Hence, referring to an average return to schooling is a quite unsatisfactory measure for describing the return to schooling for individuals from the upper respectively the lower part of the ability distribution. Since the positive relationship between the return to schooling and the score on the Military Enlistment test seems to be decreasing in the test score, it is primarily the ability specific return to schooling for the lower test groups that diverts from the average return to schooling. Particularly the lowest test score groups do have a problem completing (i.e. getting a degree) a three-year upper-secondary education programme. Furthermore, the sensitivity analysis has also shown that individuals belonging to the four lowest test score groups do not seem to receive any significant return from a higher education, besides the earnings premium from beginning the higher education. Taking into account the fact that people intentionally underachieve on the test, the lower test score groups appear to have a return to schooling that is below .025. The return to schooling seems to be about .06 for individuals in the middle of the ability distribution. One more year of education for individuals from the upper-part of the ability distribution is rewarded with an additional 2%, i.e. the return is .08. The policy implication of this is that the average academic earnings premium may decrease if more individuals from the lower part of the ability distribution decide to study at an academic education level.

The hump-shaped relationship between the return to schooling and the score on the enlistment test disappears when the sample of individuals with a licentiate or a Ph.D. degree are excluded. This is probably, partly, because people with a licentiate or a Ph.D. degree often are high-achievers on the test, but employed in the academic sector were salaries are relatively low. Another explanation might be that these people have not yet acquired a substantial amount of work experience and are still investing in on-the-job training, an investment that is often "paid" by lower earnings.

When controlling for study programme and for whether an individual has completed a degree or not, the relationship between years of schooling and earnings becomes almost linear. The study also shows that "sheepskin" effects exist in Sweden. It is particularly negative to study for a relatively long time at a higher education institution without completing a degree. Studying at a higher education institution for three years without completing a degree is associated with an expected income level that is in parity with the expected income of a person who has completed three years of upper-secondary education.

[37]From table 3.4 it can be seen that there is a large earnings premium when going from the twelfth to the thirteenth year of schooling, i.e. beginning an academic education.

[38]Given that the earnings premium for beginning an academic education is excluded.

It is primarily the problem with people intentionally underachieving on the test that biases the ability specific return to schooling. The study shows that the ability specific return to schooling for the test score groups in the lower part of the test score distribution seem to be biased upwards because people underachieve on the test. The heterogeneity in schooling level problem does, however, not seem to bias the ability specific returns to schooling a great deal.

We have also seen that the new, revised education measure allows us to compute a schooling variable that is closer to the correct number of years of schooling that an individual has completed. With this finer schooling variable, with better precision, we consequently get a return to schooling estimate that is higher than if the earlier education measure is used.

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Appendix 3

The test score groups

The data contains both the "test score group" variable, and the results on the separate tests. The transformation of the results on the separate tests into the nine-point scale has however changed during the time period. But because our data contains the results on the separate tests we are able to construct a test score measure that is time consistent, i.e. where the method for calculating the nine-point scale is the same for the entire time period. For 2.7% of the observations there is missing information for one, two or three of the separate test score results. In these cases we use the average of the other test score results as a proxy for the missing test score result. Because excluding these observations from the sample does not change our estimates we decided to keep them.

Using the sum of the separate test score results instead of G in the wage regressions does not change any of the results found in the paper. But if we instead were to divide the test score groups into 10 equally large groups, i.e. deciles, based on either G or the sum of the separate test score results, the estimates change in the tails of the ability distribution. In fact, this means that we lose the opportunity to analyze what takes place at the ends of the tails.

Family Income

Family income is computed in the following manner. Estimates of the mother's and father's average earnings, based on the earnings for the years 1970, 1975 and 1980, are first computed. All earnings are in 1980-years prices. If any of the earnings for the three years is zero, an average of the remaining positive earnings is computed. We then add the mother's and father's average incomes and obtain a measure for the family income.

Table A3.1: Descriptive Statistics for the Educational Attainment Variables.

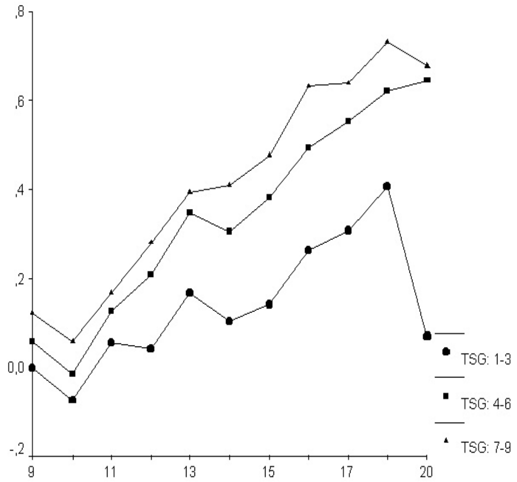
Variable:	*N:*	*Mean:*
Schooling(SUN2000)	228,840	12.11
Schooling(SUN)	228,840	12,29
No upper-sec. degree	5,934	.026
20-79p	4,098	.018
80-119p	2,988	.013
At least 120p	6,073	.027
Total without a degree	19,093	.084
Study programme:		
General	31,099	.136
Pedagogic	5,196	.023
Human. or Cultural	3,886	.017
Soc. or Journalistic	3,463	.015
Econ, Admin. or Comp.	34,795	.152
Law	1,979	.009
Natural science	2,069	.009
Technical	121,828	.532
Agricul. or Forestry	6,054	.026
Low Medicine	4,941	.022
High Medicine	1,743	.008
Services	10,979	.048
Missing	808	.035

Table A3.2: Comparison of the schooling variables.

Years of schooling:	*Schooling(SUN2000):*	*Schooling(SUN):*
9	18,305	18,305
10	4,025	-
11	101,032	105,056
12	29,862	29,862
13	25,798	-
14	13,569	39,367
15	17,030	-
16	16,030	34,471
17	1,411	-
18	360	1,779
20	1,419	-

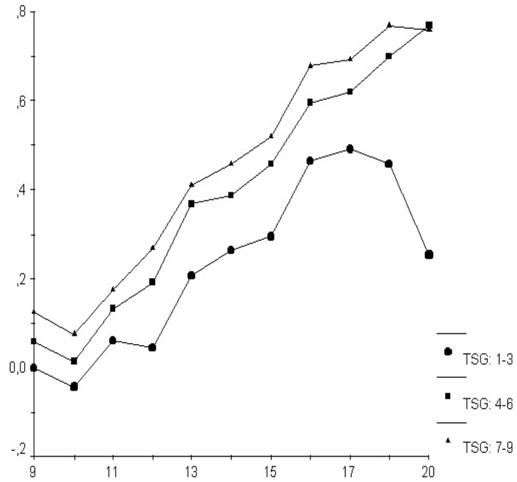
Figures A3.1-A3.3: Separate returns to education estimates for different test score levels.

Figure A3.1



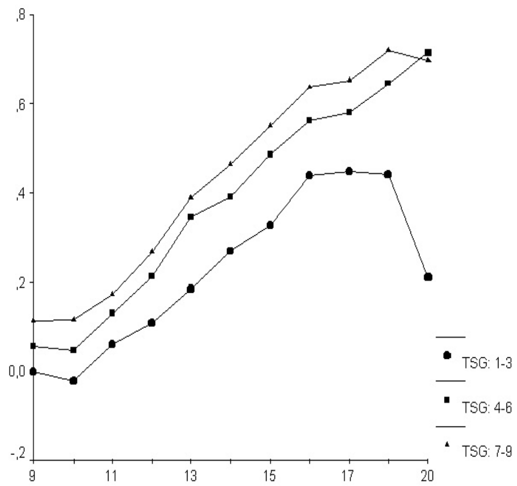
Years of schooling

Figure A3.2: Controlling for study programme.



Years of schooling

Figure A3.3: Controlling for study programme and degree.

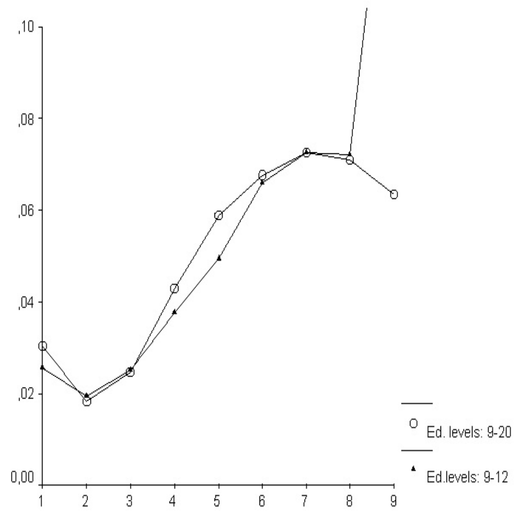


Years of schooling

Note: In all models we control for work experience, work experience squared and labour market region.

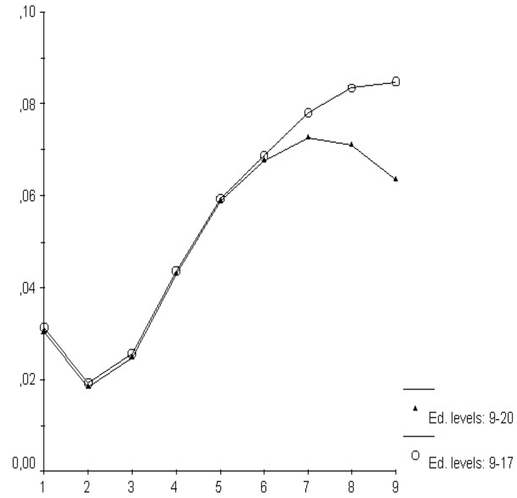
Figures A3.4-A3.7: Testing the Stability in the Ability Specific Returns to Schooling.

Figure A3.4



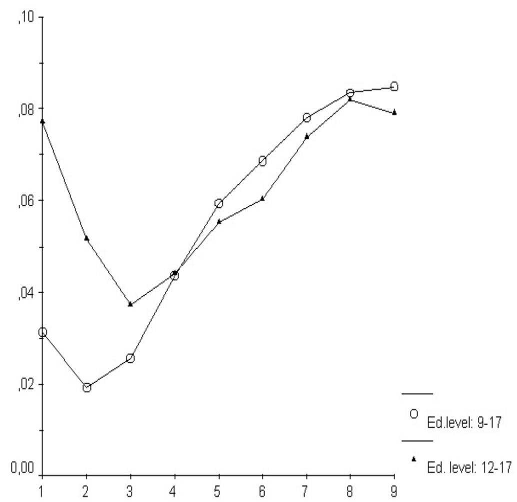
Test Score group

Figure A3.5



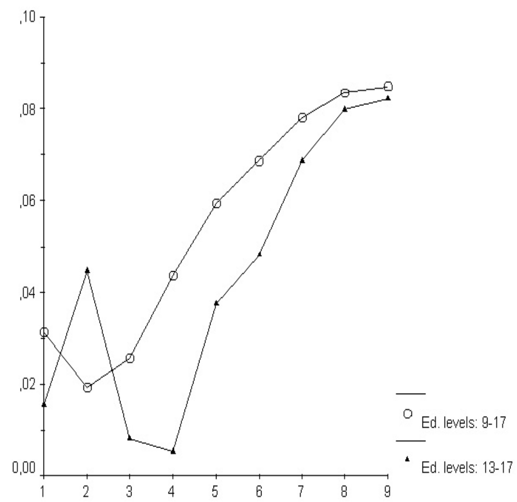
Test Score group

Figure A3.6



Test Score group

Figure A3.7



Test Score group