The Intergenerational Effect of Parental Education in Germany

Thesis Policy Economics

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July 2016

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Abstract

This study attempts to estimate the causal effect of parental education on child's education by exploiting the effect of the Second World War on the educational attainment of the parents. Using a 2SLS model the effect of paternal and maternal education on child's education is estimated. The findings are that the 2SLS estimates are several times larger than the OLS estimates, indicating a positive and significant effect of parental education. However the estimates for maternal education may suffer from a weak instrument problem. The estimates for paternal education are more robust, however the instrumental variable strategy may suffer from validity problems.

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1 Introduction

There is little uncertainty about the predictive power of parental education for the schooling achievements of their children. Every estimate of the correlation between the socioeconomic status of parents and their children is positive and significant (Hertz et al., 2007). Not only do researchers consistently find a positive relation, Haveman and Wolfe (1995) conclude in their literature review that parental education has the most predictive power for child's success in school. If this correlation is caused by highly educated parents investing more in their child's education and pushing their children to work harder, this correlation may incentivize individuals to invest and put more effort in their education. On the other hand when factors unrelated to productivity lead to a higher reward, it might lead to a misallocation of resources. Resources might be allocated to children from higher educated parents, while a child from a low educated family could have benefited more from these same resources (Krueger, 2003). However the forces driving this relationship are not as well understood. Is this phenomenon driven by genetic factors or are highly educated parents more able to provide an environment for their children to perform well in school? In fact this question is part of one the oldest arguments in social sciences, the nature vs. nurture debate (Holmlund et al., 2011; Galton, 1869).

Moreover it is of policy interest to improve our understanding of the underlying mechanisms driving the persistence of economic outcomes across generations. When inherited abilities are the main cause of the intergenerational correlation policies can only reduce the intergenerational correlation by favoring less able individuals. This will result in a loss of efficiency and a high cost to society. However when higher educated parents provide a better environment for their children, policies can create this environment for children from lower educated parents. Children from lower educated parents can reach their full potential and they will in their turn provide a better environment for their offspring, resulting in spillover effects, which will reduce inequalities over time (Black et al., 2005).

The intergenerational correlation of education has been actively researched. Hertz et al. (2007) ranked 42 countries in terms of intergenerational educational persistence. Regarding the causal effect of parental education the literature relies on three strategies; identical twins, adoptees and instrumental variables (IV) or natural experiments. Holmlund et al. (2011) review empirical studies using these strategies and apply these strategies to Swedish data. They find that the results across these strategies differ systematically, however within each strategy the effect of parental education is more consistent. Black and Devereux (2011) provide an overview of studies which attempt to deepen our understanding of the forces driving the intergenerational correlation.

This thesis will contribute to the existing literature by estimating the causal effect of parental education in Germany using an IV approach. Kemptner and Marcus (2011) use an IV setting to estimate the causal effect of maternal education in Germany. They use the number of siblings of the mother as an instrument. They find a positive effect of maternal education on grade repetition and on following the highest secondary school track. Heineck and Riphahn (2007) investigate the evolution of intergenerational educational mobility in Germany over de last five decades. They find that over time the probability of obtaining an advanced high school degree increased for all children, but the effect of parental background did not reduce over time.

This study exploits the effect of the Second World War on the educational attainment of parents. Ichino and Winter-Ebmer (2004) show that during the 1930s the progress towards higher educational attainment slowed down significantly. As a result of the war individuals born in the 1930s have experienced a loss in education. The birth cohort of the 1930s reached the age of 10 around WWII. Around the age of 10 important educational decisions are made, children have to decide which secondary track they are going to pursue. The effect of WWII is exploited using a 2SLS model.

The 2SLS model produces estimates 2.5-3 times the size of the OLS estimates. Kemptner and Marcus (2011), Chevalier (2004) and Oreopoulos et al. (2006) find similar results. Higher IV estimates than OLS estimates might be the result of a local average treatment effect or the results of the IV estimation might be more biased than the OLS results. The sensitivity analysis shows that maternal education is not robust against different model specifications, additionally the estimation with maternal education may suffer from a weak instrument problem. The results of paternal seem to be more robust, however these results might still suffer from other limitations.

The rest of this paper is structured as follows. Section 2 gives an overview of the previous literature and mostly focuses on other IV studies. Section 3 provides a description of the German education system and describes a number of reforms. Section 4 explains the identification strategy and the used data is described in section 5. The results are presented in section 6 and several sensitivity checks are performed in section 7. Section 8 provides a discussion of the research and section 9 concludes.

2 Previous Literature

2.1 Potential forces driving intergenerational educational correlation

Naturally the genetic transmission of abilities from parent to child is an important factor in the intergenerational correlation. However there are other mechanisms which may explain the nurture effect of parental education. Lower educated parents generally have a lower income and as a result are more likely to face credit constraints (Black & Devereux, 2011). Krueger (2003) argues that in a perfect world families would invest in their children's education until the marginal benefits equals the marginal cost. However poor families behave as if they have higher costs and invest less in the education of their children. A possible explanation for this is that poor families are credit constraint and as a result have to borrow at a higher rate.

Björkland and Salvanes (2010) argue that not only the investment per se, but the timing of the investment can affect child's educational attainment. Parental investment from higher educated parents may come at a more optimal age. Another explanation is that highly educated parents are better able to direct their spending to child-friendly activities (Black & Devereux, 2011). Furthermore when assuming that education is a risky investment and lower educated parents are more risk-averse, lower educated parents may invest less in their children's education (Checchi et al. 2013; Becker & Mulligan, 1997). Belzil and Leonardi (2007) find evidence that risk aversion plays a significant but small role in the level of schooling in Italy. Finally family size can affect the investment in child's education. When families are budget constraint, resources are divided among the children. Theoretic models show a trade-off between the quantity and quality of children, in other words more children in a family negatively impacts the child's quality. When education affects family size, family size may be a factor of intergenerational persistence in education (Björklund & Salvanes, 2010).

Another channel could be that highly educated parents are better aware of the value of education and pressure their children to achieve more or they are better in providing the necessary information to their children (Björklund & Salvanes, 2010). Moreover higher educated parents may allocate more time to their children's education. For instance they spend more time with their children or provide them with more books at home (Guryan et al., 2008; Evans et al., 2010). Parents may also teach their children the beliefs and customs of the dominant culture, which helps children in their school career (Bourdieu, 1986). Finally Coldron et al. (2010) show that the way parents choose schools for their offspring differs among social classes, which could contribute to the intergenerational transmission of education.

2.2 Previous empirical literature

The effect of parental education on the education of their offspring has been extensively researched. However many studies don't separate the nurture and nature effect and don't estimate the causal effect of parental education. Tverborgvik et al. (2013) for example estimate the impact of parental education in Denmark on the probability of achieving basic education. They use a logistic regression model and only control for child's year of birth, mother's age at child's birth and father's age at child's birth. They find that children with low educated parents face a three-times-higher risk of achieving only basic education than children of well-educated parents. Furthermore Azam and Bhatt (2015) simply measure the association between parental and child's education in India. They find that the average intergenerational correlation in India is relatively high.

Hertz et al. (2007) ranked 42 countries in terms of intergenerational educational persistence, in other words they measure the correlation between parental and child's education. Latin American countries have the highest intergenerational correlation, which is around 0.6. The other countries in their sample have a correlation around 0.4. They didn't include Germany in their sample, but other Western Europe countries have a correlation between 0.31 (UK) and 0.46 (Ireland and Switzerland). Additionally they provide improved estimates of long-run trends to shed more light on the global patterns of intergenerational transmission of education. They find that the regression coefficient of parental education fell considerably over the last fifty year, while the correlation between parental and child's education on average held steady. They argue that over time the standard deviation of parental education increased more than the standard deviation of child's education. As a result the regression coefficient of parental education as a predictor for child's education fell over time.

The intergenerational effect of education in Germany has been researched as well. Chevalier et al. (2003) estimate the effect of parental background in twenty countries. They use survey data to estimate the intergenerational educational mobility. They use the coefficient of variation to measure inequality, which is the standard deviation divided by the mean, to control for differences in average education in the different countries. Furthermore they use the Gini-coefficient to measure educational inequality, and the Eigen vaule Index and the Bartholomew Index to measure the intergenerational educational mobility.[1] Using these different methods they find that the measures of mobility are positively correlated and they find an inverse relation between the measures of inequality and mobility. Furthermore they estimate the effect of paternal education on the probability of attending university using a probit model. They use these estimates to rank the countries in terms of equality of opportunities in education; they rank Germany 19th out of 23.

Schnepf (2002) focuses on the transition from primary to secondary school in Germany. Schnepf studies the inequalities generated by the selection process using the surveys TIMSS and PISA. They estimate the effect of parental education on the probability of attending the highest secondary school track. By using the math and reading skills measured in the surveys they control for ability of the pupils. They use a logistic regression model to estimate the effects. They find that pupils whose parents are highly educated are 30 percent more likely to attend the most prestigious school track than children with the same abilities whose parents did not complete upper secondary schooling. Other interesting findings are that when controlling for ability children from rural areas and boys have lower chances of enrolling in the most academic track compared to children form urban areas and girls. By controlling for math and reading skills Schnepf (2002) attempts to separate the effects of nature and nurture. However math and

[1] The Gini-coefficient is calculated using the areas in the Lorenz Curve below the 45 degree line. In this case the Lorenz Curve plots the proportion of education (y-axis) that is held by the bottom x-percent of the population. When everyone has the same level of education the Lorenz Curve would be a 45 degree line. The Gini-coefficient is the area between the curve and 45 degree line divided by the entire area under the 45 degree line. The Gini-coefficient will be zero with perfect equality and perfect inequality will result in a Gini-coefficient of 1. The Eigen value index describes mobility in a transition matrix. The matrix gives the probabilities of obtaining a certain level of education, with a certain level of parental education. Finally the Bartholomew index is based on the number of changes in educational level made from the parent's to the child's generation (Chevalier et al., 2003).

reading skills are not equal to inherited abilities. Additionally there might be other unobserved factors affecting the intergenerational relationship.

Heineck and Riphahn (2007) investigate the relevance of parental education on child's education in Germany using data from the German Socio-Economic Panel. They measure the effect of parental secondary schooling attainment on the secondary schooling attainment of their children. They measure the probability that a child reaches a given level of education conditional on parental education. First they measure the average educational mobility of the birth cohort 1929-1978 using transition matrices. They simply measure the proportion of children achieving a certain level of education conditional on the educational level of their parents, thus not separating nature and nurture effects. Heineck and Riphahn find that females and males respectively have a 9 and 12 percent probability of obtaining an advanced school degree when their parents only obtained a basic school degree. They find that over time more and more children outperform their parents and fewer children are doing worse than their parents. When looking at probabilities over time they find that for individuals born in the 1930s children with highly educated parents have a 8 times higher probability of obtaining an advanced degree compared to children of parents with only a basic degree. Around the 1950s this ratio decreased to a value of 4 and hardly changed for the following birth cohorts. Furthermore the probabilities of obtaining a middle school degree don't differ as much. Since the 1950s there is barely any difference in the probabilities of obtaining a middle school degree for children from parents with basic education compared to children with middle school educated parents. These estimates indicate that parental background is especially important for the probability of obtaining the highest secondary school degree. Another conclusion is that since the 1950s opportunities hardly improved for children with lower educated parents.

In their multivariate analysis Heineck and Riphahn estimate the effect of parental education. Additionally they measure the effect of the number of siblings and the region were the individual grew up, however they don't control for abilities of the child. Using a multivariate regression analysis Heineck and Riphahn find that over time the probability of obtaining only basic education reduced for all children and the probability of obtaining a middle or advanced degree increased. However the increase in probability of obtaining an advanced degree is only significant for children with highly educated parents. Finally they find that both paternal and maternal education have a significant and similar effect on child's education, however maternal education has a stronger effect for daughters than for sons. The overall conclusion of Heineck and Riphahn is that the overall educational attainment of individuals in Germany increased, but the role of parental background hasn't changed since the 1950s.

Checchi et al. (2013) investigate the intergenerational persistence of education in Italy and find similar results as Heineck and Riphahn. They find that even in recent birth cohorts there is a high correlation between father's and child's years of education. Furthermore they show that the educational attainment of Italians increased over time, however the relative advantage of children from highly educated fathers didn't change. Measuring the probability that a child reaches a certain level of education conditional on father's education, they find that children of a college graduated father have a 50 percent higher probability of obtaining a college degree compared to children of a father with only lower secondary education or less. Checchi and Flabbi (2007) focus on how separate tracks in secondary schools affect the impact of parental education on children's school choices in Germany and Italy. On top of demographic controls Checchi and Flabbi use PISA data to control for individual abilities. They use a multinomial logit model to estimate the marginal effects of parental education on the secondary school choice of their children. They conclude that students in Germany are sorted more closely by ability and that students in Italy are sorted more closely by family background. Checchi and Flabbi argue that the low intergenerational mobility in Germany is not necessarily caused by the tracking system of secondary school, since the effect of parental background is more pronounced in Italy despite a more flexible tracking system. Additionally they find that the effect of parental background is notably reduced when they control for secondary school track in Italy. They find the same for Germany but with a much smaller reduction.

Most of the studies discussed so far estimate correlations or don't separate between the nurture and nature effects of parental education. Checchi and Flabbi (2007) and Schnepf (2002) attempt to control for inherited abilities, however these studies might suffer from omitted variables bias. The most recent literature which attempts to estimate the causal effect of parental education typically uses twin parents, adoptees or an instrumental variables approach. The twin strategy exploits differences in education within pairs of identical twin parents. This strategy estimates the effect of the difference in education between the twin parents on the education of their children. The adoptee strategy takes advantage of the fact that there is no genetic transmission between the parents and the adopted children. Finally IV estimations exploit exogenous shocks on parental education, such as educational reforms. Each of these strategies has his shortcomings. When using identical twin parents the assumption is that they are genetically identical and that their children have comparable genetic abilities. The difference in education between the two children is then the result of the difference in education between the twin parents. However even monozygotic twins may suffer from unobserved heterogeneity. Additionally twin parents differ from each other, because they are married to different partners. Adoption studies may suffer from non-random assignment of adoptees to their families. Finally IV estimations are hard to generalize over the whole population and often suffer from weak instrument problems (Holmlund et al. 2011).

In their literature review Holmlund et al. (2011) conclude that parental education has a causal effect on child's education. However they find that the intergenerational effects differ systemically across the different estimation strategies. Holmlund et al. conclude that twin studies typically find a positive effect of paternal education, while the effect of maternal education disappears. Studies applying the adoptee strategy reach the similar conclusion that father's education is more important than maternal education, although the effect of maternal education stays positive. IV studies on the other hand usually find that the schooling of the mother is more important that the schooling of the father. The authors argue that these differences are caused by the fact that each strategy affects different parts of the education distribution. Adoptees are usually found at the higher end of the parental education distribution, while twins are typically found across the whole distribution. IV studies typically use changes in compulsory schooling laws, which mostly affect the lower end of the parental education distribution.

Holmlund et al. (2011) use Swedish register data to apply all three strategies to the same dataset. When using the twin variant they find a positive effect of father's education, but no effect of maternal education. The adoption strategy shows small estimates for intergenerational effects of education. Finally when using the IV variant they find that only the mother's education has a significant effect and that the effect is relatively large. These results confirm that the identification strategy affects the intergenerational estimates of education.

Black and Devereux (2011) describe the development in intergenerational transmission literature since 1999. They provide an overview of the literature estimating the intergenerational correlation of earnings and education. Additionally they provide an overview of studies attempting to identify the causal effects of parental education and earnings. They reach the same conclusions as Holmlund et al. (2011) that the estimates differ across the different identification strategies. Some studies find that the causal effect is smaller than the OLS estimates, however many studies find the opposite. Moreover some studies argue that paternal education affect child's education the most, while other studies point to maternal education.

Some examples of studies using the twin or adoption strategy are conducted by Lundborg et al. (2011), Behrman and Rosenweig (2002), and Tsou et al. (2012). Lundborg et al. rely on both the twin and adoption strategy and use Swedish data to estimate the effect of parental education. They find that paternal education has a larger effect on cognitive and non-cognitive skills than maternal education. Behrman and Rosenweig use data from the Minnesota Twin Registry to find that the effect of maternal education disappears. Tsou et al. use adoptees from Taiwan to measure the effect of parental education. They use birth-parents' education to deal with selective placement of the adoptees. They find that adoptees with highly educated parents have completed more years of schooling and have a higher probability of obtaining a college degree. They don't find a larger effect for paternal education than for maternal education. Furthermore Björklund et al. (2006) use Swedish data to estimate the effect of both adoption parents and biological parents. They compare adoptees with samples of own-birth children who started their lives under similar circumstances and were raised under similar circumstances as the adoptees. Additionally they estimate the interaction effects between genes and environment. They find that for mother's education that genetic factors and pre-natal environment are more important than post-birth factors. For father's education, they find that post-birth factors are more important than genetics. More examples of twin and adoption studies can be found in Holmlund et al. (2011) and Black and Devereux (2011).

Since this thesis will rely on an IV setting, the remainder of this section will focus on studies with a similar strategy. Kemptner and Marcus (2011) use an IV-probit model to estimate the causal effect of maternal education on child's education and health in Germany. They instrument maternal education by the number of siblings and they control for grandparents' social status and the area where the mother spend her childhood. The reasoning is that the number of siblings affects the resources available per child and therefore affecting the educational attainment of the child. While they control for the socio-economic status of the grandparents, the correlation between fertility and educational level might still affect the estimation results. The variables of interest regarding education are the binary outcomes grade repetition and attending the highest secondary school track. Kemptner and Marcus find that the estimated effects from the IV-probit are much larger than the estimated effects from the probit model. They find that an extra year of maternal education reduces the probability of the child repeating a grade by 7.4 percentage points. Additionally the child's probability of attending the highest secondary school track increases by 9.5 percentage points.

Black et al. (2005) exploit the extension of compulsory schooling in Norway during the 1960s. Their 2SLS results are statistically insignificant, however the extension of compulsory only has a weak effect on parental education. When restricting the sample to low educated parents they find much stronger first stage results. Using the restricted sample they find that the effect of paternal education disappears completely, while the effect of maternal education only affects the education of the son. In contrast to Kemptner and Marcus, these estimated effects are smaller than their OLS estimates. Oreopoulos et al. (2006) use changes in compulsory schooling laws in the US as an instrument. They estimate the effect of parental education on the education achievement of children aged 7 till 15. They find that one year increase in combined parental education will reduce the probability that a child will repeat a grade by 2-4 percentage points. These estimates are almost two times larger than their corresponding OLS estimates.

Chevalier et al. (2013) investigate the effect of parental education and income on early school leaving in the UK. They attempt to address the endogeneity of parental education and income simultaneously. They exploit the extension of compulsory schooling and they measure the effect on the educational achievement of children aged 16. When controlling for the endogeneity of parental education and household income simultaneously they find, in contrast to the other IV studies, that only paternal education remains significant and only for daughter's education. However when they control for permanent income instead of household income even paternal education becomes insignificant. In an earlier study Chevalier (2004) looks solely at the effect of parental education, exploiting the same change of compulsory schooling laws. In this study

Chevalier finds that the effect of maternal education becomes larger in the IV estimations and that the effect of paternal education disappears. However when they restrict to sample to natural parents they find that the effect of paternal education is as large as the effect of maternal education. Additionally they find that mother's education has a more prominent effect on daughter's education, while the education of the father is more important for son's educational decisions. Note however that their results in the first stage are imprecise. Their F-tests seem to indicate that the estimation doesn't suffer from a weak instrument problem. Nevertheless the imprecise results in the first stage might affect their results.

Maurin and McNally (2008) use an IV approach to measure the causal effect of father's education on child's educational achievements. They don't take advantage of a schooling reform, but they exploit the student revolt of May 1968 in France. Chaos and student lobbying resulted in more lenient exam procedures, resulting in more students attending college. In contrast to studies using a compulsory schooling reform the affected group is not relatively low educated, but includes parents close to university educated. Their dependent variable is the educational advancement of children at age 15. They find 2SLS estimates more than 4 times larger than their OLS estimates.

Carneiro et al. (2007) estimate the effect of maternal education on grade repetition and test score performance using the National Longitudinal Survey of Youth (US). They use schooling costs such as local tuition fees, distance to college and local labor market variables (opportunity costs) as instruments. They find that the math and reading performance of children aged 7-8 increases with maternal education, but they don't find a positive effect of maternal education at ages 12-14. However the instruments used by Carneiro et al. are statistically not very strong, which may affect the results. Finally Page (2009) exploits the implementation of the G.I. Bill in the US, which resulted in exogenous variation in father's schooling attainment. She finds very similar results as Oreopoulos et al. (2006); her IV estimates show that one year increase in paternal education reduces the probability of grade repetition with 2-4 percentage points for children aged 7-15. Her OLS estimates only indicate a 1.8 percentage point reduction in the probability of repeating a grade.

Overall the studies using an instrumental variables approach find higher estimates than the corresponding OLS estimates. The IV estimates may reflect a local average treatment effect.

Most of the studies use some kind of compulsory schooling reform to deal with the endogeneity of parental education. As a result the IV estimates generally measure the effect of parental education on the lower end of the education distribution. This might explain the high IV estimates, higher parental education might be more important for children from low educated families than for children from high educated families. Magnuson (2007) for example finds using a multilevel model that maternal education doesn't affect child's education when the mother is relatively old and high educated. She finds that only for young mothers with low level of education, maternal education affects the reading level of their children. Moreover the studies by Oreopoulos et al. (2006), Carneiro et al. (2007), and Maurin and Mcnally (2008) use information on child's education when the child still lives at home. In these studies it is not clear what the effect of parental education will be when the children have completed their educational careers. Finally the instruments used in a number of studies are statistically weak and may result in biased results.

3 German education system

In Germany the country's individual states are primarily responsible for the education system. The role of the federal government is to ensure national comparability of education standards. Throughout Germany school attendance is compulsory from age six onwards. In general children start their educational career with four years of primary schooling (Grundschule) in mixed-ability classes.[2] After primary school pupils are divided into different secondary school tracks (Schnepf, 2002).

German secondary schooling has three main tracks, where the main distinction between the tracks is ability of the students. The most advanced track (Gymnasium) consists of eight to nine years of education and will result in a qualification for university entry. The intermediate track (Realschule) consists of six year additionally education after primary schooling. The intermediate track provides general knowledge and prepares students for office jobs such as administrative or managerial work. Finally Basic School (Hauptschule) provides standard education for the least able students and consists of five or six years of schooling. After Basic School most pupils start practical vocational training. Besides the three main tracks the German

[2] In the states Berlin and Brandenburg primary schooling lasts six years.

secondary school system has been expanded with Comprehensive School (Gesamtschule) and other more regional-specific school tracks. The Comprehensive School provides schooling for students with different abilities, where pupils can follow one subject at the most advanced level and another subject at a more intermediate level (Schnepf, 2002). After secondary school all students can follow vocational training or can follow education in a dual system, which will result in an occupational qualification. When students have completed vocational school they can enroll in trade and technical high schools as well. Students which followed the intermediate track can follow specialized vocational high school, which results in a university entrance qualification (OECD, 2015).

Over the years there have been a number of reforms to increase the equality in the German secondary school system. Between 1947 and 1962 secondary schooling fees for advanced schooling are abolished (Riphahn, 2012). Riphahn finds that as a result of the fee abolishment upper secondary school attainment increased by at least eight percent. It is not clear whether the fee abolition increased the educational mobility. A similar reform is the provision of textbooks free of charge and free public transportation to reduce transportation costs. The opening of more middle and advanced schools in the 1960s further reduced transportation costs. Another reform is the introduction of a scholarship program for university students in 1953.

In addition to these reforms there are a number of reforms which explicitly focused on reducing the inequality gap. In order to advance to middle or advanced school pupils had to complete a formal test. These are abolished since 1960 and instead recommendations are given by primary school teachers. Moreover the opportunities to switch between the different tracks are improved. In the 1960s compulsory schooling was extended to at least 9 years, in order to decrease the opportunity cost of attending Middle school instead of Basic school. Finally the vocational educational system started to provide educational degrees together with vocational training (Heineck & Riphahn, 2007).

4 Identification strategy

The identification strategy consists of two parts; the first part will use a single equation model, OLS, to estimate the effect of parental education. The second part will estimate a 2SLS model to deal with the endogeneity of parental education. Furthermore the effects of paternal and maternal education are estimated separately because the education of partners tends to be highly correlated. Higher educated females typically marry men which are higher educated as well (Berhman & Rosenzweig, 2002). This dataset shows a correlation of 0.57 between paternal and maternal education.

The single equation model will use the following specifications:

$$E_c = \beta_0 + \beta_1 * E_f + BY_c + G_c + Si_c + R_c + FS_c + \varepsilon_c \quad (1)$$

$$E_c = \beta_0 + \beta_1 * E_m + BY_c + G_c + Si_c + R_c + FS_c + \varepsilon_c \quad (2)$$

The subscripts c, f, and m represent child, father and mother and β_1 is the coefficient of interest. Specification (1) is used to estimate the effect of paternal education and specification (2) is used to estimate the effect of maternal education on child's education. The education of the child (E_c) and the education of the father and mother (E_f and E_m) are measured in number of years of education.[3] BY_c controls for the increasing trend of educational attainment by measuring the effect of child's birth year. G_c and Si_c control for child's gender and the number of siblings of the child. R_c is a dummy which is 0 when the respondent is living in a more rural region and takes the value of 1 when the respondent is living in a more urban region. FS_c controls for fixed effects of federal states and ε_c is the child specific error term. The estimates of this model are only reliable when unobserved factors are not correlated with parental education. The expectation is that the effect of parental education is affected by unobserved factors such as inherited abilities and that the estimates of this model are biased.

In order to deal with the endogeneity of parental education an IV strategy will be implemented. An IV strategy will estimate the causal effect of the endogenous variable by using a third variable (the instrument) which affects the dependent variable through the endogenous independent variable. The instrument has to meet two conditions. First the instrument only affects the

[3] In the sensitivity analysis other measures of educational attainment will be used.

independent through the dependent variable and therefore has to be uncorrelated with the error term. Secondly the instrument has to have a meaningful effect on the dependent variable (Kemptner and Marcus, 2011). This study will exploit the effect of WWII on the educational attainment of the parents. Ichino and Winter-Ebmer (2004) show that during the 1930s the advancement toward higher education slowed down significantly. Parents born in the 1930s were around the age of 10 over the course of WWII. The age of 10 was and is an important age regarding educational decisions, especially in Germany. In Germany children are 10 years old when they finish primary school, which means that they have to choose which secondary school track they are going to follow (Ichino & Winter-Ebmer, 2004). The expectation is thus that the war negatively affected the secondary schooling attainment of the parents. Their children on the other hand were able to follow education during peacetime, therefore the war should only affect child's education through parental education. Lower educational attainment for these children, compared to children whose parents completed their education before the war, is then the result of lower parental education.

This instrument however may suffer from validity problems, since WWII may have affected not only parent's education, but also other factors which in turn affected child's education. For example as a result of the war parents suffered from traumas and couldn't assist their children in their educational career. In order to deal with this problem this study will use a control group which experienced WWII but already finished their secondary education before the war. The control group in this study will be parents born between 1915 and 1920. One might argue that WWI may affected the educational attainment of these parents, however these parents started going to school after the First World War. The treatment group will be parents which were the age of 10 during WWII, therefore the birth cohort 1930-1934. Parents born in 1935 are excluded since the war ended in 1945 and they may have advanced to secondary school after WWII. For the same reason individuals born in 1929 are excluded, because some individuals born in 1929 advanced to high school before the war started. One might notice that the control group covers six years, while the treatment group covers only five, which is done to ensure sufficient observations in the control group.

The IV model is estimated using two stage least squares (2SLS). Paternal and maternal education from (1) and (2) are instrumented by a dummy variable which takes the value of 1 when the parent was born between 1930 and 1934 and 0 otherwise. The second stage of the 2SLS model uses the same control variables as in the OLS specification. Finally all models are estimated with standard errors clustered by household to control for correlation between children of the same parents.

5 Data

The data used in this thesis is taken from the German Socio-Economic Panel (GSOEP). The GSOEP is an annual representative survey of private households and started in 1984. The survey includes around 11,000 households and 30,000 persons every year. Since the survey is sufficiently long and collects information at the micro level this dataset is suited to analyze intergenerational relationships. In general the GSOEP collects data in face to face interviews and uses three different versions of questionnaires. In the household questionnaire the head of the household provides information about children under the age of 16 and about members of the family who are in need of long term care. Additionally the household head provides information about the household as a whole. In the personal questionnaire each household member aged 16 or older completes an individual questionnaire every year. Finally the first time a respondent is interviewed central biographical information is collected through a biography questionnaire (SOEP Group, 2001).

This thesis will use the 2003 wave of SOEP. This wave consists of almost 23,000 individuals and consists of almost 1,500 different variables. Following Heineck and Riphahn (2007) this study will exclude non German citizens and those who lived in the former East Germany to create a more homogenous sample. Additionally this study will exclude respondents when one of their parents died during WWII.

The outcome variable is the number of years of education followed by the child. The least educated individuals followed 7 years of education, which equals some secondary education. The individuals with the highest educational attainment followed 18 years of education, which represents a university degree. The explanatory variable of interest is educational attainment of the father and mother. The SOEP data only reports the secondary school degree obtained by the parents. As mentioned in section 3 there are three different secondary school tracks, basic, middle and advanced. In addition a small portion of parents in this dataset obtained a technical degree. The secondary school degree is converted in years of education. Following Kemptner et al. (2011) a basic degree equals 9 years of schooling, the intermediate track equals 10 years of schooling, a technical degree equals 12 years of schooling and the highest secondary school track equals 13 years of schooling. Furthermore Kemptner et al. attribute 9 years of schooling to individuals with no degree, however it is hard to argue that no degree equals a basic school degree. Therefore parents with no degree are excluded from the regression sample. Additionally parents who completed a different school track or have missing information are excluded from the regression sample.[4] Other explanatory variables are the number of siblings, region, birth year, and federal state. The number of siblings is converted in a categorical variable. Region includes a dummy variable which takes the value of 0 when the respondent lives in a more rural area and takes the value of 1 when the respondent lives in a more urban area.

Table 5.1 and 5.2 show some descriptive statistics of the regression sample. Using at t-test it is examined whether the means of the different variables differ significantly between the two birth cohorts. The regression sample for paternal education shows that the means of almost all variables differ significantly at the 1 percent level. The exceptions are gender and the proportion of fathers who obtained a technical degree. The significant difference in paternal education may be the result of the war. The significant difference in child's education may be the intergenerational effect of parental education. Since the treatment and control group are separated by birth year of the parents, the significant difference in child's age is expected. The significant difference between the number of siblings and the region where the children currently live is more surprising.

Table 5.2 shows that the difference in maternal education between the two birth cohorts is less significant than for paternal education. Only the proportion of mother with no degree is significant at the 1 percent level. Additionally the years of education followed by the children doesn't differ significantly. Furthermore the age difference between the treatment and control group is expected. In contrast to the regression sample of paternal education the proportion of boys and girls differ significantly between the control and treatment group. On the other hand

[4] The sensitivity analysis includes individuals with no degree and a different degree.

the region where the children currently live does not differ significantly. Finally consistent with the paternal regression sample is a significant difference in the number of siblings.

Table 5.1: Descriptive statistics father's birth cohorts 1915-20 & 1930-34

Variable	father's birth cohort 1915-20			father's birth cohort 1930-34			
	mean (s.d.)	min	max	mean (s.d.)	min	max	
age	52.7 (6.62)	19	67	41.8 (5.47)	21	56	***
gender(male=1, female=2)	1.52 (0.50)	1	2	1.51 (0.50)	1	2	
years of education	12.7 (3.02)	7	18	12.3 (2.60)	7	18	***
number of siblings	2.01 (1.76)	0	12	2.33 (1.97)	0	12	***
region (rural=0, urban=1)	0.77 (0.42)	0	1	0.71 (0.45)	0	1	***
education father: no degree	0.020 (0.14)	0	1	0.056 (0.23)	0	1	***
education father: basic	0.694 (0.46)	0	1	0.747 (0.43)	0	1	***
education father: middle	0.136 (0.34)	0	1	0.096 (0.29)	0	1	***
education father: technical	0.007 (0.08)	0	1	0.006 (0.08)	0	1	
education father: advanced	0.143 (0.35)	0	1	0.094 (0.29)	0	1	***
number of observations	846			1154			

*, **, *** means differ significantly at the 10,5, and 1 percent level.

Table 5.2: Descriptive statistics mother's birth cohorts 1915-20 & 1930-34

variable	mother's birth cohort 1915-20			mother's birth cohort 1930-34			
	mean (s.d.)	min	max	mean (s.d.)	min	max	
age	56.7 (5.99)	34	69	43.9 (5.28)	25	60	***
gender(male=1, female=2)	1.47 (0.50)	1	2	1.53 (0.50)	1	2	**
years of education	12.5 (2.97)	7	18	12.5 (2.71)	7	18	
number of siblings	1.92 (1.59)	0	11	2.27 (1.92)	0	12	**
region (rural=0, urban=1)	0.75 (0.43)	0	1	0.73 (0.44)	0	1	
education mother: no degree	0.026 (0.16)	0	1	0.054 (0.23)	0	1	***
education mother: basic	0.762 (0.43)	0	1	0.775 (0.42)	0	1	**
education mother: middle	0.144 (0.35)	0	1	0.124 (0.33)	0	1	*
education mother: technical	0.004 (0.07)	0	1	0.003 (0.06)	0	1	
education mother: advanced	0.064 (0.25)	0	1	0.043 (0.20)	0	1	**
number of observations	933			1160			

*, **, *** means differ significantly at the 10, 5, and 1 percent level

6 Results

6.1 First stage results

Before looking at the OLS and second stage results the first stage results are presented. First the effect of the WWII is graphically shown in figure 6.1. The left part of the figure represents paternal education and the right part maternal education. The blue line is the trend of parental education and the vertical red line indicates the start of WWII. The figure clearly shows an increasing trend of parental education. Moreover the figure shows that the educational attainment of parents born in the 1930s is well below the trend, which is likely the effect of WWII.

Figure 6.1 parental education in years

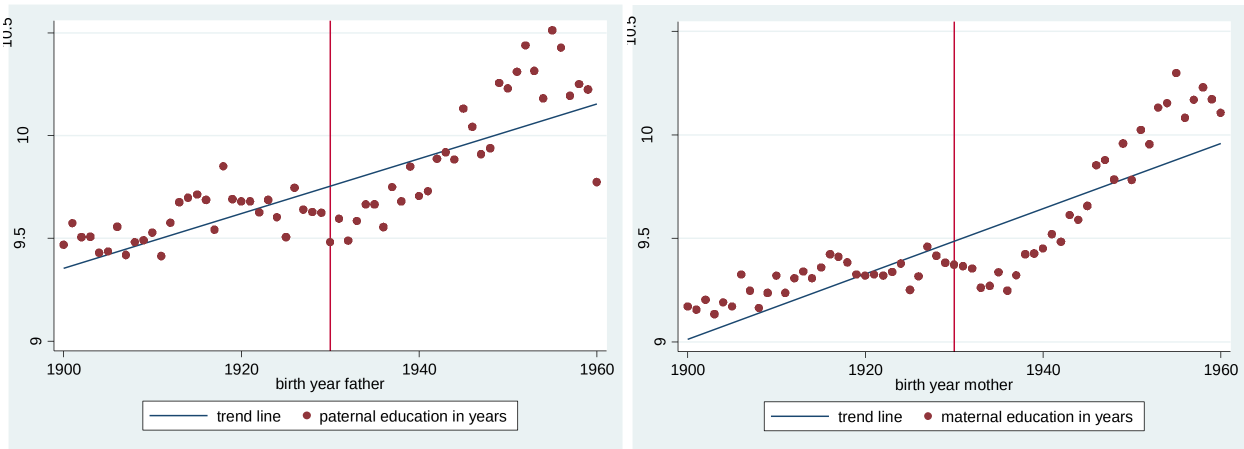

Table 6.1 shows the results of the first stage regressions. The first stage estimations confirm the descriptive evidence of table 5.1 and 5.2 and figure 6.1 that the war affected the educational attainment of parents born in the 1930s. The war resulted in a drop of 0.43 of a year in educational attainment for fathers, while the educational attainment of mother dropped by 0.26 of a year. These coefficients are significant at the 1 percent level. These estimates don't seem very large, however parental education only ranges from 9 till 13 years in this dataset. Furthermore the effect of the war has a larger effect on fathers, which may be explained by the fact that fathers were higher educated before the war than mothers. As a result fathers could experience a larger drop in educational attainment than mothers.

Table 6.1 First stage results

2SLS model first stage endogenous variable: parental education in years	father's education	mother's education
variable	coefficient (std. err.)	coefficient (std. err.)
WWII (instrument)	-0.430 (0.080)***	-0.261 (0.067)***
gender:		
female	-0.050 (0.058)	-0.011 (0.042)
birth year	0.023 (0.005)***	0.015 (0.004)***
siblings:		
1 sibling	-0.074 (0.105)	0.028 (0.073)
2 siblings	-0.167 (0.111)	0.079 (0.074)
3 siblings	-0.149 (0.128)	-0.149 (0.076)**
4 siblings or more	-0.412 (0.113)***	-0.175 (0.071)**
region:		
urban	0.203 (0.079)**	0.108 (0.052)**
F-test of excluded instruments	28.70	15.11
number of observations	1918	2006

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

In order to test whether the instrument has a strong enough predictive value for the endogenous variable a common used statistic is the F-statistic of the first stage. The F-test tests the null hypothesis that there is no effect of the instrument given the other variables. The rule of thumb used in most studies is when the F-statistic exceeds the value of 10 the IV estimation doesn't suffer from a weak instrument problem (Nichols, 2006; Kemptner & Marcus, 2011). The first stage F-statistics are included in table 6.1. The F-values are greater than 10 in both regressions; 28.7 for paternal education and 15.1 for maternal education. Nichols (2006) argues however that when the F-value is greater than 10, the estimation might still suffer from a weak instrument problem. Stock and Yogo (2005) provide a table of F-values to test the weakness of instruments. The F-values they provide reject the hypothesis of at least a given maximum relative bias at the 5 percent significance level. The F-value to reject at least a 10 percent bias with one endogenous variable and one instrument at the 5 percent level equals 16.38. The F-value of paternal education still comfortably exceeds this value, however the estimation for maternal education might suffer from a weak instrument problem. In other words for maternal education a bias greater than 10 percent cannot be excluded. The F-value to reject a bias of at least 15 percent equals 8.96. Therefore a bias of greater than 15 percent can be excluded, however the results of maternal should be interpreted with more caution.

6.2 OLS and 2SLS results

Table 6.2 shows the OLS estimates of parental education on child's education. The OLS estimation shows that maternal education is more important than paternal education. One year increase in maternal education raises child's education with 0.92 of a year, while one year increase in paternal education raises child's education with 0.78 of a year. Both Black et al. (2005) and Holmlund et al. (2011) find higher OLS estimates for maternal education than for paternal education as well. Furthermore the found estimates seem rather large. Other studies typically found that one year increase in parental education raises child's education between 0.2 and 0.4 of a year (Black & Devereux, 2011). The data used in the regression may explain these results. The educational attainment of the children ranges from 7 till 18 years, while the education of the parents only ranges from 9 till 13 years. Therefore a one year increase in parental education is relatively much larger than a one year increase in child's education.

Other results indicate that girls are less educated than boys. Furthermore the OLS estimations show that children from urban regions are higher educated than children from more rural areas, which is consistent with the findings of Heineck and Riphahn (2007). Finally children with siblings tend to have completed less years of education than children with no siblings, which is found by Heineck and Riphahn as well.

Table 6.3 shows the results of the second stage of the 2SLS estimation. The results show that increasing paternal education with one year raises child's education with 2.34 years, while an increase of one year in maternal education raises child's education with 2.46 years. These coefficients seem very large, however as argued above the range of parental education is rather small. Additionally parental education didn't drop with a whole year as a result of the war, but dropped by 0.43 and 0.26 of a year for paternal and maternal education respectively. As a result of the war child's education dropped then by 1 year through paternal education and by 0.64 of a year through maternal education.

Table 6.2 OLS results

OLS model dep. variable: child's education in years	father's education	mother's education
variable	coefficient (std. err.)	coefficient (std. err.)
parental education	0.783 (0.050)***	0.923 (0.067)***
gender:		
female	-0.382 (0.116)***	-0.659 (0.110)***
birth year	0.031 (0.007)***	0.033 (0.007)***
siblings:		
1 sibling	-0.045 (0.200)	-0.309 (0.206)
2 siblings	-0.234 (0.205)	-0.801 (0.218)***
3 siblings	-0.517 (0.213)**	-0.973 (0.236)***
4 siblings or more	-1.271 (0.212)***	-1.543 (0.227)***
region:		
urban	0.730 (0.169)***	0.792 (0.172)***
R-squared	0.2134	0.1900
number of observations	1918	2006

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table 6.3 2SLS results

2SLS model second stage dep. variable: child's education in years	father's education	mother's education
Variable	coefficient (std. err.)	coefficient (std. err.)
parental education	2.344 (0.481)***	2.455 (0.782)***
gender:		
female	-0.320 (0.146)**	-0.628 (0.126)***
birth year	0.023 (0.011)**	0.028 (0.008)***
siblings:		
1 sibling	0.053 (0.270)	-0.362 (0.236)
2 siblings	0.009 (0.283)	-0.933 (0.263)***
3 siblings	-0.300 (0.311)	-0.757 (0.287)***
4 siblings or more	-0.654 (0.342)*	-1.301 (0.279)***
region:		
urban	0.394 (0.195)**	0.620 (0.201)***
number of observations	1918	2006

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

As argued before because of the nature of the data the absolute estimates are hard to compare to other studies. However like other studies using an IV setting the 2SLS estimates are several times larger than de OLS estimates. The 2SLS estimates for paternal education and maternal education are respectively 3 and 2.7 times as large as the OLS estimates. Oreopoulos et al. (2006) estimate the effect of paternal education on the probability of repeating a grade. Their IV estimates are 1.9 times larger than their OLS estimates. Kemptner and Marcus (2011) estimate the effect of maternal education on the probability of being on the most advanced secondary school track. They find using an IV-probit model estimates 1.4 times larger than their regular probit model estimates. However when the dependent variable is grade repetition they find IV estimates more than 4 times as large as their probit estimates. Moreover Maurin and McNally (2008) look at the effect of paternal education on child's educational advancement and find IV estimates 4.3 as large as their corresponding OLS estimates. On the other hand Black et al. (2005) estimate the effect of parental education on child's education in years and find IV estimates substantially smaller than their OLS estimates, moreover their IV results are not significant. Holmlund et al. (2011) find a significant effect of maternal education, but smaller than in their OLS regression. Moreover both Holmlund et al. and Black et al. find that the effect of paternal education disappears in their IV model.

Finding higher IV estimates than OLS estimates may be the result of a bias in the IV strategy which outweighs the omitted variables bias in the OLS estimation (Oreopoulos et al., 2006). Another explanation is that unobserved variables in the OLS regression are negatively correlated with parental education, but are positively correlated with child's education (Kemptner and Marcus, 2011). Finally the IV estimates might reflect a local average treatment effect (LATE). In other words the IV estimates only reflect the effect on a specific part of the population. Angrist, Imbens and Rubin (1996) argue that IV estimates represent the effect on the group affected by the instrument. Most studies using compulsory schooling reforms argue that only the bottom of the education distribution is affected by the changing laws. The effect of an additional year of parental education is likely to have a larger effect on the bottom of the education distribution. Ichino and Winter-Ebmer (2004) find that the war mostly affected parents at the lower end of the education distribution. The effect of the war for parents from highly educated families is even positive, however around the 1930s only a very small percentage of the population was highly educated. Nevertheless the results might reflect a local average treatment effect. Unfortunately the data doesn't allow investigating the potential presence of a LATE.

In addition to the above regressions the effect of paternal and maternal is estimated on sons and daughters separately. Table 6.4 summarizes the results of the OLS and IV estimations. Table A.1-A.6 in the appendix show the full results of the OLS and IV models. Important to notice is that when estimating the effects on sons and daughters separately the F-values of the first stage drop substantially. Only when the effect of paternal education on son's education is estimated the F-value is greater than the critical value of 16.38. The F-values of maternal education even drop below the less conservative values of 10 and 8.96. When looking at the OLS estimations both paternal and maternal have a larger effect on daughter's education than on their son's education. The 2SLS estimates mirror the results of the OLS regressions. In the IV setting the effect of paternal education on son's education is 1.7 times larger than the effect of paternal education on daughter's education. The effect of maternal education on son's education is even larger and has a 2SLS-OLS ratio of almost 4. The effect of maternal education on daughter's education becomes insignificant in the IV estimation.

Table 6.4 summary OLS and 2SLS results

Model dep. variable: child's education in years	OLS	2SLS
father – all	0.783 (0.050)***	2.344 (0.481)***
father – son	0.751 (0.068)***	2.987 (0.712)***
father – daughter	0.839 (0.071)***	1.725 (0.638)***
mother – all	0.923 (0.067)***	2.455 (0.782)***
mother – son	0.899 (0.092)***	3.535 (1.373)**
mother – daughter	0.936 (0.099)***	1.521 (0.962)

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.

These results are inconsistent with results find by Chevalier (2004). He finds that maternal education is more important for daughters while paternal education is more important for sons. Kemptner and Marcus (2011) on the other hand find similar results when the dependent variable is grade repetition. They find in their probit model that maternal education is more important for daughters than for sons. In their IV-probit they find that maternal education has a larger effect on the grade repetition of sons. Interesting is that when their dependent variable is the probability of being in the most advanced secondary school track they find opposite results. When the dependent variable is being in the advanced track the probit results indicate a larger effect for sons and the IV-probit results indicate a larger effect for daughters. Black et al. (2005) have the same dependent variable and run separate regressions for sons and daughters as well. Despite that their IV estimates are smaller than their OLS estimates they find similar effects regarding sons and daughters. In their OLS estimates both paternal and maternal education are more important for daughters than for sons. In their IV setting they find that parental education has a larger effect on sons.

7 Sensitivity analysis

In this section different model specifications and different variables are used to check the robustness of the results. First the found effect of the instrument might be the result of an age effect instead of the effect of WWII. Different birth cohorts are used as treatment and control groups to test the strength of the instrument. The main analysis is replicated in the sense that parents in the treatment group are born 15 years later than parents in the control group. Two different treatment groups are chosen; parents born between 1955 and 1960 and parents born between 1920 and 1925. Consequently the control groups are the birth cohorts 1940-1945 and 1905-1910. The results of these regressions are summarized in table 7.1 and 7.2.

Table 7.1 First stage results with different treatment groups

Model dep. var.: child's education in years	First stage effect of instrument	First stage F-statistic
Father's birth cohort 1955-60	-0.332 (0.155)**	4.60
Father's birth cohort 1920-25	-0.125 (0.073)*	2.93
Mother's birth cohort 1955-60	-0.042 (0.101)	0.17
Mother's birth cohort 1920-25	-0.101 (0.053)*	3.56

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.

Table 7.2 OLS and 2SLS results with different treatment groups

Model dep. var.: child's education in years	OLS	2SLS	2SLS/OLS ratio
Father's birth cohort 1955-60	0.600 (0.046)***	4.584 (1.952)**	7.64
Father's birth cohort 1920-25	0.806 (0.043)***	1.240 (1.254)	1.54
Mother's birth cohort 1955-60	0.610 (0.057)***	33.796 (79.647)	55.40
Mother's birth cohort 1920-25	1.075 (0.073)***	4.299 (2.388)*	4.00

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.

The first stage results show that the instrument picks up some kind of trend effect. The results show that when different birth cohorts are used the instrument still has a negative impact on parental education, although the coefficient is smaller and less significant. Additionally the F-statistic of the first stage drops substantially to values below five.

Table 7.2 shows the OLS results, which are consistent with the main analysis. The size of the coefficients is comparable to the main analysis and the found effects remain highly significant. Note however that the more recent birth cohorts show smaller coefficients, while the older birth cohorts show larger coefficients, which is also found by Hertz et al. (2007). They show in their analysis that the regression coefficient of parental education fell over time. The 2SLS results are presented in table 7.2 as well. These results are widely different than the 2SLS results of the main analysis. The coefficients are larger, less consistent and the results become more imprecise. Both the first stage and second stage results indicate that the found effect of the instrument is not only some kind of trend effect, but likely represents the effect of WWII.

Because of the nature of the data individuals can be observed when estimating the effect of paternal education and when estimating the effect of maternal education. In other words some individuals are measured twice, which may affect the results. In total 755 children are observed in both the paternal and maternal regressions. 1163 children are only observed when estimating the effect of paternal education and the regression for maternal education contains 1251 unique children. Separate regressions are run for children who are observed twice and for children who are observed only once. Note that children who are observed once are not necessarily from a single parent household, the parent who is not observed just doesn't meet the requirements to be in the regression sample. Table 7.3 summarizes the results of the separate regressions.

Table 7.3 OLS and 2SLS results with separate regressions for children observed once and twice

Model dep. var.: child's education in years	OLS	2SLS	2SLS/OLS ratio	First stage F-statistic
Father - children observed twice	0.800 (0.085)***	2.398 (0.735)***	3.00	10.60
Father - children observed once	0.761 (0.062)***	2.214 (0.662)***	2.91	14.39
Mother - children observed twice	1.045 (0.112)***	6.604 (3.663)*	6.32	2.85
Mother - children observed once	0.844 (0.086)***	1.359 (0.776)*	1.61	11.05

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.

The results of table 7.3 show that both the OLS and 2SLS results of paternal education are consistent with the main analysis. The F-statistics of the first stage drop considerably, which is likely the result of fewer observations in the separate regressions. The 2SLS results for maternal education differ substantially from the main analysis and the coefficients are only significant at the 10 percent level. Additionally the F-statistics of the first stage drop as well. The separate regressions indicate that the results of paternal education are more reliable than the results of maternal education.

The third robustness check involves a different measure of parental education. In the main analysis parental education is converted from secondary schooling degree to years of education. In the main analysis parents with no degree or other degree are excluded from the regression sample. Table 7.4 summarizes the results when parents with a different school degree or with no degree are added to the regression sample. Following Kemptner et al. (2011) parents with a different degree are attributed 10 years of schooling. As mentioned before Kemptner et al. (2011) attribute 9 years of schooling to parents with basic degree and with no degree. Since it is hard to argue that no degree equals a basic degree, parents with no degree are attributed 8 years of schooling instead of 9. Additionally parental education will be converted in a binary variable, which takes the value of 1 when the parent completed the advanced track or the intermediate track or obtained a technical degree. The binary variable takes the value of 0 when parents completed the basic secondary school track or didn't obtain a secondary school degree. A summary of these results are presented in table 7.5.

The results of table 7.4 show that the estimates don't change substantially when parents with no degree and a different degree are included in the regression sample. The size of the estimates and the IV/OLS ratios are somewhat smaller but seem consistent with the results of the main estimation.

Table 7.4 OLS and 2SLS results inclusion of parents with no degree and a different degree

Model dep. var.: child's education in years	OLS	2SLS	2SLS/OLS ratio	First stage F-statistic
Father's education	0.778 (0.048)***	2.075 (0.400)***	2.67	36.35
Mother's education	0.912 (0.065)***	2.174 (0.719)***	2.38	15.74

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.

The results of table 7.5 are also consistent with the results of the main analysis. The estimates are difficult to compare in size, however the IV estimates remain 2-3 times larger than the OLS estimates. However note that in contrast with the main analysis paternal education has a larger effect on child's education than maternal education in the 2SLS model.

Table 7.5 OLS and 2SLS results with parental education as binary variable

Model dep. var.: child's education in years	OLS	2SLS	2SLS/OLS ratio	First stage F-statistic
Father's education	2.509 (0.155)***	6.823 (1.270)***	2.72	34.06
Mother's education	2.716 (0.161)***	6.386 (2.004)***	2.35	16.33

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.

The next sensitivity test uses a different measure of child's education. Following Kemptner and Marcus (2011) child's education is reflected by binary variable taking the value of 1 when the child completed the advanced secondary school track and the value of 0 otherwise. In order to compare results to Kemptner and Marcus more precisely, this specification runs separate regressions for sons and daughters as well. The results are summarized in table 7.6. Full results of the regressions with the whole sample can be found in the appendix. The probit model results are presented in table B.1. The first stage regressions are reported in table B.2, including the first stage F-statistics which are obtained using the 2SLS model. Finally the second stage results of the IV-probit model are shown in table B.3. It is worth pointing out that the parameter estimates from the IV-probit model may be biased by non-normally distributed errors or heteroscedasticity (Kemptner and Marcus, 2011).

The probit results indicate that an additional year of paternal schooling increases the probability of completing the most advanced school track with 8.3 percentage points. One year increase in maternal education raises the probability with 9.2 percentage points. Kemptner and Marcus find that an additional year of maternal education raises the probability with 6.8 percentage points, however they find that their estimates increase in size when they use the same method as this paper to convert maternal secondary schooling attainment in years of education. Unfortunately they don't provide the exact estimates.

Table 7.6 Summary probit and IV-probit results

Model dep. var.: prob. academic track	Probit	IV-probit	Probit/IV ratio	First stage F-statistic
father – all	0.083 (0.005)***	0.183 (0.018)***	2.20	29.58
father – son	0.081 (0.008)***	0.196 (0.020)***	2.41	18.24
father – daughter	0.089 (0.008)***	0.156 (0.036)***	1.75	11.35
mother – all	0.092 (0.009)***	0.247 (0.050)***	2.68	15.11
mother – son	0.094 (0.013)***	0.298 (0.047)***	3.17	7.82
mother – daughter	0.087 (0.011)***	0.150 (0.090)*	1.72	6.50

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.

The IV-probit results are consistent with the IV results in the sense that the IV-probit results are several times larger than the probit results. Compared to the main results the ratios are somewhat smaller, but are still substantially larger than the ratios found by Kemptner and Marcus (2011).

The results show that the effect of paternal education on sons and daughters separately is consistent with the estimates of the main estimation. In the probit estimation paternal education has a larger effect on daughters, while the IV-probit regression indicates a larger effect on sons. Maternal education on the other has a larger effect on sons in both the probit and IV-probit. In their probit model Kemptner and Marcus find a larger effect of maternal education on sons as well. In their IV-probit however they find that maternal education has a larger effect on daughter's education.

Finally regressions are run where the control and treatment group cover the same number of years. A set of regressions is run where parents born in 1935 are added to the treatment group and a set of regressions is run where parents born in 1920 are excluded from the control group. The estimated effects from these regressions are only slightly different than the results in the main analysis. Table B.4 summarizes the results.

8 Discussion

In this section the limitations of the research are discussed. First the general shortcomings of an IV strategy are discussed, followed by a discussion of more specific problems of the research. The last part of this section will discuss the policy implications of the results and will give some recommendations for future research.

IV studies exploit an exogenous shock to parental education to estimate the causal effect of parental education. Most of the discussed IV studies exploit changes in compulsory schooling. Other events simultaneously affecting the education system is a possible threat to the reliability of the IV estimates. For example the changes in compulsory schooling laws may affect the demand for teachers and as a result may affect teacher quality (Holmlund et al., 2011). Similar concerns may arise when using WWII as an instrumental variable. Parents born between 1930 and 1934 were not only affected by the war during their schooling career, but were born in the

Great Depression as well, which for example may have reduced earnings of the parents and consequently the educational attainment of their children (Ichino & Winter-Ebmer, 2004). Depending on the event interfering with the IV strategy the estimates are biased upwards or downwards. The Great Depression would likely result in upward biased estimates, because the expectation is that a reduction in household income negatively affects child's educational attainment.

Another bias is that IV estimates often represent a local average treatment effect. In other words the IV estimates represent the effect on the individuals which are affected by the instrument (Angrist et al., 1996). For example when using an extension of compulsory schooling as instrument, the lower end of the education distribution is mostly affected. The results of the IV estimation then reflect the effect of parental education on individuals at that part of the education distribution. Ichino and Winter-Ebmer (2004) find that students whose father didn't have a high school diploma experienced a slightly larger drop in education. Additionally children whose father was highly educated experienced a smaller drop or no drop at all in educational attainment. These findings indicate that the found results might reflect a local average treatment effect. On the other hand the descriptive statistics show that the percentage of parents following the advanced or intermediate school track decreased as well, which may indicate that the war affected the whole education distribution. If the war mostly affects the lower end of the education distribution and the effect of parental education is larger at the bottom of the education distribution the estimates are biased upwards.

As mentioned before the instrument used in an IV setting has to be sufficiently correlated with the endogenous independent variable and has to be uncorrelated with the error term. The results of the first stage show that the war has a meaningful effect on the educational attainment of parents, at least on paternal education. The estimation for maternal education however may suffer from a weak instrument problem. The first stage F-statistic of maternal education is above the value of 10, but below the more conservative value of 16.38.

Next the assumption that the war only affected the educational attainment of children through parental education might not hold in practice. As mentioned individuals born in the 1930s were born during the Great Depression as well, which may affected the educational attainment of their children. Moreover there are other factors which may had an effect on the educational attainment of parents and their children. For example as a result of the war parents suffered from traumas and as a result were less able to support their children in their educational career. Less supported children are likely to perform worse in school, as a result their drop in education is not only the result of lower parental education. In that case the found estimates are biased upwards. However the control group, the parents whose education was not affected by the war, experienced the war as well. Parents in the control group were between 20 and 25 years of age during WWII. It seems likely that they suffered from the war and might be less able to support their children as well. Nevertheless the parents in the treatment and control group experienced the war in a different way, which may affect the reliability of the IV estimates.

Another limitation of this research is the measurement of parental education in the data. Parental education is only measured in secondary schooling attainment. Estimating the difference between parents who only completed primary education compared to college educated parents may be more informative. Additionally the obtained estimates reflect the situation of educational mobility in the mid twentieth century. In order words the results don't provide information on the current situation of educational mobility in Germany. Moreover the estimates may be biased as the result of assortative mating, the phenomenon that fathers or mothers often have partners with a comparable level of education (Kemptner and Marcus, 2011). The data shows a correlation of 0.57 between paternal and maternal education. The found effects than represents the effect of both partners, resulting in upwards biased estimates.

To summarize the limitations, it seems that most of the limitations indicate an overestimation of the causal effect of parental education. Nevertheless the results are consistent with other IV studies which attempt to estimate the causal effect of parental education. It is hard to say whether this means that the found estimates are reliable or that the previous research suffers from the same problems as this research. The remainder of this section will discuss some policy implications of the results and will provide some recommendations for future research.

Since the estimates may be biased upwards and the estimates reflect the effect of parental education in the mid twentieth century, it is not possible to provide concrete policy advice. However the found effects in combination with the results of Kemptner and Marcus (2011) indicate that there is very likely some intergenerational effect of parental education in Germany. These results indicate that children from low educated families may not reach their full educational potential. As argued by Krueger (2003) resources might be misallocated to children from highly educated families. Policymakers may want to implement policies leading to a more optimal allocation of resources. Moreover policymakers may exploit the intergenerational effect when they wish to reduce educational inequality. Alleviating the inequality in the current generations may spillover to the next generation and inequality will reduce or might even disappear over time.

Future research might focus on the forces driving the intergenerational relationship. Policy recommendations would be more concrete and the reliability of the estimates would increase when the forces driving the intergenerational effect are better understood. Future research could potentially focus on the effect of household income on the child's education in combination with the intergenerational effect of parental education. Chevalier et al. (2013) for example find different results when controlling for household income. Moreover the issue of assortative mating can be addressed by controlling for the educational level of the partner. On a final note it seems that the choice of identification strategy affects the results, therefore using different identification strategies with comparable data might give more insight in the intergenerational effect of parental education (Holmlund et al., 2011)

9 Conclusion

The effect of parental education on the education of their children is extensively researched. Despite that there is a consensus that parental education has a positive effect on child's education, the forces behind this relation are less well understood. Different strategies are used to estimate the causal effect of parental education. Recent studies rely mostly on twin parents, adopted children or on natural experiments. The estimates found by these studies differ substantially across the three strategies. Moreover even studies using the same strategy find inconsistent estimates.

This thesis contributed to the existing literature by attempting to estimate the causal effect of parental education in Germany. This research exploits the effect of the Second World War on the educational attainment of parents. As a result of the war individuals born in the 1930s experienced a drop in education. Parents born in the 1930s were around the age of 10 during

WWII; when children are 10 years old they decide which secondary school track they are going to follow. The effect of the war is exploited using a 2SLS model.

The obtained 2SLS estimates are several times larger than the OLS estimates. Furthermore the estimates indicate that maternal education is more important than paternal education. The OLS regressions shows that one year increase in paternal education raises child's education with 0.78 of a year and one year increase in maternal education raises child's education with 0.92 of a years. In the 2SLS estimation one year increase in paternal and maternal education raises child's education with respectively 2.34 and 2.46 years. These estimates seem huge, however parental education only ranges from 9 till 13 years, while child's education ranges from 7 till 18 years. Therefore a one year increase in parental education is relatively much larger than a one year increase in child's education. The results are similar to other studies in the sense that the IV estimates are several times larger than the OLS estimates. This thesis finds IV estimates almost 3 times the size of the OLS estimates. Oreopoulos et al. (2006), Kemptner and Marcus (2011) and Maurin and McNally (2008) find IV estimates between 1.4 and 4.3 times the size of their OLS estimates. Black et al. (2005) and Holmlund et al. (2011) have the same outcome variable as this study, however they find IV estimates smaller in size than their corresponding OLS estimates.

Furthermore the OLS results indicate that parental education is more important for daughters, however the 2SLS results indicate that parental education has a larger effect on sons. Black et al. (2011) reach similar conclusions, however other studies find different results. Chevalier (2004) for example find that maternal education is more important for daughters while paternal education is more important for sons.

The high IV estimates might reflect a local average treatment effect. Ichino and Winter-Ebmer (2004) show that the war had a larger effect on parents at the lower end of the education distribution. Parental education may have a larger effect on children from lower educated families. Another explanation may be that the bias in the IV strategy outweighs the omitted variables bias in the OLS estimation. Finally finding higher IV than OLS estimates may be caused by unobserved factors in the OLS estimation which are negatively correlated with parental education, but are positively correlated with child's education.

The sensitivity analysis shows that the results of paternal education are consistent for different model specifications. The results of maternal education on the hand change drastically when different model specifications are used. Additionally the regressions from maternal education may suffer from a weak instrument problem. The F-value of the first stage is never above the most conservative critical value. Another limitation of the research is the validity of the instrument. The war may have affected child's education not only through parental education, but through other channels as well. For example parents who grew up during the war may have suffered from mental traumas and were as a result less able to support their children in their educational career.

Overall the findings of this research are similar to other studies using an instrumental variables approach. Whether that means that the results are reliable, or that this research simply suffers from the same problems as the previous literature is not clear. It does seem that the results of maternal education are biased, the instrument is not particular strong and the results change a lot in the sensitivity analysis. The results of paternal education remain consistent, but may reflect a local average treatment effect. Additionally the regression may suffer from validity problems. Nevertheless in combination with the results of Kemptner and Marcus (2011) there is very likely an intergenerational effect of parental education in Germany. Policymakers may take into account these intergenerational effects when making policy decisions.

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Appendix A Separate regressions sons and daughters

Table A.1 OLS estimations sons

OLS model dep. variable: son's education in years	father's education	mother's education
variable	coefficient (std. err.)	coefficient (std. err.)
parental education	0.751 (0.068)***	0.899 (0.092)***
birth year	0.016 (0.011)	0.016 (0.010)
siblings:		
1 sibling	-0.247 (0.296)	-0.414 (0.292)
2 siblings	-0.531 (0.312)*	-1.014 (0.311)***
3 siblings	-0.648 (0.338)*	-1.286 (0.352)***
4 siblings or more	-1.829 (0.318)***	-1.933 (0.336)***
region:		
urban	1.153 (0.232)***	0.975 (0.220)***
R-squared	0.2167	0.1740
number of observations	931	998

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table A.2 OLS estimations daughters

OLS model dep. var.: daughter's education in years	father's education	mother's education
variable	coefficient (std. err.)	coefficient (std. err.)
parental education	0.839 (0.071)***	0.936 (0.099)***
birth year	0.041 (0.009)***	0.050 (0.008)***
siblings:		
1 sibling	0.182 (0.248)	-0.171 (0.264)
2 siblings	0.071 (0.243)	-0.593 (0.268)**
3 siblings	-0.342 (0.266)	-0.647 (0.293)**
4 siblings or more	-0.682 (0.261)***	-1.108 (0.281)***
region:		
urban	0.352 (0.193)*	0.613 (0.210)***
R-squared	0.2317	0.2060
number of observations	987	1008

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table A.3 First stage results sons

2SLS model first stage endogenous variable: parental education in years	father's education	mother's education
variable	coefficient (std. err.)	coefficient (std. err.)
WWII (instrument)	-0.460 (0.111)***	-0.263 (0.094)***
birth year	0.020 (0.008)***	0.013 (0.005)**
siblings:		
1 sibling	-0.097 (0.148)	0.009 (0.101)
2 siblings	-0.128 (0.154)	0.101 (0.107)
3 siblings	-0.071 (0.172)	-0.188 (0.106)*
4 siblings or more	-0.247 (0.169)	-0.179 (0.103)*
region:		
urban	0.205 (0.110)*	0.093 (0.078)
F-test of excluded instruments	17.07	7.82
number of observations	931	998

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table A.4 Second stage results sons

2SLS model second stage *dep. variable: son's education in years*	father's education	mother's education
variable	*coefficient (std. err.)*	*coefficient (std. err.)*
parental education	2.987 (0.712)***	3.535 (1.373)**
birth year	0.017 (0.019)	0.013 (0.013)
siblings:		
1 sibling	-0.006 (0.446)	-0.439 (0.409)
2 siblings	-0.239 (0.476)	-1.303 (0.464)***
3 siblings	-0.469 (0.544)	-0.804 (0.548)
4 siblings or more	-1.309 (0.521)**	-1.539 (0.491)***
region:		
urban	0.688 (0.335)**	0.733 (0.333)**
number of observations	931	998

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table A.5 First stage results daughters

2SLS model first stage end. var.: parental education in years	father's education	mother's education
Variable	coefficient (std. err.)	coefficient (std. err.)
WWII (instrument)	-0.388 (0.115)***	-0.255 (0.100)**
birth year	0.026 (0.007)***	0.017 (0.006)***
siblings:		
1 sibling	-0.079 (0.155)	0.050 (0.105)
2 siblings	-0.219 (0.157)	0.053 (0.104)
3 siblings	-0.233 (0.175)	-0.110 (0.110)
4 siblings or more	-0.573 (0.159)***	-0.173 (0.097)*
region:		
urban	0.184 (0.099)	0.123 (0.066)*
F-test of excluded instruments	11.35	6.50
number of observations	987	1008

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table A.6 Second stage results daughters

2SLS model second stage dep. var.: daughter's education in years	father's education	mother's education
Variable	coefficient (std. err.)	coefficient (std. err.)
parental education	1.725 (0.638)***	1.521 (0.962)
birth year	0.032 (0.013)**	0.047 (0.010)***
siblings:		
1 sibling	0.226 (0.306)	-0.208 (0.282)
2 siblings	0.242 (0.319)	-0.627 (0.287)**
3 siblings	-0.159 (0.346)	-0.589 (0.309)*
4 siblings or more	-0.194 (0.474)	-1.010 (0.319)***
region:		
urban	0.173 (0.228)	0.536 (0.242)**
number of observations	987	1008

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Appendix B Sensitivity analysis

Table B.1 Probit average marginal effects

Probit model dep. var.: prob. academic track	father's education	mother's education
variable	coefficient (std. err.)	coefficient (std. err.)
parental education	0.083 (0.005)***	0.092 (0.009)***
gender:		
female	-0.019 (0.018)	-0.069 (0.016)***
birth year	0.006 (0.001)***	0.004 (0.001)***
siblings:		
1 sibling	-0.012 (0.034)	-0.054 (0.033)*
2 siblings	-0.029 (0.034)	-0.108 (0.033)***
3 siblings	-0.087 (0.035)**	-0.145 (0.035)***
4 siblings or more	-0.183 (0.034)***	-0.199 (0.033)***
region:		
urban	0.113 (0.023)***	0.094 (0.023)***
Pseudo R-squared	0.1579	0.1215
number of observations	1919	2006

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table B.2 IV-probit results: first stage results

IV-probit model first stage end. var.: parental education in years	father's education	mother's education
variable	coefficient (std. err.)	coefficient (std. err.)
WWII (instrument)	-0.438 (0.080)***	-0.261 (0.067)***
gender:		
female	-0.054 (0.58)	-0.011 (0.042)
birth year	0.024 (0.005)***	0.015 (0.004)***
siblings:		
1 sibling	-0.070 (0.104)	0.028 (0.073)
2 siblings	-0.168 (0.110)	0.079 (0.073)
3 siblings	-0.151 (0.127)	-0.149 (0.075)**
4 siblings or more	-0.414 (0.112)***	-0.175 (0.070)**
region:		
urban	0.208 (0.079)***	0.108 (0.052)**
F-test of excluded instruments	29.58	15.11
number of observations	1919	2006

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table B.3 IV-probit second stage average marginal effects

IV-probit model second stage dep. var.: prob. academic track	father's education	mother's education
Variable	coefficient (std. err.)	coefficient (std. err.)
parental education	0.183 (0.0183)***	0.247 (0.050)***
gender:		
female	-0.005 (0.013)	-0.045 (0.016)***
birth year	0.003 (0.001)**	0.002 (0.001)**
siblings:		
1 sibling	0.002 (0.024)	-0.044 (0.029)
2 siblings	0.007 (0.025)	-0.089 (0.029)***
3 siblings	-0.029 (0.028)	-0.076 (0.039)*
4 siblings or more	-0.062 (0.034)*	-0.120 (0.042)***
region:		
urban	0.038 (0.019)**	0.050 (0.025)**
number of observations	1919	2006

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level. The estimation is controlled for fixed effects at the level of federal states.

Table B.4 OLS and 2SLS results when treatment and control cover same number of years

Model dep. var.: child's education in years	OLS	2SLS	2SLS/OLS ratio	First stage F-statistic
Father – inclusion of 1935	0.792 (0.045)***	2.209 (0.428)***	2.79	32.59
Father – exclusion of 1920	0.775 (0.054)***	2.082 (0.425)***	2.69	33.35
Mother – inclusion of 1935	0.935 (0.064)***	2.603 (0.768)***	2.78	16.37
Mother – exclusion of 1920	0.928 (0.073)***	2.285 (0.746)***	2.46	15.09

*, **, *** significant at the 1, 5, and 10 percent level, standard errors are clustered at the household level.