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Faculty of Social Sciences
Institute of Economic Studies

BACHELOR THESIS

Variation of Relationship between Individual and Parental Education across OECD Countries

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Prague, July 29, 2016

Signature

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Abstract

This thesis investigates the presence of intergenerational transitions of education and how it relates to wealth. The analysis is conducted on a set of 30 OECD countries. Linear regression is used to show the presence of positive, significant effects of maternal and paternal education on individual's education. Additionally, we evaluate the functional form of the relationship between marginal effects of parental education and wealth. The datasets do not provide any supportive evidence for the hypothesis increasing of marginal effects being increasing and concave function of wealth on the interval of feasible wealth values. Moreover, the obtained positive marginal effects are likely to suffer by endogeneity bias.

JEL Classification	I20, I21, J62
Keywords	parental education, intergenerational transitions,intergenerational mobility , educational spillovers, country comaprison

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Abstrakt

Následující práce zkoumá vztah bohatství na mezigenerační mobilitu vzdělání. Analýza je provedena pro 30 zemí OECD. Pozitivní a signifikantni vztah vzdělání rodičů na vzdělání jejich potomků je ukázán pomocí lineární regrese. Dále zkoumáme funkční formu mezních efektů rodičovského vzdělání, jakožto funkci bohatství. Získaná data nevykazují schopnost podpořit hypotézu mezních efektů, jakožto kvadratické funkce, konkávní na intervalu určeném možnými hodnotami bohatství. Navíc je prvděpodobné že získané mezní efekty rodičovského vzdělání jsou kvůli problémům s endogenitou nesprávné a liší se od populčních hodnot.

Klasifikace JEL	I20, I21, J62
Klíčová slova	rodičovské vzdělaní, mezigenerační přesuny, mezigenerační mobilita, přelévání vzdělanosti, srovnání států

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Contents

List of Tables

List of Figures

Acronyms

GDP Gross domestic profuct

IALS International Adult Literacy Survey

ICT Information and Communication Technologies

IV Instrumental variable

JK-1 Jackknife 1

LFS Labour market and Labour force survey by OECD

OECD Organisation for Economic Co-operation and Development

OLS Ordinary least squares

PIAAC Programme for the International Assessment of Adult Competencies

USSR Soviet Union

VIF Variance inflation factor

Bachelor Thesis Proposal

Author	Michal Todt
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Proposed topic	Variation of Relationship between Individual and Parental Education across OECD Countries

Topic characteristics The landmark study, ordered by government of United States of America in the second half of twentieth century called "Coleman Report" (Coleman et al. 1966) suggested that the variation in school quality (per pupil expenditure, size of school library, and so on) showed little association with level of education attainment.

On the other hand differences in student?s family background showed substantial association. Based on the ideas proposed by Coleman, attempts to show the relationship between the parental education and individual?s education were made. The results suggest, there may a correlation between those variables as well as correlation with income. (Kodde et al. 1988) Some studies failed to show the connection between the variables (e.g. Bäckström 2011), however the majority of researchers examining the link found it . The scope of the studies on the topic is merely national and no comparison of different countries were made. Following from lack of international view on the issue, the main research question of the thesis is: "Does parental education predict individual education more in high-income countries or in middle-income countries?"

Hypotheses

(1) Parent?s education is positively correlated with the education of their offspring.

(2) There are differences across the countries based on the income.

(3) The parental education will predict individual?s education better in countries with higher income, because of saturation of basic needs and excess income.

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Methodology Topic will be investigated based on national data from PIAAC survey with use of regression in various countries with different income. Sample of investigated countries will differ in income as well as state of development, however countries will be chosen carefully to hold as much as possible other factors same to provide relevant results. Based on regression lines of different countries the results will be interpret and reported.

Outline

1. Introduction
2. Literature review
3. Comments on data and the method of gathering it and sources of possible biases
4. Methodology and Model
5. Data analysis and Empirical evidence
6. Outcomes and Effects (summary)
7. Conclusion

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Chapter 1

Introduction

There is no doubt that the destiny of children is affected by their parents. How much time they spend, how much money they invest and much more that can affect the children while growing. There are also effects which cannot be influenced by the parents and they affect the child, for example, social status or intelligence. A lot has been written about parents passing on characteristics in many categories to their children. Intergenerational transition of knowledge, earnings, social status, and education are among the most frequently investigated. Economic intuition suggests that the education of an individual should depend on innate abilities, but it might be influenced by socio-economic background as well.

The purpose of this thesis is to investigate the intergenerational transition of education between parents and their children and, to investigate how the relationship changes with respect to the level of wealth in the country. More specifically, thesis tries to find supporting or evidence following hypotheses:

(1) Parental education predicts individual's education across OECD countries.

(2) The effect of parental education on individual's education is increasing in wealth.

(3) Effect of additional wealth on intergenerational transition of education is diminishing.

A lot has been written about (1) hypothesis, with mixed results (see chapter 2). Hypothesis (2) and (3) are more unique and imply that the marginal effects of parental education expressed as a function of wealth are increasing but concave (at least for the internal which covers all values of wealth within the dataset).

Hypotheses (2) and (3) have not been studied on such a scale as intergenerational transition itself, but what makes this thesis unique, is the scope of the research. There seem to be only a few papers comparing the effects of parental education on individual education across different countries. Holmlund *et al.* (2011) compare the results of previous papers, but those were conducted with different data. Comparison based on data from the same source was used by Iannelli *et al.* (2002), who compares twelve European countries. Her datasets comes from year 2000, hence the estimation with more recent data might provide useful insights. This thesis uses data from 30 countries (26 OECD countries and four partner countries) from the year 2012 and compares the results for each of them.

Iannelli *et al.* (2002) pointed that marginal effects of education seems to be decreasing in wealth. She observed smaller effects on wealthier countries from northern Europe compared to the higher marginal effects of less wealthy countries from eastern Europe. But aside from wealth, her results might be attributable to structural differences between Nordic and eastern countries.

Hypothesis (2) contradicts Iannelli's findings. On the other hand Grawe & Mulligan (2002) discuss how credit constraints prevents individual's from achieving desirable level of education. We expect individual to adjust their educational demand based on education of their parents (according to the first hypothesis). But the demanded education cannot always be obtained. Poorer countries have less developed credit markets and it is natural to assume that the correlation between parental education and individual's education should be higher when the credit constraints are not an obstacle.

Intuitively, parental education should be correlated with individual's education because parents have possibly the greatest formative effect on their children, and therefore, the transitions should occur. The children might achieve the level of education of their parents simply because they are expected to do so. Alternatively, well educated parents might explain the importance of education better and influence decision of their children that way. But we expect an individual to maximize their level of well-being as well. The sacrifice of time, hard-work and mostly even money might not be outweighed by the possibly higher income in the future. Individual is expected to be maximizing their utility and to be influenced by parents as well. Those two channels of influence might clash and we expect the first one to outweigh the other more often when the country is relatively wealthier. In the countries where level of well-being is relatively low, every addition to it is welcomed, therefore, the individual would seek every opportunity to increase their level of well-being, which education may provide in the form of higher future income. On the other hand if the country is wealthy and everyone enjoys good standards of living despite the education level, the investment in education might not be as desirable. Therefore in wealthy countries the effect of parental influence and the effect of optimization are more often expected to be in conflict, leading to smaller transitions between parents and children.

Importance of studying intergeneration transition of education can hardly be questioned. Implications of proper results would be widely applicable and relevant for setting up future policies. If hypothesis (1) holds, it will be possible to use the results to outline a proper subsidy plan for education. Onetime investment in education would benefit all the upcoming generations therefore it might be much more convenient than smaller subsidies every year. If hypotheses (2) and (3) both hold, it will imply the conditional convergence of education. Provided the same conditions in the countries differ only in the level of initial education and wealth, the catch-up effect would take place. The marginal effects of parental education of a country with previously lower level of education and wealth would approach the marginal effects of parental education of a previously more developed country. The diversity of OECD countries also suggests that the results obtained in this thesis might be a useful link for studying the question in other parts of the world.

The thesis is structured as follows: Chapter two present previous findings related to the research question. In Chapter 3, the data are described and methodology of research is presented. Chapter four summarizes the obtained results from different identification methods. Chapter five discusses the reliability of the used assumptions and describes the limitations of the research. In that chapter, the validity of the used method is investigated as well. The last Chapter concludes the results.

Chapter 2

Literature review

According to educational choice theories, education can be viewed as a consumption activity, similar to luxury goods (Lazear, 1975). This branch of theories suggests that causal link between education and income has opposite direction, than was initially expected. Other group of the theories suggests that education has only a labeling effect (see e.g. Cohn & Geske (1990)). Those reject the value of education itself and propose that education works only as a filter, sorting out more productive and more able children. Starting from Becker (1975) education has been viewed as an integral part of the human capital (i.e. individual's stock of knowledge,abilities, etc. producing economic value). Becker proposed to look at the education as an investment, which one only accepts if he or she expects positive returns in form of upcoming income.

Following Becker's theory Bäckström (2011) concluded, that role of expected income after graduation is crucial for individual's educational choice. He investigates how young individuals in Sweden form their expectations and assumed that bias in the expectations will be present as suggest Dominitz & Manski (1997), and expectations would be influenced by how much the education of individual's parents corresponds with their income. But he failed to find evidence for such a bias, which may support theory of rational expectations.

As an secondary result, Bäckström (2011) controlled for parental education in the probit model he used, and found it to be significant factor in determining the demand for higher education. Parental education was found significant for explaining schooling choices in various countries around the world other than Sweden (Bäckström, 2011) such as Netherlands (Kodde & Ritzen, 1988), Guinea (Glick & Sahn, 2000) and Britain (Chevalier, 2004) as well.

Effects of parental education on individual's education differ amongst studies. Coefficients for paternal and maternal education tend to have different magnitudes, and in some cases, even opposite signs. Moreover, effects have been found to be gender dependent. The positive correlation was observed with significant effects on individual's education but, for example, Black *et al.* (2003) did not find sufficient evidence to support the hypothesis about correlation of education across generation, except for specific mother-son relationship. In general, links between mother's education and child's education were stronger (e.g. Kodde & Ritzen (1988), Bäckström (2011), Chevalier *et al.* (2013)) than in case of the father's education (e.g. Plug (2004)). That might be used as a counter argument against Behrman & Rosenzweig (2001) who do not find any relationship between mother's schooling and schooling of her children. They attributed previous positive results to upward bias caused by correlations between inherited abilities and schooling as well as non-random matching in the marriage market. The research conducted with American data was questioned by Antonovics & Goldberger (2005) for not being robust enough and for being policy dependent (Behrman & Rosenzweig, 2005).

Table A.1 & table A.2 show the resuls of previous findings and methods. The original commentary from Holmlund *et al.* (2011) follows.

> *"There are a number of common features of these studies when we consider the estimates reported in the first two columns. All the estimates indicate that higher parental education is associated with more years of schooling of own children, and that in most cases the influence of the mother's schooling is somewhat larger than that of the father. The results are, as such, fully in line with those findings reported and summarized in HW* [1]*. Second, those studies that control for assortative mating effects indicate that the partial effects of both parents' schooling fall, yet always remain positive. It is interesting to see that the partial schooling effects of both parents are almost always identical."* (Holmlund *et al.*, 2011)

There are many reasons for parental education to be endogenous. For instance, inherited abilities we can not control for, will most likely affect individual's educational attainment and are correlated with parental education. More educated women may be inclined to marrying wealthier and more educated men and therefore increasing their offspring's genetic predispositions (Black *et al.*, 2003). Nevertheless, Glick & Sahn (2000) found endogeneity not to be

[1] Author's note: HW stands for Haveman & Wolfe (1995)

influential in results. As does Chevalier (2004) in the case of United Kingdom, but his results may not fully represent the whole society. He used one time policy changes from 1972 affecting the school leaving age, therefore he obtained only data for citizens with lesser taste for education. The approach to compare the state of education under different policies is more common in studies conducted in developed countries such as Norway (Black *et al.*, 2003) and Sweden (Holmlund, 2006).

Aside from papers based on one time policy changes, possibly nonrepresentative sample of individuals might be a problem for Glick & Sahn (2000) as well. They assume that a child will usually start their education early on. Therefore, they restricted the sample only to children aged 10-18 living at least with one parent. In fact, the children in third world countries do not usually start their education patches that young which was observed by Glewwe & Jacoby (1994). It might be right for developed countries like United Kingdom to assume that education starts at the same age for everyone and there are not any time gaps present between different stages of education, but in case of developing countries the assumption is troublesome and, ideally, data for individuals who have already finished their education should be used.

Contradictions among results were addressed by Holmlund *et al.* (2011) in a paper summing up-to-date available results. Their main source of discrepancies were differences in data and methods. The studies conducted in different countries in different years using data obtained by different methods tend to have different results. The educational policy of the country will also affect the observed results (Holmlund, 2006). Moreover, general trend is hard to observe and some of the studies might suffer from heterogeneity (e.i. discovered relationship only for subpopulation). In addition, underlying problems with estimation methods were found. The models are as good as are their assumptions and sensitivity to these assumptions differs across methods. Therefore, the effects are mostly overestimated. After remedying the potential biases, smaller but significant effects were found.

In general, we can divide studies on the topic into groups based on the approach the researchers used. Firstly, the ordinary least squares regression (OLS) is used to get a notion of the topic. The OLS model might suffer by endogeneity as already mentioned, which would lead to overestimating[2] the effect. Use of instrumental variables (IVs) is possible way how to correct the problem. Holmlund *et al.* (2011) pointed out that there is a visible pattern and IV models

[2] Underestimating is also possible but much less common.

mostly found superior relationship between mothers and their children and no effect or very little effect of paternal education. *"The IV models take advantage of policy changes using them as an argument to parental education"* (Holmlund *et al.*, 2011). There have been more instruments used to prove the point. For example Carneiro *et al.* (2013) used the variation in school costs when mother was growing up as an instrument. In addition to OLS models, there seems to be inclination to binary dependent variables and either probabilistic or logistic models. It is the optimal approach to predict the chance that an individual will take part in higher education, hence the models provide strictly positive estimates corresponding with probability. On the other hand, binary dependent variable models lack precision obtainable by predicting the exact length of schooling. The models by definition also suffer from heteroscedasticity, forcing researches to use heteroscedasticity robust statistics, leading to larger standard errors.

To avoid the effects of inherited abilities, a sample of monozygotic twin parents (from the same egg) might help, because of the identical genes and identical household conditions (see e.g. Behrman & Rosenzweig (2001)). The effect of family specific properties may be cancelling out by the subtracting the equations for both twins from each other and utilizing the first differences estimation model. Differences in schooling between twins are not randomly assigned as pointed out Bound & Solon (1999), which might case endogeneity as well. Even though the estimates from samples of twins are inconsistent due to endogeneity, they may still offer valuable insights. *"If one believes that the correlation between schooling and the wage equation's error term is positive both in the cross section and within twin pairs, then, once measurement error has been treated, both conventional cross-sectional estimation tend to overestimate the returns to schooling. While it is theoretically unclear which estimator's upward inconsistency is less severe, most of the empirical evidence so far suggests that the between-twins estimates tend to be at least a little smaller and therefore provide a tighter upper bound on the return to schooling."*(Bound & Solon, 1999)

The approach allowing us to differentiate between the causal effects of parental education and influence of child's surroundings might be based on investigating adoptees (see e.g. Plug (2004)). In their case, we can clearly distinguish between what is inherent and what is learned. In order to use adoption approach we need three assumptions to be satisfied. Firstly, parents have to treat all their children the same, no matter whether the child is adopted or not. The adopted child has to be randomly assigned to the family. Lastly, the adoptive parents have to differ from the biological parents in the parental educational attainments (Bjorklund *et al.*, 2004).

Grawe & Mulligan (2002) investigate the economic theory behind intergenerational transitions. The economists do not have a single theory to explain the transitions and do not agree with theories from other fields. In the paper Grawe & Mulligan (2002) investigate in depth the theory of family investment and intergenerational mobility, which follows from Becker (1975), and assumes that the family will invest the resources into the child's human capital instead of investing resources into financial instruments, only if expected returns to education are higher. Returns to education tend to be concave and diminishing, therefore one can expect to see greater level of investment from the family to the children in the child's young age, when the expected returns will be highest. Family can also borrow funds to finance child's human capital and leave the child with debt, so we would expect to see attempts to smoothen the consumption across generations (Grawe & Mulligan, 2002). Despite the family's intentions, ideal investment in human capital cannot be always achieved. The theory allows negative financial wealth, which means the family can borrow money. The imperfection of the credit market therefore have to affect the intergenerational transitions negatively. This is exactly what Grawe & Mulligan (2002) have observed in the case of intergenerational transition of earnings. The credit market constraints affect the poor families and the families with children of higher abilities more, due to their willingness to invest more in their children.

Chapter 3

Data and Methodology

3.1 Dataset description

OECD countries were looking for tools to allow them to identify and measure differences between individuals across countries, asses the performance of educational and training systems, asses the impact of economic and social background on competencies etc., which led to the development of Programme for the International Assessment of Adult Competencies (PIAAC) (Schleicher, 2008). PIAAC is an international survey conducted in over 40 countries with individuals ageing from 16 to 65. So far, two waves of the survey took place within the selected countries and four partners besides OECD.(Complete list of countries is provided in the table A.4.) For every participating country at least 5 000 observations were required. In reality, the number of observations varies from 4 500 to 27 000 (around 200 000 in total), depending on the country.

Countries were provided with the option to oversample in order to obtain more reliable estimates within the specific geographical region, allowing them to adjust policies on a smaller scale or within the specific groups of citizens, for example, immigrants (Schleicher, 2008). Previous assessment program of the competencies from 1990s called IALS (International Adult Literacy Survey) was mostly concerned with maximizing the coverage of the cognitive competence areas, sacrificing proper depth within each area. Depth and width cannot be both obtained in the same survey due to the time constraints imposed by the interviewees, who are willing to devote only a certain amount of time to answering the questionnaire. In contrast with IALS, PIAAC takes different approach and focuses more on the socio-economic variables, which are more usable for policy analysis (Schleicher, 2008). Moreover the reporting scales are cross-nationally and cross-culturally comparable, making analysis easier.

It is important to have as many countries as possible for the purpose of this thesis and to also have as big variety in wealth as possible. The latter is measured by the GDP per capita in the thesis. Datasets are not theoretically completely comparable due to the two different stages of surveying. First round took place from 2008 to 2013 and the second one from 2012 to 2016. Because of different time periods the GDP per capita is not fully comparable (even after adjustments for inflation), but omitting the countries surveyed in different time period would restrict our sample by nearly 30% (9 out of 32 countries). Given the relatively negligible changes in socio-economical variables in such a short time period and minor institutional changes, which might have occurred in those countries during 4 years,we will include them all in the analysis because the author believes that benefits of higher sample outweighs the costs of minor time gap.

Interviews were held via laptop or paper by trained staff in interviewee's home or other place previously agreed on. Some parts of the survey were optional (for instance ICT competency test), but socio-economic background questions were required from all respondents. In the process of such a magnitude, one can hardly believe that all the entries are correct. Considering the trained interviewers, systematic error is unlikely. Random errors, which might have occurred during the process will not cause the bias in model (Wooldridge, 2015).

Summary of key variables is presented in table 3.1. Countries are sorted to four wealth categories based on GDP per capita. Countries from the wealth categories one or two will be referred to as poor and countries from wealth categories three and four will be referred as rich. Full list of countries is presented in appendix (A.4).

Individual's education is measured in years of the schooling, but the maternal and paternal education are both measured by categorical variables which only takes values 1, 2, or 3. These values represent range of ISCED (International Standard Classification of Education) levels in predictable manner explained by table 3.2. (For ISCED levels definition see table A.3 from appendix.)

A few patterns emerged in data. Education is higher in the rich countries and it holds for individual's education and for the parental education as well. Maternal education is universally smaller than paternal which suggest possible problems with equa access to education. These patterns coincide with the

Table 3.1: Summary of the dataset

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
	Whole dataset				
Age	166 284	42.229	13.179	16	65
Gender	166 284	0.533	0.499	0	1
Individual's education	164 108	12.669	3.203	3	23
Paternal education	164 266	1.665	0.749	1	3
Maternal education	164 266	1.580	0.728	1	3
Score	114 319	11.356	0.987	4	12
	Wealth category 1				
Age	30 070	39.492	13.332	16	65
Gender	30 070	0.568	0.495	0	1
Individual's education	29 993	11.782	3.686	4	23
Paternal education	29 933	1.518	0.690	1	3
Maternal education	29 933	1.480	0.688	1	3
Score	13 864	11.213	1.135	4	12
	Wealth category 2				
Age	40 248	43.247	12.564	16	65
Gender	40 248	0.532	0.499	0	1
Individual's education	40 052	12.214	3.236	3	22
Paternal education	40 053	1.583	0.686	1	3
Maternal education	40 053	1.461	0.637	1	3
Score	25 394	11.329	0.990	4	12
	Wealth category 3				
Age	67 857	42.251	13.404	16	65
Gender	67 857	0.529	0.499	0	1
Individual's education	66 415	12.993	2.844	5	22
Paternal education	66 572	1.759	0.780	1	3
Maternal education	66 572	1.688	0.765	1	3
Score	53 001	11.374	0.965	4	12
	Wealth category 4				
Age	28 109	43.644	12.885	16	65
Gender	28 109	0.509	0.500	0	1
Individual's education	27 708	13.506	3.075	6	21
Paternal education	27 708	1.720	0.782	1	3
Maternal education	27 708	1.603	0.757	1	3
Score	22 060	11.430	0.927	4	12

Table 3.2: Parental education representation on ISCED scale

Parental education level	coresponding ISCED levels
1	level 0, level 1, level 2
2	level 3, level 4
3	level 5, level 6

source: OECD (1999)

intuition. A higher number of observation for the third category is attributable to Canada. The canadian sample exceeds the minimal number of observations five times.

3.2 Country specification

In total, datasets for 30 countries were obtained from countries all across the world. There are many structural differences among them. One can find different political systems, ranging from monarchy to democracy, with different degrees of trade openness and with different long term aspirations as well. Unfortunately, differences can be found between the datasets as well. In some countries some questions were not asked, leading to different sets of variables, at times, even in different order.

The GDP per capita of the countries ranges from 3 346 to 74 734 (in thousands 2015 US dollars). For the entire world GDP per capita ranges from 275 to 101 000. The countries from the sample cover nearly two thirds of the scale, ranging from the 34th percentile to the 96th. Distribution of the GDP per capita values is presented in Figure 3.1.

Heavy-tailed distribution is desirable, but it is not the case if we consider the whole world. Considering the whole world, the distribution of GDP per capita is skewed to the poorer countries and a third of the dataset is under value the 3 000. Situation is depicted in figure 3.2. Proportion of countries which we include in the analysis is marked in red.

3.2.1 Notes on predicate power of the dataset

The results obtained by this thesis might be applicable in other countries to get an idea of how parental education influences an individual's education even

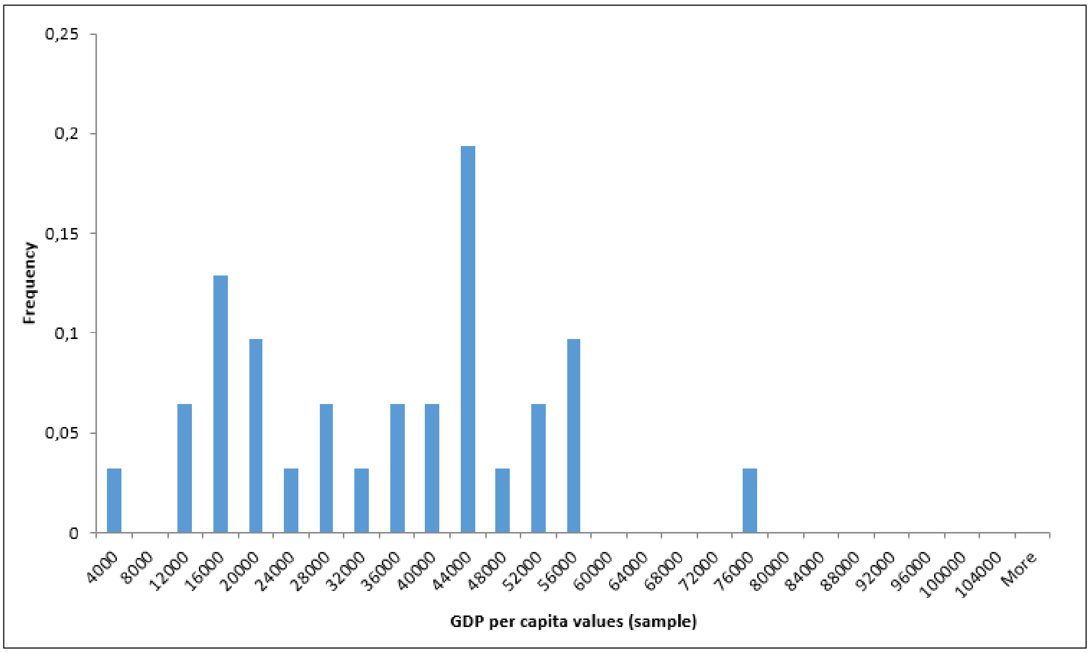

Figure 3.1: Sample distribution of GDP per capita
Source: Author's creation with data from The World Bank (2016)

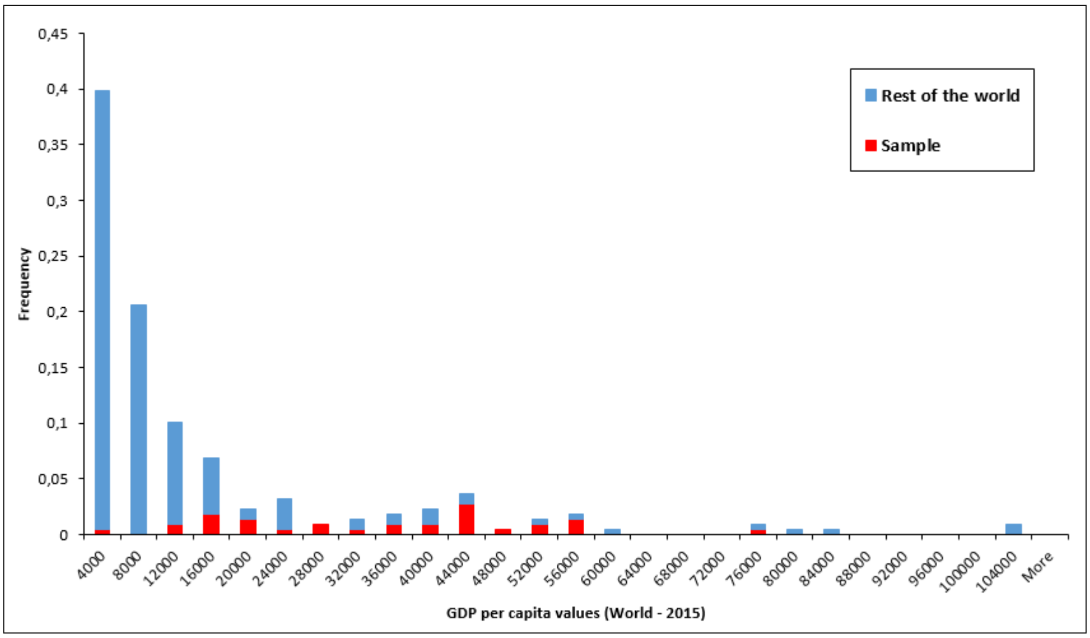

Figure 3.2: Position of the sample with World GDP per capita distribution
Source: Author's creation with data from The World Bank (2016)

beyond OECD. We have no data from countries with low GDP per capita values. Moreover, those countries usually have less developed institutions and in many cases, they are not politically stable. These facts make them poor candidates for generalization of our results and for drawing any conclusion. Many of them are located on the African continent which we have no data on. The population parameters might be very different even if the same model holds. On the other hand the results might serve as a valuable hint for the rest of European countries and for other countries covered within the GDP per capita band of our sample.

3.3 Methodology

To identify the effect of a country's wealth on the relationship between parental education and an individual's education, we use two different methods. Firstly, we use country specific regression, allowing us to find the coefficients in front of variables of interest (which are mother's education and father's education) for each country separately compare them alongside the regressions and inspect whether or not they seems to follow the hypothesis. Secondly, we will merge countries to one larger dataset, which brings wealth variation to the model and it allows us to investigate the effect of wealth on the intergenerational transitions.

We use two methods to estimate coefficients in our regression. Firstly, Ordinary least squares (OLS) estimation is used. Given the dataset, there is a feasible bias in the OLS estimates due to the sampling problems. OLS rely on sample randomly drawn from the population which does not have to hold in case of our dataset. As mentioned in the previous section, the individual countries were provided with the option to oversample specific groups. Therefore, if country used the option OLS no longer remain unbiased.

Moreover, a survey sampling is usually done without replacement. Sampling without replacement means that an individual who has been previously selected for survey can not be selected again for the same survey. In addition they would be hardly ever willing to provide the answers again.

Unbiased estimates can still be obtained if we take the sampling strategy into account. Resulting from the previous paragraphs, we will estimate the regression coefficients by using Jackknife (JK-1) method as well and compare it to the estimates obtained by OLS. JK-1 is a method usable for deriving estimates of the bias and standard errors. Moreover, Jackknife is designed to work in cases of sampling without replacement (McIntosh, 2016). Thus, Jackknife and OLS will be compared.

The Reason for incorporating two different estimation methods is the insufficient description of the datasets by the participating countries. Particular countries do not state whether or not they oversampled some subpopulation. Therefore, OLS might be still the best estimation method, overperforming the Jackknife method.

In chapter 2 the problem of inclusion individuals with incomplete education (i.e. students) was mentioned. Fortunately, in the datasets provided by OECD (2016) one of the background questions asked about current work status and "pupil or student" was one of the possible answers, therefore those observations can be easily identified and dropped.

3.3.1 Individual country method of identification

Our regression model for each country is as follows:

$$educ_{ch} = \beta_0 + \beta_1 * gender + \beta_2 * educ_{f_2} + \beta_3 * educ_{f_3} + \beta_4 * educ_{m_2} + \beta_5 * educ_{m_3} +$$

$$+ \beta_6 * score + \beta_7 * age + u$$

The dependent variable in our model is a discrete variable, measuring the level of individual's eduction in years. Variables $educ_{m_2}$, $educ_{m_3}$ and $educ_{f_2}$, $educ_{m_3}$ are dummy variables which represent the educational level of mother and father respectively. They are measured on a ISCED scale with three possible answers as was already specified. First category which is a reference group in the model represents parents with lowest education. For table of ISCED levels and educational attainment it represents, see table A.3 in the appendix. Inclusion of the variables $educ_m$ and $educ_f$ in their initial forms (one categorical variable with possible values 1,2,3) would be certainly possible, but adding two dummy variables for each of them is better because it allows the effects to be non-linear[1]. The reported values are not linked to biological parents but to actual people who raised the children (i.e. parent or guardian).

We suppose that level of education an individual obtain is dependent on

[1]Different measurement for educational attainment may seem missleading at first sight. But we do not have information on the exact length of parental schooling and categories are too vague to derive it by ourself. Education of an individual is convertible into categorical scale used for parental education, but the author believes that it would make interpretation less intuitive.

their abilities as well. Therefore, we will use the individual's score from PIAAC core assessment test[2] as a proxy variable for innate abilities. It might be troublesome to believe that such a highly learnable skillset[3] will be any good to control for innate ability in general. But in case of OECD countries, where the school attendance is compulsory, every individual most likely had a chance to learn those basics needed for PIAAC test. Therefore, the variable is usable in our situation, and it is better to include it because if we believe that innate abilities of individual are relevant, not controlling for them would cause bias in our estimates. Using a proxy variable will mitigate the bias if the proxy is highly correlated with unobservable variable and if the unobservable variable is not correlated with other independent variables (Wooldridge, 2015). The letter condition is speculative. The innate abilities of child should not be correlated with educational attainment of the parents. Using the same logic as before, education of the parents depends on their innate abilities. If the innate abilities are heritable, we get the correlation by transitivity[4]. On the other hand recent research suggests that heritability of IQ is relatively small (Devlin *et al.*, 1997).(Which is only relevant if we believe that IQ is a precise measurement of innate abilities, but that is beyond the scope of this text.) Variables *gender* and *age* are self-explanatory.

The reason for including the age in the regression model is variability of educational length in time. It has been observed by OECD (2011a) that rates of graduates are not constant and adding age to the model allow as to account for the differences. Original commentary from OECD (2011a) follows:

> *"During the past 50 years, the expansion of education has contributed to a fundamental transformation of societies in OECD countries. In 1961, higher education was the privilege of the few, and even upper secondary education was denied to the majority of young people in many countries. Today, the great majority of the population completes secondary education, one in three young adults has a tertiary degree and, in some countries, half of the population could soon hold a tertiary degree."* (OECD, 2011a)

[2] We only use respondents who filled in the computer based test, because scores are not comparable with paper based test and we have a higher sample of individuals who took the computer based test.

[3] The test consisted of "key information-processing competencies" such as literacy, numeracy and problem solving (OECD, 2011b)

[4] Correlation is not transitive in general but it might happen in specific cases. In the our case, economic intuition suggests possible correlation.

Unfortunately, some of the countries did not provide the exact age of the respond, and provided only a categorical variable, allowing us to identify a five year interval, based on LFS (Labour market and Labour force survey by OECD) grouping, where exact age belongs. In those cases, estimate of the exact age was made by taking rounded midpoint of the age interval.

For every country coefficient of maternal and paternal education (i.e. marginal effects of parental education) would be compared with the GDP per capita of that country and its statistical and economical significance would be considered.

3.3.2 Joint method of identification

For the purpose of the second identification method, we will combine our datasets together. The obtained dataset set will contain individuals from all countries. It is conceivable, that the relationship does not hold for every country and this method will allow us to investigate whether it holds within the whole combined dataset. It will allow us to say with more confidence whether institutional background within country or wealth matters, which was hard with the previous identification method. We can add a variable to differentiate wealthier countries from those relatively more poor as well. In the combined dataset variation is, such a variable which was not the case of country specific regression will be present, and therefore, we could not use it before.

Wealth of countries is frequently compared via their GDPs but this thesis will rather use GDP per capita which is less common. The main issue with this identification strategy is the fast nature of changes in GDP per capita. It is useless to include GDP per capita from the year of survey because it is not a factor which affected educational decision of the individual. Such a decision happened many years ago and the year is not uniform for all people from the dataset. Introducing the categories for relative wealth will help us to solve the problem.

We will divide countries to categories based on relative wealth. This procedure need specific assumption to hold. The ratio of corresponding GDPs per capita for every pair of the countries has to be stable over time. The assumption assures that the countries, which were relatively poor compared to the rest, remained relatively poor with respect to the rest of the dataset. Stability of the ratio has to hold at least for the last two or three generation, because it is the period when PIAAC interviewees had made their educational decisions.

In this identification method it is important to note that the wealth is relative and the values are ordinal (exact size lacks meaning and the only important thing is the relative magnitude with respect to others). Also, the method fails to provide any insight about the trend in the data. Regression will only provide enough information to tell whether or not for the given sample the relationship seems to be dependent on how wealthy country is.

Firstly, the analysis will be conducted on rich and poor countries separately to find differences, and afterwards, we will conduct the analysis within each of the wealth categories. These estimates will be used to compare the marginal effects of parental education at different wealth levels. Lastly, estimates for whole dataset will be computed, allowing us to introduce interaction terms and dummy variables for wealth.

Purpose of grouping countries is clear. It allows us to obtain variation and wealth and therefore include wealth in the model. Reasons for stratifying in two different ways (2-category stratification, 4-category stratification) is reasonable because 2-category stratification provides more general results, but the pattern might remain hidden if the effect of wealth is noticeable only between the first and second wealth category or third or fourth wealth category. Also 2-category stratification results might seem consistent with the research question by coincidence and 4-category stratification might uncover underlying problems which were previously invisible. Moreover 2-category stratification is less strict on one of the key assumptions (see section 5.1.2). In fact, Individual country method of identification can be viewed as special case of stratification. In the light of the joint identification method it can be perceived as 30 category stratification. Only difference is that state's policy impact on regression may be canceled out by other states if broader wealth categories are introduced.

T regression model for the subpopulations stratified by wealth will be the same as the model for individual countries. The regression model for the entire combined dataset will be constructed as follows:

$$educ_{ch} = \beta_0 + \beta_1 * gender + \beta_2 * educ_{f_2} + \beta_2 * educ_{f_3} + \beta_3 * educ_{m_2} + \beta_3 * educ_{m_3} + \beta_4 * score +$$

$$+ \beta_5 * age + \sum_{i=1,\dots n} \beta_{y_i} * wealth\_category_i + \sum_{k=1,\dots n, j=2,3} \beta_{x_{kj}} * wealth\_category_k * educ_{f_j} +$$

$$+ \sum_{l=1,\dots n, j=2,3} \beta_{x_{lj}} * wealth\_category_l * educ_{m_j} + u$$

Variables $educ_{ch}, gender, educ_{f_i}, educ_{m_i}, score, age$ were explained earlier and they have the same meaning in this identification method. The $\sum\limits_{l=1,...n} \beta_{y_l} * wealth\_category_l$ are a set of n dummy variables representing the wealth category or the wealth status. (In case of our previously defined categories and statuses n can only take values 3 or 1 because we have 4 wealth categories and two wealth statuses. We have to exclude one category in order to avoid the dummy variable trap.) Sums $\sum\limits_{k=1,...n,j=1,2} \beta_{x_{kj}} * wealth\_category_k * educ_{f_j}$ and $\sum\limits_{l=1,...n,j=1,2} \beta_{x_{lj}} * wealth\_category_l * educ_{m_j}$ represent a set of all feasible interaction terms.

Marginal effect of maternal education from the second category for the model is as follows:

$$\frac{\partial educ_{ch}}{\partial educ_m} = \beta_3 + \beta_{x_{l2}}$$

, where l represents the wealth category or status. This approach allows us to investigate how wealth of the country affects the relationship more rigorously. As has been just shown, the effects of maternal education has been allowed to differ depending on the relative wealth category. The same holds for paternal education.

Therefore, according to our hypothesis of the positive wealth effect on marginal effects, coefficients $\beta_{x_{kj}}$ and $\beta_{x_{lj}}$ should be in increasing order (meaning that if k or l increase and j remains constant, then $\beta_{x_{kj}}$ and $\beta_{x_{lj}}$ should increase as well) and all positive. Positiveness is essential because it implies increasing marginal effect with respect to the reference group. Reference group in the model is represented by individuals who live in the poorest countries and educational attainment of their parents do not exceeds second the ISCED category. Also the distance $\beta_{x_{k2}}$ and zero should be larger than the distance between $\beta_{x_{k2}}$ and $\beta_{x_{k3}}$ if plotted on the real line. (Same should hold if we change k indices from the previous sentence to l indices.

Chapter 4

Results

4.1 Interpretation of predicted values

Our regression models predict the individual's education for every set of explanatory variable's values, but nothing guarantees that those values are be integers. Educational attainment is a random variable which takes only integer values. Predicted values are very unlikely to be integers. The meaning of non-integer values of predicted educational attainment become clear when we look apart from the particular individual and focus on wider population. It is clear that no individual can achieve non-integer years of schooling. But if we collect a sample of individuals who satisfy our constraints given by the values of independent variables, average of their schooling years will be somehow close to predicted value. If we take even larger sample of such individuals, sample mean will get even closer to the predicted value. Approaching of the sample mean when sample gets larger is a direct implication of the Law of Large Numbers.

4.2 Country specific results

The results from country specific regressions show a few patterns. Firstly, all but two marginal effects of parental education are positive. That is consistent with our intuition. Marginal effects represents expected increase (or decrease in minority of cases) of an individual's years of schooling with respect to the reference group. Our reference group consists of individuals with relatively uneducated parents compared to others (category 1). For instance, the expected educational attainment of an individual from the Czech Republic who has highly educated parents (both from category 3) is higher than it is for an individual with both parents from category 1 by 4.355 years (on average).

In case of Canada, we had to use a different procedure. In the Canadian questionnaire the question about work status had not been asked, therefore the students cannot be excluded from the dataset. A similar problem appeared in case of Indonesia where PIAAC standardized test were not used.

The resulting marginal effects of parental education are displayed in table 4.1 and 4.2. Due to spacial constraints other coefficient were excluded. The variable *score* was statistically significant in most cases. *Gender* seemed to be significant less often than *score*, but it is still statistically significant in more than 80% of cases. Insignificance of the variable *gender* might suggest that the predicted educational attainment is not gender dependent.

Magnitudes of the coefficients seem relatively uniform across countries expect for Indonesia. The results might by attributable to different geographical conditions compared to the rest of the sample (mostly from Europe) or different cultural background compared to the rest of the sample. Moreover, a different procedure was used to estimate the equation. In most cases, marginal effects do not seem to have suspiciously big magnitudes.

Comparison of magnitudes between the second and the third category within each country provides a valuable assessment as well. Intuitively, the higher the parental education is, higher the transitions should be present That is what we see in our results. For both maternal and paternal education the marginal effects are higher for category three than category two in most cases.

Previous results presented by Holmlund *et al.* (2011) (see Appendix A.1 & A.2) seem to be in line with our results. The comparison is not straightforward because we did not observe one-to.one effect (how additional year of parental education includes expected educational attainment of an individual). Our categories based on ISCED represent a bigger change in parental education hence the bigger values of our marginal effect in absolute terms.

On the other hand, contradictory to Holmlund *et al.* (2011), relatively high portion of the obtained results shows a stronger link between father's and their children (smaller p-values and higher magnitudes). Studies which found stronger links between fathers than mothers are mostly those later accused of endogeneity.

The number of independent variables we use is rather low, but we do not have much other relevant information obtainable from the dataset. A Low number of independent variables is common across studies but we did not have a chance to account for parental income which seems to be relevant and based on Plug (2004) and others. Omission of parental income may introduce bias.

The overall performance of the regressions seems to be decent. F-test for overall significance was passed by all regression without any exceptions. However Ramsey RESET test for functional misspecification is troublesome. Nearly the half of our regressions did not pass the test, which suggests possible violation of the zero conditional mean assumption. Collinearity in the model does not seem to cause any problems according to low VIF values in all countries but Austria.

Austria in general is a country, where our model fits worst. Estimates are fairly inconsistent with results from other countries and one might ask, whether the data were truly the same as the data for other countries. However after investigation of the data no reasons for being suspicious were found (see table A.7 from appendix).

Values of the statistics used to asses the regression performance are displayed in tables A.5 & A.6. There seem to be only a little differences between both estimation methods for most of the countries which supports the conjecture of randomly drawn sample points.

4.3 Joint method results

In case of the combined dataset, the results do not support our hypotheses. A complete list of coefficients with respective standard errors is displayed in tables 4.3 and 4.4. Even though wealth positively influence years of schooling, it is not variable of interest for us. We are interested in the effects of wealth on the marginal effects of parental education. However, coefficients in front of the interaction terms, which can be interpreted as increases of intergenerational transition when the wealth increases, are almost exclusively negative, contradicting hypothesis (2). Concavity of the relationship seems plausible but only in case of marginal effects being concave and decreasing t the same time, when the wealth increases.

Majority of controlled variables are statistically significant with very little p-values, leading to the suspicion about the validity of the standard errors. Intuitive expectation is supported by high F-statistics from the RESET tests. Most of the statistically insignificant coefficients in the model are those rep-

[1] Corresponding F-statistic
[2] Corresponding F-statistic

Table 4.1: Parental effects from country specific regressions

Country	Marginal effect of education: maternal category 2	maternal category 3	paternal category 2	paternal category 3	Joint significance[1] (maternal)	(paternal)
Austria	0.217*	0.222	−0.685**	0.153	2.67	35.04**
(3326)	0.402	0.931	−0.260	0.535	1.23	19.33**
Belgium	0.611**	1.134**	0.842**	1.668**	38.26**	94.02**
(3433)	0.614**	1.135**	0.845**	1.669**	36.44**	72.73**
Canada	0.570**	0.728**	0.674**	1.401**	113.53**	386.57**
(19705)	0.498**	0.685**	0.636**	1.344**	31.42**	176.88**
Czech Republic	0.816**	2.349**	0.493**	2.006**	65.79**	61.59**
(3535)	0.997**	2.767**	0.661**	2.155**	57.29**	40.35**
Denmark	0.450**	1.067**	0.411**	1.426**	47.75**	97.84**
(5256)	0.456**	1.047**	0.347**	1.387**	31.38**	58.03**
Estonia	0.756**	1.319**	0.529**	1.101**	52.44**	40.88**
(4175)	0.723**	1.337**	0.512**	1.061**	70.35**	32.42**
Finland	0.531**	1.066**	0.410**	1.378**	18.53**	35.69**
(3739)	0.502**	0.979**	0.407**	1.446**	14.80**	37.99**
France	0.687**	1.698**	0.525**	1.800**	54.31**	66.72**
(3624)	0.658**	1.759**	0.538**	1.820**	82.67**	74.41**
Greece	1.053**	1.440**	0.691**	1.321**	34.73**	25.10**
(2109)	1.474**	2.089**	0.614*	1.083**	38.13**	10.08**
Chille	0.859**	1.697**	0.646**	1.762**	46.49**	55.64**
(2595)	0.828**	1.650**	0.715**	2.012**	13.81**	70.16**
Indonesia	2.679**	1.058	4.038**	5.348**	32.10**	184.54**
(6513)	2.835**	1.076	3.878**	5.051**	26.95**	99.21**
Ireland	0.598**	0.965**	0.663**	1.273**	38.33**	68.12**
(3462)	0.671**	1.000**	0.565**	1.359**	23.41**	68.77**
Israel	0.329**	0.739**	0.419**	0.920**	18.40**	29.46**
(2794)	0.460**	0.851**	0.343**	0.892**	30.80**	28.78**
Italy	1.366**	2.315**	1.467**	2.754**	35.96**	54.54**
(2488)	1.752**	2.388**	1.782**	3.086**	31.29**	60.14**
Japan	0.646**	1.171**	0.512**	1.400**	30.75**	61.39**
(2770)	0.673**	1.206**	0.528**	1.493**	22.24**	58.50**
Korea	0.153	0.269	0.686**	1.325**	1.41	52.53**
(3768)	0.175	0.290	0.683**	1.352**	1.42	49.56**
Lithuania	0.284*	1.257**	0.260*	1.263**	48.06**	48.61**
(3299)	0.418**	1.155**	0.274	1.326**	29.11**	43.90**
Netherlands	0.405**	0.857**	0.795**	1.427**	20.97**	95.68**
(3977)	0.432**	0.966**	0.791**	1.371**	21.81**	63.35**
New Zealand	0.584**	0.894**	0.465**	1.266**	47.56**	93.00**
(4299)	0.539**	0.892**	0.454**	1.227**	29.41**	48.04**
Norway	0.549**	0.862**	0.470**	1.319**	31.75**	78.81**
(3623)	0.564**	0.887**	0.497**	1.382**	34.66**	69.39**
Poland	1.113**	2.008**	0.619**	1.631**	68.76**	40.81**
(3931)	1.104**	1.990**	0.493**	1.659**	32.95**	26.37**
Russian Federation	0.981**	2.270**	0.217	1.668**	61.30**	42.97**
(2078)	0.863**	2.300**	0.450	1.807**	14.75**	12.13**
Singapore	0.544**	0.744**	0.464**	1.205**	20.99**	51.63**
(3436)	0.617**	0.868**	0.477**	1.283**	22.22**	55.11**
Slovak Republic	0.900**	1.947**	0.723**	2.448**	47.79**	70.91**
(2871)	0.930**	1.858**	0.643**	2.350**	35.97**	55.03**
Slovenia	0.589**	1.123**	0.431**	1.190**	61.40**	62.21**
(3156)	0.570**	1.157**	0.468**	1.240**	52.99**	59.88**

*p-value smaller than 0.05

**p-value smaller than 0.01

Number of observations is in parentheses

First row presents OLS results, second row presents JK-1 results.

Table 4.2: Parental effects from country specific regressions - continuing

Country	Marginal effect of education: maternal category 2	maternal category 3	paternal category 2	paternal category 3	Joint significance[2] (maternal)	(paternal)
Spain	0.614*	1.285**	1.346**	2.298**	20.50**	97.54**
(3292)	0.526**	1.168**	1.268**	2.364**	17.81**	81.94**
Sweden	0.350**	0.850**	0.519**	1.216**	26.16**	62.91**
(3228)	0.329**	0.862**	0.545**	1.254**	22.51**	53.49**
Turkey	1.409**	1.003**	1.863**	2.444**	27.12**	112.55**
(1961)	1.548**	1.167**	2.091**	2.820**	32.18**	73.14**
United Kingdom	0.656**	1.234**	0.306**	1.193**	79.81**	83.67**
(5313)	663**	1.050**	0.227*	1.329**	26.51**	46.22**
United States	0.627**	1.683**	0.776**	1.614**	65.19**	62.34**
(3055)	0.627**	1.656**	0.771**	1.640**	46.98**	43.03**

* p-value smaller than 0.05
** p-value smaller than 0.01
Number of observations is in parentheses
First row presents OLS results, second row presents JK-1 results.

resenting the interaction terms. Interaction terms as a whole are jointly significant for both models, but only if we believe that the F-statistics are valid. Moreover, Jackknife and OLS do not coincide anymore. Differences between estimates gets larger.

Even looking aside from the combined models and visually inspecting coefficients of parental education for each category or status, one might hardly believe that transitions are increasing in wealth for the OECD countries. In fact, uniformly decreasing trend provides a fine argument for believers to negative effect of wealth on intergenerational transitions to education. Combined with the previous findings by Iannelli *et al.* (2002), it seems possible that economic theory behind the research question of this thesis is not valid or is only valid in countries with less developed credit markets and more complicated access to education.

Table 4.3: Results from 2-category stratification

Variable	Wealth status: Poor	Rich	Combined
Age	0.033^{**} 0.036^{**}	0.038^{**} 0.041^{**}	0.036^{**} 0.040^{**}
Gender	0.594^{**} 0.617^{**}	0.221^{**} 0.109^{*}	0.347^{**} 0.297^{**}
$educ_{f_2}$	0.711^{**} 1.176^{**}	0.435^{**} 0.628^{**}	0.728^{**} 1.186^{**}
$educ_{f_3}$	1.723^{**} 2.230^{**}	1.275^{**} 1.529^{**}	1.725^{**} 2.240^{**}
$educ_{m_2}$	0.793^{**} 1.152^{**}	0.582^{**} 1.542^{**}	0.814^{**} 1.161^{**}
$educ_{m_3}$	1.436^{**} 2.216^{**}	0.943^{**} 1.542^{**}	1.464^{**} 2.223^{**}
Score	0.444^{**} 0.441^{**}	0.448^{**} 0.472^{**}	0.447^{**} 0.458^{**}
Rich			0.500^{**} 0.473^{**}
$Rich * educ_{m_2}$			-0.241^{**} -0.404^{**}
$Rich * educ_{m_3}$			-0.535^{**} -0.688^{**}
$Rich * educ_{f_2}$			-0.288^{**} -0.559^{**}
$Rich * educ_{f_3}$			-0.452^{**} -0.712^{**}

* p-value smaller than 0.05

** p-value smaller than 0.01

Number of observations is in parentheses

First row presents OLS results, second row presents JK-1 results.

Table 4.4: Results from 4-category stratification

Variable	Wealth category: 1	2	3	4	Combined
Age	0.052**	0.023**	0.045**	0.018**	0.036**
	0.452**	0.017**	0.032**	0.045**	0.038**
Gender	0.750**	0.483**	0.209**	0.286**	0.352**
	0.727**	0.452**	−0.048	0.228**	0.289**
$educ_{f_2}$	0.905**	0.642**	0.484**	0.362**	0.836**
	1.181**	1.229**	0.474**	0.746**	1.167**
$educ_{f_3}$	1.827**	1.699**	1.324**	1.171**	1.823**
	2.322**	2.200**	1.447**	1.604**	2.309**
$educ_{m_2}$	1.268**	0.554**	0.593**	0.647**	1.164**
	1.593**	0.742**	0.711**	0.655**	1.571**
$educ_{m_3}$	2.115**	0.844**	0.946**	1.030**	2.023**
	2.835**	1.251**	1.186**	1.619**	2.792**
$score$	0.437**	0.452**	0.437**	0.441**	0.441**
	0.341**	0.555**	0.423**	0.520**	0.460**
Wealth2					0.330**
					0.818**
Wealth3					0.568**
					0.897**
Wealth4					1.071**
					1.088**
$Wealth2 * educ_{m_2}$					−0.526**
					−0.692**
$Wealth2 * educ_{m_3}$					−1.064**
					−1.373**
$Wealth2 * educ_{f_2}$					−0.182*
					0.104
$Wealth2 * educ_{f_3}$					−0.141
					−0.116
$Wealth3 * educ_{m_2}$					−0.630**
					−0.828**
$Wealth3 * educ_{m_3}$					−1.167**
					−1.558**
$Wealth3 * educ_{f_2}$					−0.380**
					−0.685**
$Wealth3 * educ_{f_3}$					−0.525**
					−0.863**
$Wealth4 * educ_{m_2}$					−0.387**
					−0.915**
$Wealth4 * educ_{m_3}$					−0.815**
					−1.194**
$Wealth4 * educ_{f_2}$					−0.449**
					−0.418
$Wealth4 * educ_{f_3}$					−0.648**
					−0.696*

* p-value smaller than 0.05

** p-value smaller than 0.01

Number of observations is in parentheses

First row presents OLS results, second row presents JK-1 results.

Chapter 5

Limitations and Discussion

5.1 Validity of assumptions

Previously, we needed to set specific set of assumptions in order to perform the analysis but we have not tested their validity yet. In the following part, we will do that.

5.1.1 Regression assumptions

The first identification method we have used leads to 30 separate regression equations with similar meaning for each examined state. Therefore, the procedure used to test the assumptions is fairly uniform. Firstly, the data had to be checked for unusual sample points and outliers. No reason for suspicion was found. All the variables seem to behave predictably (see table 3.1).

From definition of the models linearity in parameters is satisfied. Population model has to follow the stated equation otherwise estimates would be biased. We need the population model to follow the equation, we predict otherwise model would be biased as well. To test this assumption Ramsey's RESET of misspecification is utilized.

The random sampling assumption is problematic as discussed earlier, due to the potential oversampling in certain cases. The distinction has to be made between endogoenous and exogenous sample selection. If we define selection indicator s_i for each $i, s_i = 1$ when we observe values of all of $(y_i, x_{1i}, ..., x_{ni})$ and $s_i = 0$ otherwise (Wooldridge, 2015). Then estimates $\hat{\beta}_\mathrm{i}$ are consistent if the error term has zero mean and is uncorrelated with every explanatory variable. The Usual OLS assumptions for consistency might be altered to $\mathbb{E}(su) = 0$ and

$\mathbb{E}[(sx_j)(su)] = \mathbb{E}(sx_j u) = 0$. Following same logic, Wooldridge (2015) shows that key assumption of unbiasedness is $\mathbb{E}(su|sx_1, ..., sx_k) = 0$.

The unbiasedness and consistency of the estimator depends on which variable was defining for oversampling. Oversampling different regions is exogenous to our model therefore OLS estimates remain unbiased and consistent. After oversampling imigrants the same holds. On the other hand, when individuals who attained only compulsory education were oversampled, OLS no longer have its desirable properties. In case of oversampling within our dataset precise oversampling procedure which countries might have done are not reported. It is conceivable that oversampling people with low educational attainment happened, likelihood of that is relatively small with respect to other variables which might have been used for oversampling if the oversampling happened at all.

No perfect collinearity or in other words full column rank of matrix X has to be satisfied. None of independent variables is constant in our case, and none of the variables have perfect linear relationship. The perfect collinearity is a necessary condition, but the high degree of correlation (multicollinearity) among independent variables is undesirable but allowed. Multicollinearity among the independent variables leads to higher variance of $\hat{\beta}_i$, leading to less precision in inference because of greater standard errors (Wooldridge, 2015) (For detailed explanation see appendix A.1). The degree of multicollinearity might be measured by the Variation inflation factor (VIF), and generally, values of VIF greater than 10 are suspicious and deserve further investigation (Bruin, 2011) (for VIFs see tables A.5 and A.6).

The zero conditional mean assumption, given the explanatory variables covers various misspecification types such as omitted variables or correlation between the error term and the independent variables. In every model we have created, we expected individual's education attainment to be dependent on their abilities. We cannot measure abilities therefore we used score from PIAAC core assessment as a proxy variable. The approach might be problematic because the test score and educational attainment might have been determined simultaneously (i.e. more educated people will get higher scores because of education). Test score and educational attainment might both have been determined within the simultaneous equation system. If this is the case and high test score can be explained by a high educational attainment because individual learn some skills which increases their score, then the model suffers from endogeneity of the regressors. Endogeneity leads to biased estimates. Our treatment to avoid endogeneity due to omitted variable bias is likely to bring engoneity due to simulteneity, but sizes of the particular biases are unclear, and therefore deciding which bias is more severe is complicated.

According to those four assumption, there is a chance that our estimates are unbiased and even consistent. In fact, we do not need all four to hold for consistency. For consistency the fourth assumption of zero conditional mean can be altered to its less strict version. Zero correlation between error term and explanatory variables is sufficient. Zero conditional mean implies zero correlations, so if our estimates are unbiased they have to be consistent as well. However, the likelihood of biased estimates due to endogeneity is much greater.

Under those four assumptions asymptotically valid standard errors can be obtained, therefore the usual inference is valid and we can test hypotheses, without the need for homoscedastic errors. For large samples, White's standard errors are asymptotically valid for any form of Homoscedasticity (Wooldridge, 2015). Heteroscedasticity assumption stated by Wooldridge (2015) as $Var(u|x_1, ..., x_k) = \sigma^2$ can be reformulated to the form $Var(y|x_1, ..., x_k) = \sigma^2$, where y denotes dependent variable and $x_1, ..., x_k$ denotes the set of all independent variables. In our model dependent variable is a discrete one, therefore, its variance can be calculated by $\mathbb{E}(y^2) - \mathbb{E}(y)^2$. Expected value of y can be computed by multiplying respective probabilities by values of educational attainment. Expected value of y^2 can be calculated similarly. The Exact probabilities does not have to be calculated to see their dependence on $x_1, ..., x_k$. Section 4.1 presented evidence that predicted values $\hat{y}$ directly affects the probability of y being equal to the specific value. From the definition of predicted values $\hat{y} := \hat{\beta}_0 + \hat{\beta}_1 x_1 + ... + \hat{\beta}_k x_k$ it is possible to see that the probabilities are affected by values of $x_1, ..., x_k$ and that is in clear conflict with homoscedasticity assumption $Var(y|x_1, ..., x_k) = \sigma^2$ because the variance is dependent on $x_1, ..., x_k$[1]. For that reason we only use heteroscedasticity robust standard errors.

Testing for normality is pointless in our case because homoscedasticity is violated by definition, so we are forced to use heteroscedasticity robust inference anyway.

Table A.5 shows the statistics relevant to asses the regression performance.

[1]The analysis is based on similar proof for Linear probability model which is special case of model with discrete independent variable

Table 5.1: Mobility between wealth categories

		2015			
		wealth lvl. 1	wealth lvl 2	wealth lvl. 3	wealth lvl. 4
1960	wealth lvl. 1	2	3	1	1
	wealth lvl. 2	0	1	2	1
	wealth lvl. 3	0	0	5	2
	wealth lvl. 4	0	0	2	2

5.1.2 Stability of the wealth categories

For the second identification method we needed to assume that the relative order between GDP per capita values did not change over the last two generations. In the set of 30 countries we can form 435 pairs and for every pair the GDPs per capita ratio should be roughly the same (GDP per capita has to be measured in real values) for all years from 1960 to 2015. Therefore, when we depict the relationship between GDPs per capita for every pair, all the scatter points representing the ratios between GDP per capita values for that pair should lie on a straight line. Such a line represents linear relationship between changes of the respective GDPs per capita. More specifically, $\frac{\Delta GDP_{countr_i}}{\Delta GDP_{countr_j}} \approx c_i \quad \forall i, j = 1, ..., 30 \quad i \neq j$ for some fixed c_i. The easiest way to evaluate the validity of the assumption is to look at those graphs for every pair of the countries. Due to the spacial constraints, the whole set of 435 graphs will not be displayed.

Investigating mobility between wealth classes is a simplification of the previous method, which is more transparent. The wealth categories which have been already introduced should remain constant over time. Therefore, the mobility between classes should be as small as possible. Table 5.1 presents mobility between years 1960 and 2015[2]. Numbers in the particular cells represents how many countries belonged to the wealth categories determined by the coordinates of a cell. Therefore, the highest numbers should be on the diagonal. High numbers far from the diagonal mean a violation of the stability of the relative order.

In the table numbers do not add up to 30 which is the number of our states. This issue is caused by the unavailability of GDPs per capita for all countries[3]. Moreover, the matrix can be easily manipulated by changing the categories,

[2] Years were chosen with respect to ages from our sample

[3] Some of the countries did not exist. For instance, countries formed by the split of USSR

Table 5.2: Mobility between wealth statuses

		2015 poor	2015 rich
1960	poor	6	5
	rich	0	11

and it does not show closeness to the category boundary[4]. Because of that table 5.1 should be interpreted with caution. Similar table with respect to our division between rich and poor is below (table 5.2). Division between rich and poor is less sensitive to the stability of GDP per capita over time. The reason for that is option to move between the wealth categories one and two or three and four without diverging from the diagonal of the matrix.

From table 5.1 it is tempting to conclude that during the years 1960 and 2015 only upward mobility occurred. Sum of the numbers under the diagonal is clearly smaller than the sum above the diagonal. But we have only included a subset of countries due to the data availability. Moreover, outcomes of the mobility matrix are sensitive to the chosen boundaries.

5.2 Estimates of age and measurement error

In order to obtain the biggest dataset possible, we had to derive *age* ourself for some countries[5]. Total amount of generated ages is 42 454 which is more than 20% of the sample. Excluding those countries would be significant loss for sample size. Ages were derived from five year intervals which were provided for all countries. A problematic property of the approach is that the exact age was not possible to derive, therefore, our values matched the real ages only approximately. The Difference between derived and actual age might be treated as a measurement error. Let's say that t_i^* is the exact age. We only observe t_i and measurement error may be expressed $e_0 = t_i - t_i^*$. Under the assumption $Cov(t_i, e_0) = 0$ OLS remains consistent only with higher variance of the error term (Wooldridge, 2015).

We do have reasons to believe that our measurement error is uncorrelated with age we have derived earlier. The procedure of derivation consists of choosing the midpoint of 5 year bands. The measurement error is not bigger that

[4]Displayed matrices use 15 000, 30 000, 45 000 as a boundaries for year 2015 and 550, 1 100, 1 650 for year 1960 (in thousand of 2015 US dollars)

[5]Namely: Austria, New Zealand, Singapore, United States.

3 years and knowing the derived value does not provide any additional information about the magnitude or sign of the measurement error. Therefore, generating the variable should not affect the consistency and unbiasedness at all.

5.3 Endogeneity of parental education

In chapter 2 endogeneity of parental education was mentioned as a common reason for bias in the estimates. We do not use any instrumental variable to solve the problem, because there are not any. The inferred questions are based on current situation of interviewee. Our estimates from chapter 4 show suspicious pattern. Often the p-vales for the paternal education tend to be higher than p-values for maternal education. Same situation appears within the papers which were accused of endogeneity (see chapter 2). On the other hand Glick & Sahn (2000) found out that endogeneity might not be present necessarily.

5.4 Dropped observations

For the purposes of estimation, some part of observations has to be dropped because the interviewers did not get the answers. Such observations are coded with three non-numeric values representing their meaning. The answer might not be stated or inferred at all, the interviewee might not know the answer or the interviewee refused to answer the question. Dropping these observations will only limit our sample size in case of random distribution of those individuals across the population. There does not have to be any pattern connecting those individuals. Most troublesome group are people who refused to answer. The conceivable reason for refusing to answer might be shame of revealing the answer far away from the median answer. In that case the random sampling assumption would be violated.

On the other hand we dropped some observations earlier. Our sample consist of individuals aged from 16 to 65 and for the analysis we only need those who have already finished their education. Dropping an individual who do not satisfy the condition does not affect the results of our analysis, as they are not part of target group.

Table 5.3: Reasons for omission of observations

Reason	Loss of observations
Student or pupil	20 133
Non-numeric answers to individual's education	2 027
Non-numeric answers to maternal education	5 365
Non-numeric answers to paternal education	4 266
Non-numeric answers to gender	1

Total sample size	Used sample size
197 901	166 886

Quantitatively, we have lost almost 20% of observations because of the reasons stated in table 5.3.

The most often reason to exclude an observation from the sample, because of a non-numeric answer, was that the individual did not know the answer. This reason excluded nearly 10 000 individuals because the individuals did not know the education of their parents. Other to reasons (Not stated or inferred, Refused) exclude only a few individuals from the sample. The leading reason for exclusion because of the answer to individual's education question was: "Not stated or inferred" which accounted for excluding of about 1 900 observations and there were only 92 individuals excluded from the sample because they did not know their education or they refused to answer.[6]

Results seems promising. It is possible that some proportion of people might lie about their parental education rather than refuse but the overall numbers of exclusion do not provide any reason for being concerned.

[6]Numbers are not completely precise because we have already excluded sample points which do not count.(i.e. We can not exclude what has already been excluded.)

Chapter 6

Conclusion

We have intended to identify intergenerational transitions of education and show their correlation with the level of wealth for the set of countries we analyzed. Moreover, in case of the correlation was found, we wanted to evaluate functional form of the marginal effects of parental education as a function of wealth. We believed that these marginal effect would depend on wealth quadratically and the function would be increasing and concave over the interval determined by possible GDP per capita values which we used to measure wealth. The reason for such a believe came from behavioral economics and a conjecture that residents of less wealthy countries will face more severe credit constraints, obstructing the intergenerational transitions.

We did not draw any conclusion about the functional form. The datasets we used did not provide any supportive evidence for our believes about functional form. Nevertheless, we succeeded to identify intergenerational transitions of education across the dataset. They had desirable signs and magnitudes backed by economic theory and previous literature as well. They were found statistically significant, but the reliability of standard errors is questionable due to a possible endogeneity bias.

The results were obtained using linear regression model with heterosceasticity robust inference on data from The Programme for the International Assessment of Adult Competencies. For comparison, estimates from Jackknife method were used as well, due to possibly non-random selection of respondents.

Despite the fact that the data do not seem to follow our hypotheses, reestimating the model for a different set of countries in the future might provide valuable insights. A possible reason for the inability of to draw conclusion about the functional form might be due to highly developed credit markets of OECD countries. Therefore, if any suitable datasets appear in the following years, it could provide an evidence about differences between intergenerational transition of education between developed and developing countries. Moreover, if some instrumental variables were be found, the model would be much less prone to bias.

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Appendix A

Appendix

A.1 Standard errors and influence of multicollinearity

Standard error of estimator $\hat{\beta}_j$ is defined according to Wooldridge (2015) as :

$$se(\widehat{\beta}_j) = \frac{\widehat{\sigma}}{\sqrt{SST_j(1 - R_j^2)}}$$

, where SST_j is total variation in x_j, R_j^2 is R^2 from regression of x_j on other independent variables and $\widehat{\sigma}$ represents estimate of variance. In case of highly correlated independent variables R^2 will be high and therefore $1 - R^2$ would be small number, leading to the greater standard error $se(\widehat{\beta}_j)$.

A.2 Supportive tables

[1] Table sorted by GDP per capita
[1] Boundaries for the wealth categories are 15 000, 30 000,and 45 000
[1] GDP capita from 2015 in current US dollars
[1] Status and wealth category are determined based on GDP per capita

Causal estimates of intergenerational effects of schooling – Summary of previous literature

Author	Sample characteristics	Child's outcome	Assort. mating	Estimates			
				OLS estimates		Difference estimates	
				Father	Mother	Father	Mother
				(1)	(2)	(3)	(4)
	A. Twin/Sibling studies						
Behrman Rosenzweig (2002)	MTR[a], 1994: 244 twin fathers and 424 twin mothers; average birth year parent 1947; sample 1947 and 1971.	Years of schooling	(no)	0.47[b]	0.33	0.36	-0.25
				*0.05***	*0.05***	*0.16***	*0.15*
			(yes)	0.33[c]	0.14[c]	0.34[c]	-0.27[c]
				*0.07***	*0.05***	*0.16***	*0.15*
Antonovics Goldberger (2005)	MTR, 1994: 92 twin fathers and 180 twin mothers; sample restricted to children of 18 and older, not in school.	Years of schooling	(no)	0.49	0.28	0.48	0.03
				*0.09***	*0.09***	*0.16*	*0.27*
			(yes)	0.50	0.10	0.48	-0.003
				NA	NA	NA	NA
				OLS estimates using own-birth children		OLS estimates using adopted children	
	B. Adoption studies						
Dearden Machin Reed (1997)	NCDS, 1991: 4030 own birth children and 41 adopted children. Birth year child: 1958.	Years of schooling	(no)	0.42		0.356	
				*0.02***		*0.123***	
Sacerdote (2000)	NLSY, 1979: 5614 own birth and 170 adopted children. Average birth year child: 1961.	Years of schooling	(no)	0.28	0.35	0.16	0.22
				*0.01***	*0.01***	*0.04***	*0.06***
			(yes)			0.11[c,d]	0.11[c]
						*0.04**	*0.07*
Plug (2004)	WLS, 1992: 15871 own birth and 610 adopted children. Birth year mother: 1940, average birth year adopted and birth child: 1969 and 1965.	Years of schooling	(no)	0.39	0.54	0.27	0.28
				*0.01***	*0.02***	*0.04***	*0.10***
			(yes)	0.30[c]	0.30[c]	0.23[c]	0.10[c]
				*0.01***	*0.02***	*0.04***	*0.08***
Sacerdote (2007)	HICS, 2003: 1051 own birth and 1256 adopted children from Korea. Average birth year adopted and birth child: 1975 and 1969.	Years of schooling	(no)		0.32		0.09
					*0.04***		*0.03***
Björklund Lindahl Plug (2004)	SAR, 1999: 148496 own birth and 7498 adopted children all born in Sweden; average birth year adotive mother; 1934; average birth year child: 1966.	Years of schooling	(no)	0.23	0.24	0.13	0.11
				*0.00***	*0.00***	*0.01***	*0.01***
			(yes)	0.16[c]	0.16[c]	0.10[c]	0.06[c]
				*0.00***	*0.00***	*0.01***	*0.01***
Björklund Lindahl Plug (2006)	SAR, 1999: 94079 own birth and 2125 adopted children all born in Sweden; average birth year mother: 1932; average birth year child: 1964.	Years of schooling	(no)	0.24	0.24	0.11	0.07
				*0.00***	*0.00***	*0.01***	*0.01***
			(yes)	0.17[c]	0.16[c]	0.09[c]	0.02[c]
				*0.00***	*0.00***	*0.01***	*0.01***

Table A.1: Summary of previous findings

Source: Holmlund *et al.* (2011)

Author	Sample characteristics	Child's outcome	Assort. mating	OLS estimates Father (1)	OLS estimates Mother (2)	IV estimates Father (3)	IV estimates Mother (4)
	C. IV studies						
Black Devereux Salvanes (2005)	NAR, 2000: 239854/172671 children 1965-75; birth year parent: 1947-58; instrument MSLA reform in 1960-1972.	Years of schooling	(no)	0.22 *0.003***	0.24 *0.003***	0.03 *0.13*	0.08 *0.14*
			(no)	0.21[e] *0.02***	0.21[e] *0.02***	0.04[e] *0.06*	0.12[e] *0.04***
Chevalier (2004)	BFRS 1994-2002: 12593 children aged 16-18 living at home; birth year parent: 1938-67; instrument MSLA reform in 1972.	Post-compuls. school attend.	(yes)	0.04[c,f] *0.00***	0.04[c,f] *0.00***	-0.01[c,f] *0.06***	0.11[c,f] *0.04***
Oreopoulos Page Stevens (2003)	IPUMS 1960-80: 711072 children aged 7-15 living at home; average birth year father and child: 1920-40 and 1950-70; instrument: MLSA reforms between 1915-70.	Grade repetition (actual-normal)	(no)	-0.03 *0.00***	-0.04 *0.00***	-0.06 *0.01***	-0.05 *0.01***
			(no)	-0.04[e] *0.00***	-0.04[e] *0.00***	-0.07[e] *0.01***	-0.06[e] *0.01***
Maurin McNally (2008)	FLFS 1990-2001: 5087 children aged 15 and living at home; birth year father 1946-52; instrument: university reform in 1968.	Grade repetition (actual-normal)	(no)	-0.08 *0.00***		-0.33 *0.12***	
Carneiro Meghir Parey (2007)	NLSY, 1979: 1958 white children aged 12-14; instruments: local tuition fees, unemployment rates and wages.	Grade repetition (actual-normal)	(no)		-0.023 *0.005***		-0.028 *0.011**

[a] Abbreviations: MTR – Minnesota Twin Registry; SAR – Swedish Administrative Records; NCDS – National Child Development Survey; NLSY - National Longitudinal Survey of Youth; WLS – Wisconsin Longitudinal Study; HICS – Holt International Children's Service; NAR – Norweigan Administrative Records; BFRS – British Family Resources Survey; IPUMS – Integrated Public Microdata Series; FLFS – French Labor Force Survey; MLSA - Minimum School Leaving Age.
[b] Standard errors in italics; ** significant at 1% level; * significant at 5% level. Each coefficient is from a separate regression of the child's outcome on parent's years of schooling. Most regressions include individual controls for the child's age and gender and parent's age.
[c] These coefficients come from regressions that include the years of schooling of both parents simultaneously. Resulting estimates take into account the intergenerational effect of the marriage partner.
[d] We are grateful to Bruce Sacerdote for running this specification – which was not included in his paper – especially for us.
[e] These coefficients come from a restricted sample of parents with less than 10(12) years of schooling in Norway(The United States).
[f] These coefficients come from probit regressions.

Table A.2: Summary of previous findings - continuing

Source: Holmlund *et al.* (2011)

Table A.3: ISCED levels definitions

ISCED classification	corresponding educational attainment
Level 0	Pre-primary education
Level 1	Primary education or first stage of basic education
Level 2	Lower secondary or second stage of basic education
Level 3	(Upper) secondary education
Level 4	Post-secondary non-tertiary education
Level 5	First stage of tertiary education
Level 6	Second stage of tertiary education

source: OECD (1999)

Table A.4: Country list with wealth categories statuses

Country[1]	relative wealth category	GDP per capita	Wealth status
Indonesia	1	3 346	Poor
Russian federation	1	9 057	Poor
Turkey	1	9 130	Poor
Poland	1	12 494	Poor
Chille	1	13 384	Poor
Lithuania	1	14 172	Poor
Slovak Republic	2	15 962	Poor
Czech Republic	2	17 231	Poor
Estonia	2	17 295	Poor
Greece	2	18 036	Poor
Slovenia	2	20 713	Poor
Spain	2	25 832	Poor
Korea, Rep.	2	27 221	Poor
Italy	2	29 847	Poor
Japan	3	32 477	Rich
Israel	3	35 330	Rich
France	3	36 248	Rich
New Zealand	3	37 808	Rich
Belgium	3	40 231	Rich
Finland	3	41 921	Rich
Canada	3	43 248	Rich
Austria	3	43 439	Rich
United Kingdom	3	43 734	Rich
Netherlands	3	44 433	Rich
Sweden	4	50 272	Rich
Ireland	4	51 290	Rich
Denmark	4	52 002	Rich
Singapore	4	52 889	Rich
United States	4	55 836	Rich
Norway	4	74 735	Rich

Table A.5: Regression performance assessment

Country	F statistic	RESET	VIF > 10	R^2
Austria	31.30**	9.03**	4×	0.0650
	30.32**	107.95**		0.0908
Belgium	110.02**	0.30	0×	0.1636
	100.79**	0.62		0.1623
Canada	572.29**	10.26**	0×	0.1658
	187.35**	7.34**		0.1487
Czech Republic	93.88**	4.25**	0×	0.1596
	64.36**	0.88		0.1822
Denmark	128.41**	0.26	0×	0.1360
	91.22**	0.29		0.1361
Estonia	116.13**	0.67	0×	0.1497
	110.65**	0.74		0.1452
Finland	57.82**	5.12**	0×	0.0947
	52.54**	4.89		0.0934
France	122.62**	2.58	0×	0.1860
	157.95**	1.47		0.1881
Greece	59.54**	0.70	0×	0.1384
	38.64**	1.45		0.1623
Chile	132.82**	4.90**	0×	0.2540
	89.74**	0.76		0.2806
Indonesia	193.89**	24.82**	0×	0.1456
	174.03**	26.77**		0.1596
Ireland	87.56**	9.64**	0×	0.1431
	75.40**	7.28**		0.1513
Israel	100.55**	4.08**	0×	0.2142
	130.76**	2.59		0.2108
Italy	102.51**	1.33	0×	0.1907
	95.49**	0.46		0.2263
Japan	65.77**	0.66	0×	0.1367
	49.40**	0.38		0.1395
Korea	54.28**	6.69**	0×	0.0910
	47.91**	2.39		0.0857
Lithuania	118.05**	0.70	0×	0.1933
	113.88**	0.16		0.1966
Netherlands	82.22**	2.59	0×	0.1282
	67.73**	1.85		0.1335
New Zealand	105.45**	0.49	0×	0.1341
	61.23**	1.12		0.1328

* p-value smaller than 0.05

** p-value smaller than 0.01

First row presents OLS results, second row presents JK-1 results.

Table A.6: Regression performance assessment - continuing

Country	F statistic	RESET	VIF > 10	R^2
Norway	81.68**	1.28	0×	0.1294
	79.78**	1.45		0.1337
Poland	161.20**	11.59**	0×	0.2040
	53.23**	5.79**		0.1656
Russian federation	79.99**	1.38	0×	0.1794
	16.59**	3.01**		0.1620
Singapore	95.75**	7.80**	0×	0.1537
	102.21**	18.53**		0.1788
Slovak Republic	109.16**	1.85	0×	0.1985
	90.51**	3.58*		0.1940
Slovenia	150.23**	4.59**	0×	0.2214
	247.66**	8.29**		0.2268
Spain	132.62**	0.86	0×	0.1772
	131.54**	1.91		0.1624
Sweden	65.43**	5.85**	0×	0.1187
	82.89**	7.19**		0.1200
Turkey	112.41**	5.79**	0×	0.1668
	88.55**	3.06*		0.1693
United Kingdom	123.81**	6.37**	0×	0.1195
	61.27**	6.28**		0.1242
United States	157.76**	1.48	0×	0.2429
	110.89**	1.25		0.2325

*p-value smaller than 0.05

**p-value smaller than 0.01

First row presents OLS results, second row presents JK-1 results.

Table A.7: Summary of the Austrian dataset

Variable	Number of observations	Mean	Standard deviation	Minimum	Maximum
	Austria				
Age	4 539	42.169	13.179	16	62
Gender	4 540	1.504	0.500	0	1
Individual's education	4 434	12.248	2.720	7	19
Paternal education	4 434	1.850	0.683	1	3
Maternal education	4 434	1.550	0.611	1	3
score education	3 333	11.460	0.866	5	12