Dissertation:

Economic returns to schooling – cross-country evidence for 51 countries

Abstract:

Economic returns to schooling are estimated for various OLS and IV specifications for 51 countries using comparable micro-data for 1985-2012 from the International Social Survey Programme. Considerable cross-country variation is found, with a mean return to schooling equal to approximately 7% and 10-18% for OLS and IV estimates respectively. Females have higher returns by roughly 18-40% when accounted for endogeneity in schooling. Use of incorrect measure of experience and adding controls correlated with schooling cause downward bias in schooling coefficient up to 15%.

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1) Introduction

This dissertation examines the cross-country returns for schooling for 51 countries. In that sense it complements recent paper by Montenegro and Patrinos from 2014[1]. It utilizes comparable micro dataset based on International Social Survey Programme (ISSP) 1985-2012. In addition to standard cross-country analysis using Mincer's (1974) Ordinary Least Squares (OLS) models, it uses parents and spouse's education to account for ability bias using IV models. So it can be thought of as a follow up on Trostel *et al.* (2002) paper which utilized ISSP for 1985-1995.

More specifically it is trying to analyse cross country heterogeneity which is very high – return to schooling range from 2.82% in Venezuela to 19.93% in Chile for females using OLS estimates. The mean schooling for OLS is approximately 7% for both sexes. But is much more varied for IV models – approximately 10-18% depending on instrument used and gender. Returns for females are higher by approximately 18-40%.

Furthermore, it utilizes few different OLS and IV specifications. It starts from (Model (I)) a basic Mincerian (1974) wage schooling equation using logarithm of hourly earnings as dependent variable; and schooling, years of potential experience and its square as independent variables. It is contrasted with the same model with added country and year fixed effects (Model (II)). It is followed by a specification proposed by Trostel *et al.* (2002) with added marital status and union status dummies (Model (III)). The reason for different specifications is to pin point an optimal amount of controls as heterogeneity in how human capital has been observed. Specifications have been tailored in that aspect. It is followed by a model using education categories (Model IV) since it has been suggested by the literature, e.g. Grenet (2013). It indicates that only completed stages of education have impact on earnings. The subsequent section contains a casual test of impact of 2007-08 crisis on returns on schooling. Finally experience is replaced with age to decide which variable is empirically optimal. All those specifications, with an exception of the crisis model and the stages of education model, are followed by the counterparts using IV estimator to account for endogeneity of schooling (Models (V.I-III)). Analysis of IV models concentrates on pooled equations because only scarce fraction of dataset used possess proper instruments. Section on IV estimators is concluded with exclusion F-tests to check for strength of instruments being used to proxy for years of schooling.

In broader context this dissertation is an attempt to answer the question on how we should structure spending on education. Should we be most concerned with primary, secondary or tertiary education? Do crises impact return to schooling? And should estimates of returns of schooling be used as a policy prescription or rough guide in shaping education bills?

Section 2 starts with literature review concentrating on parts directly relevant to this paper. Then in Section 3 and 4 data and methodology is discussed respectively. Section 5 contains all results and analysis for OLS and IV specifications. Section 6 concludes. Bibliography and appendices can be found in Section 7 and 8 respectively.

[1] *"Comparable Estimates of Returns to Schooling Around the World" (Montenegro & Patrinos, 2014)*

2) Literature Review

Why do we model human capital to begin with? At first sight this research might seem to have limited use. But if one gives it a careful consideration it is needed to answer many major questions in economics. Significant part of macroeconomics try to explain and model growth. Human capital has very important part in those explanations. For example Benhabib and Spiegel (1994, p.1) find that human capital has a positive role in accounting for growth in a model based upon the Cobb-Douglass aggregate production function. If we know exactly how education affects economy we can direct our policies in the most cost effective way. It is an especially important issue internationally if we want the less developed countries to catch up with the developed ones. This opens a door to equity consideration, e.g. since private returns to tertiary education are the highest (Montenegro & Patrinos, 2014, p.10) should we stop subsidizing it and concentrate on expanding secondary and primary education? Also if we know returns to schooling for different groups we can research educational attainment in order to create policies aimed at the most disadvantaged individuals. One can think that individuals who come from a high income background should be paying for all education so that we can subsidize low income groups. However it might be a bad policy since Becker and Tomes (1986, p.1) found out that all earnings advantages disappear after three generations so instead of creating more equitable society such policy might have opposite results. Furthermore if we want to the forecast performance of a new pension scheme we need to know how to determine earnings of the population of interest and schooling is one of the most crucial predictors. For more direct uses of human capital models we should look at a well-known Blinder-Oaxaca regression analysis (Blinder, 1973; Oaxaca, 1973) where Mincerian wage equation is modified in order to decompose wages for different reference groups so we could study discrimination. All in all, applications are endless.

One of the earliest and most robust contributions in establishing earnings-schooling relationship was Hansen (1963, p. 128) who points out that already at the time of his research there were many different methodologies: *"For example, Miller calculates life-time income values by level of schooling, Houthakker estimates, on the basis of alternative discount rates, the present value of income streams associated with different levels of schooling, Schultz provides estimates of total resource costs of education by broad level of schooling, and Becker and Schultz calculate for several levels of education the expected rates of return, sometimes on a total re-source cost basis and at other times on a private resource cost basis."* Back in the day lack of precise and comparable data and powerful computing engines were major obstacles so results were not nearly as robust as presently. Nowadays we have an access to a vast amount of high quality data and we can rely on advanced econometric estimations techniques. We can recognize three most popular ways of research: precise models covering relatively small population, like one country, and trying to disassemble all effects and issues (like ability bias), e.g. Blackburn and Neumark (1993); cross-country research concentrating on differences inter-country differences, e.g. Psacharopolous (1994) and Psacharopolous and Patrinos (2004); and assessment of natural experiments mostly in form of policies that raise school leaving age, e.g. Grenet (2013), and studies on twins.

The first two categories usually utilize Mincer's (1974) wage earning equation where a logarithm of earnings is regressed on using years of schooling and vector of controls (most basic kind of this model is represented by Model (I) described in Section 4 using Ordinary Least Squares (OLS)). The biggest downfall of Mincerian OLS models is endogeneity bias that arises from either a measurement error in schooling or the fact that individuals with a higher inherent ability chose more schooling (so called ability bias). The former problem is simply addressed by the use of precise micro-datasets like Walker and Zhu (2011) do. Nonetheless, in the past even with good quality data we would be stuck with the problem of ability bias. That is where the third category comes in – by using natural experiments like raising of school leaving age (RoSLA) policies (e.g. Grenet, 2013) or using studies on twins we could separate impact of ability on schooling. Very often in this case we use difference-in-difference methodology which is precise in establishing the direction and magnitude between two reference groups e.g. individuals affected and unaffected by RoSLA. The problem with this research is that it cannot be used to determine average returns to schooling. That is why this dissertation is mostly concentrated on the previous two types but natural experiment literature plays an important role as well. Namely, as suggested by Grenet (2013, p.208) RoSLA does not have an impact unless it leads to obtaining an additional qualification. That has led to a creation of the model (IV)[2] that replaces years of schooling with dummy variables for different stages of education (primary, secondary and tertiary).

Thankfully nowadays we have many other methods to deal with ability bias without use of natural experiments. Originally researchers tried to use IQ and other test scores to proxy for cognitive ability. However those measures are a poor embodiment of overall ability. Starting from Card (1999) one of the leading methods is the use of the IV estimator. Where we proxy schooling with variable that is highly correlated with schooling but uncorrelated with earnings and use the 2-Step Least Squares (2SLS) or the Generalized Method of Moments (GMM) to run the regressions. But as pointed by Bound *et al.* (1995, p.433) it has its own problems since IV estimates may be highly inconsistent if instruments and the endogenous variable they proxy are not highly correlated. That is why, as suggested by Bound *et al*. (1995, pp.447-449), this paper utilizes F-tests, checking for exclusion in the first and second stage equations, to check for validity of instruments.

As one can imagine the second category concentrating on cross-country comparison had even more pronounced problems with endogeneity bias and comparability due to a lack of precise data. The evolution of this strand of research is well represented by Psacharopoulos who has been researching it for over 30 years (1973; Lee & Psacharopoulos, 1979; 1985; 1994; Psacharopoulos & Patrinos, 2004). In Lee and Psacharopolous (1979) they have analysed educational planning using educational indicators based on adult literacy rates, enrolment ratios and number of doctors which is far less than what we can do with precise data nowadays. Then in Psacharopolous (1985) full human capital model with data for 60 different countries has been introduced. It presents considerable findings: *"(...) that returns are highest for primary education, the general curricula, the education of women and countries with the lowest per capita income."* (Psacharopoulos, 1985, p.583) Those are very interesting since higher returns for women are validated in a later research by Trostel *et al.* (2002, pp.4-6) but the research disagrees when it comes to considerable cross-country trends. As a matter of fact this dissertation also finds that returns for women are higher yet, similarly to Montenegro & Patrinos (2014), it indicates that returns are the highest for the tertiary education. The next problem after utilizing precise cross-country datasets was to account for ability. One of the more successful papers doing that was by Trostel *et al.* (2002) where they used data on parents and spouse's schooling to instrument for schooling in an IV model. The most recent literature encompasses precise national labour survey in building the vast, detailed datasets which eliminate most issues and explore new problems e.g. Montenegro and Patrinos (2013; 2014). Surprisingly cross-country estimates of schooling are quite stable and on average equal to 6-9% (Psacharopoulos, 1994) and at least 20% higher for models using IV estimator (Trostel *et al.*, 2002). Because of that, this paper uses a precise, comparable and original dataset based on ISSP 1985-2012 that allows for cross-country comparison while dealing with endogeneity bias.

[2] For further details please see Section 4 and 5.

The last issue concerning human capital models is the potential selectivity bias, created by dropping unemployed and self-employed individuals from the sample, which is a regular practice in this line of research. For example Trostel *et al.* (2002, p.4) remarks that employment selectivity seems to have *"(…) little or no impact on estimates of schooling returns."* Originally this paper was supposed to verify that by using Heckman (1979) correction but using it while accounting for the ability bias it would have need additional instruments, so that all equations in the model could have been identified. Therefore it lays outside of the scope of this dissertation and is left out for further research.

3) Data

This research utilized International Social Survey Programme (ISSP) for 1985-2012[3] to build comparable dataset. It excludes 1999 because there was no proper documentation for this year. In a sense it is a follow up on research by Trostel *et al.* (2002) which used the same dataset limited to 1985-1995 only. Questions in ISSP surveys change every year but always contain number of core questions including earnings, schooling, age and sex. The data covers total of 51 countries (some were added/dropped over the years). Year range and schooling characteristics can be found for all of the countries in *Table 1*.

Table 1 – Descriptive Statistics

Country	Years	Males			Females		
		Sample Size	Mean Schooling	Standard Deviation	Sample Size	Mean Schooling	Standard Deviation
Australia	1987-2012	5158	13.84	3.35	5366	14.10	3.34
West Germany	1985-2012	4442	11.56	3.51	3446	11.85	3.31
Great Britain	1985-2012	5628	12.26	2.47	5923	12.29	2.39
USA	1985-2012	7420	13.78	2.83	7685	13.91	2.59
Austria	1985-2012	2760	11.25	2.66	2506	11.33	2.57
Hungary	1996-2009	1860	11.99	2.48	1747	12.28	2.63
Netherlands	1988-2011	3709	14.23	3.73	2714	14.25	3.40
Italy	1989-2009	1228	12.01	4.08	825	12.66	4.10
Ireland	1988-2012	2559	13.18	3.30	2621	14.07	3.16
Norway	1990-2012	7134	13.65	3.19	6831	13.84	3.23
Switzerland	1987-2012	4487	12.53	3.41	3837	12.12	3.17
Slovenia	1996-2012	4487	12.53	3.41	2616	12.67	3.12
Sweden	1996-2012	3994	12.79	3.27	4126	13.31	3.15
Czech Republic	1996-2012	2860	12.86	2.20	3113	12.78	2.11
Poland	1996-2012	2820	12.04	2.84	2788	13.02	3.08
New Zealand	1991-2010	3319	13.79	2.90	3547	14.02	2.77
Bulgaria	1996-2012	1803	12.48	2.98	2013	13.01	3.16
Russia	1994-2012	4209	12.31	2.59	5471	12.94	2.48
Canada	1996-2012	2237	14.78	3.28	1964	14.77	3.11
Philippines	1996-2012	4306	9.30	3.55	2422	10.00	3.51
Israel	1993-2012	3484	13.18	2.85	3552	13.87	2.73
Japan	1993-2012	4266	13.48	2.56	3390	13.00	2.03
Spain	1993-2012	3887	12.63	4.46	2849	13.51	4.49
Latvia	1996-2012	2243	12.63	2.71	2786	13.45	2.68
Slovak Republic	1998-2012	2608	13.00	2.59	2951	13.22	2.61

[3] Raw ISSP data can be obtained from their website at: http://www.issp.org/page.php?pageId=4. For the compiled dataset please contact the author directly.

East Germany	1990-2009	547	11.26	2.79	478	11.68	2.93
Northern Ireland	1989-1993	524	11.65	1.50	519	11.80	1.39
France	1996-2012	3831	14.50	3.44	4703	14.86	3.14
Cyprus	2007-2009	994	12.64	3.43	871	13.07	2.91
Portugal	1998-2011	1543	10.98	4.49	1752	11.27	4.64
Denmark	1998-2012	3809	13.71	4.23	4105	13.94	3.83
Bangladesh	1997	842	11.68	4.34	588	12.32	3.77
Chile	2000-2012	2851	11.07	4.16	2703	11.37	4.18
Finland	2000-2012	3921	12.03	4.66	3953	13.20	4.36
Mexico	2000-2012	1559	11.43	4.63	1135	11.46	4.43
South Africa	2004-2011	4100	12.21	3.78	3325	12.10	3.77
Belgium	2007-2011	1758	13.82	3.00	1719	14.20	2.72
Taiwan	2002-2012	6356	12.69	3.48	5600	12.70	3.63
Venezuela	2006-2012	1037	10.07	3.51	734	10.95	3.50
South Korea	2003-2012	3226	13.69	2.89	2424	13.16	2.97
Uruguay	2003-2008	1529	10.71	4.04	1499	11.19	4.07
Dominican Republic	2006-2008	1728	9.70	4.35	1058	10.95	4.21
Croatia	2006-2012	1220	12.35	2.35	1257	12.68	2.51
Argentina	2007-2012	1242	11.03	4.03	951	11.95	4.10
Turkey	2008-2011	1046	8.95	3.85	231	11.10	4.14
Ukraine	2008-2009	394	12.96	2.41	648	13.23	2.42
China	2009-2012	2542	9.95	3.69	1917	9.67	3.89
Estonia	2009	115	12.89	2.64	188	13.91	2.72
Iceland	2009-2012	579	15.66	3.54	579	16.01	3.51
Lithuania	2010-2012	501	13.25	2.56	814	14.13	2.44
India	2012	395	9.59	4.59	114	8.65	5.42

It is a precise micro-dataset which is very well suited for modelling human capital, since there is no measurement error in independent variables. It was restricted to sample of employed individuals, aged 21-59. Unemployed and self-employed individuals were excluded because there were not enough instruments to use Heckman correction in conjunction with IV estimator. That might lead to selectivity bias but following Trostel *et al.* (2002, p.4) it seems the exclusion of unemployed individuals have *“(…) little or no impact on estimates of schooling returns.”* Endogeneity bias is accounted for by using data on education of parents and/or spouse. The biggest downfall of this dataset is the fact that for some years instead of precise earnings only intervals were recorded. Mincer (1974, p. 44) notes that the use of data with income and schooling intervals overstates the coefficients of determination. However given sample size the distribution of earnings should be approximately normal.

4) Methodology

The starting point is the classic Mincerian wage-schooling equation (Mincer, 1974), of the following form:

$$(I)\ y_i = \beta_0 C + \beta_1 S_i + \beta_2 EXP_i + \beta_3 EXP_i^2 + \mu_i$$

Where y_i is a logarithm of hourly earnings, C is a constant term, S_i is years of schoolings, EXP_i are years of potential job experience (defined as AGE_i-S_i-6, *AGE* standing for age), EXP_i^2 years of potential job experience squared (interpreted as a productivity loss due to aging), μ_i is a random disturbance which in this case can be interpreted as a returns to unobserved abilities, $_i$ subscript stands for individuals.

Since considerable time and country specific effects are expected, Model (I) was augmented with year and country fixed effects giving rise to next specification:

$$(II)\ y_i = \beta_0 C + \beta_1 S_i + \beta_2 EXP_i + \beta_3 EXP_i^2 + \beta_{4-55} CFIX_{1-51} + \beta_{56-83} YFIX_{1985-2012} + \mu_i$$ [4]

Where all variables have the same interpretation as before, and CFIX are countries fixed effects and YFIX are year fixed effects. This model will be contrasted by using control variables suggested by Trostel *et al.* (2002):

$$(III)\quad y_i = \beta_0 C + \beta_1 S_i + \beta_2 EXP_i + \beta_3 EXP_i^2 + \beta_4 M_i + \beta_5 U_i + \beta_{6-57} CFIX_{1-51} + \beta_{58-85} YFIX_{1985-2012} + \mu_i$$

Where all variables have the same interpretation as before, and M_i is marital status (equal to 1 for married individuals and 0 otherwise), U_i is union status (equal to 1 for individuals being part of the union and 0 otherwise). As suggested by research on raising school leaving age, e.g. Grenet (2013), additional year of schooling does not increase earnings unless it leads to obtaining additional qualifications. So next model will replace schooling years with dummy variables for each stage of education:

$$(IV)\ y_i = \beta_0 C + \beta_1 PRIM_i + \beta_2 SECO_i + \beta_3 TERT_i + \beta_4 EXP_i + \beta_5 EXP_i^2 + \beta_{6-57} CFIX_{1-51} + \beta_{58-85} YFIX_{1985-2012} + \mu_i$$

Where all variables have the same interpretation as before, and $PRIM_i$ is a dummy variable for primary education (1 for completed and 0 otherwise), $SECO_i$ is a dummy variable for secondary education (1 for completed and 0 otherwise) and $TERT_i$ is a dummy variable for tertiary education (1 for completed and 0 otherwise). No education is an omitted category.

Above model will be followed by Model (I) being tested on subsample of years before 2007 and after. It will allow for casual test of effects of 2007-2008 crisis on returns to schooling.

Following recent research on discrimination, e.g. Christofides *et al.* (2013), all above models were run separately for males and females to account for possible differences in covariance matrices. In addition all models except Model (I) utilize robust standard errors (RSE).

I will conclude OLS models with pooled regressions replacing potential years of job experience with age that give rise to following specifications:

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[4] Please note that all regressions of respective countries contain only year fixed effects. And all specifications containing fixed effects have omitted category (first year and country of the sample – usually 1985 and Australia respectively).

- $(I.I)\ y_i = \beta_0 C + \beta_1 S_i + \beta_2 AGE_i + \beta_3 AGE_i^2 + \mu_i$
- $(II.I)\ y_i = \beta_0 C + \beta_1 S_i + \beta_2 AGE_i + \beta_3 AGE_i^2 + \beta_{4-55} CFIX_{1-51} + \beta_{56-83} YFIX_{1985-2012} + \mu_i$
- $(III.I) y_i = \beta_0 C + \beta_1 S_i + \beta_2 AGE_i + \beta_3 AGE_i^2 + \beta_4 M_i + \beta_5 U_i + \beta_{6-57} CFIX_{1-51} + \beta_{58-85} YFIX_{1985-2012} + \mu_i$
- $(IV.I)\ y_i = \beta_0 C + \beta_1 PRIM_i + \beta_2 SECO_i + \beta_3 TERT_i + \beta_4 AGE_i + \beta_5 AGE_i^2 + \beta_{6-57} CFIX_{1-51} + \beta_{58-85} YFIX_{1985-2012} + \mu_i$

Above specifications will allow to test for empirical validity of using years of potential job experience instead of age as suggested by theory (Mincer, 1974; Montenegro & Patrinos 2014). Whilst theoretical choice between the two have been established since Mincer's paper in 1974 the literature is largely indifferent between the two, e.g. Trostel *et al.* (2002) use age.

One of the major problems with OLS models of human capital is the endogeneity of schooling. Firstly, it can arise from the measurement error. It is not the case in this research since precise ISSP dataset is used. Moreover if one was aware of measurement error in dependent variable OLS would not be an appropriate regression tool since it would not be the best minimum variance estimator anymore. In addition, as suggested by Lang (1993), Card (1999) and Trostel *et al.* (2002) endogeneity arises because of omitted ability bias i.e. individuals with higher ability choose higher levels of schooling therefore obtaining higher wages. Thus beta coefficients of schooling should be biased downwards and as shown by Card (1999) and Trostel *et al.* (2002) they indeed are. To account for that following 2SLS joint models were tested:

$$(V.I.I)\ \ y_i = \beta_0 C + \beta_1 Z_i + \beta_2 EXP_i + \beta_3 EXP_i^2 + \mu_i$$

$$(V.I.II)\ \ Z_i = \beta_0 C + \beta_1 V_i + v_i$$

$$(V.II.I)\ \ y_i = \beta_0 C + \beta_1 Z_i + \beta_2 EXP_i + \beta_3 EXP_i^2 + \beta_{4-55} CFIX_{1-51} + \beta_{56-83} YFIX_{1985-2012} + \mu_i$$

$$(V.II.II)\ \ Z_i = \beta_0 C + \beta_1 V_i + v_i$$

$$\begin{aligned}(V.III.I)\ \ y_i = \beta_0 C + \beta_1 Z_i + \beta_2 EXP_i + \beta_3 EXP_i^2 + \beta_4 M_i + \beta_5 U_i + \beta_{6-57} CFIX_{1-51} \\ + \beta_{58-85} YFIX_{1985-2012} + \mu_i\end{aligned}$$

$$(V.III.II)\ \ Z_i = \beta_0 C + \beta_1 V_i + v_i$$

Where all variables have the same interpretation as before except that schooling (*S)* is proxied by *Z* which is a function of V_i – vector of observable variables correlated with schooling but not with wage rate and v_i which is a random disturbance term. *V* consists of father's schooling, mother's schooling and spouse's schooling. Model (IV) was not estimated using IV technique because there was no sufficient amount of proxies – data contain at most two out of three instruments in a given year. As before each model is estimated separately for males and females. They also utilize robust standard errors except for model (V.I.I-II).The pre- and post-crisis equivalent of OLS is not estimated because there is not enough variables for equation to be identified. That is followed by analysis equivalent to what was done with OLS models – experience is replaced with age.

Next following Bound *et al.* (1995) validity of each instrument was tested by running the F test for the exclusion of instruments on first stage and second stage equations.

5) Analysis

Note that for whole Section 5 when we refer to changes in coefficients it is not a linear change. All models are log-linear. So to obtain actual change from additional year of schooling we would need to take a difference between exponents[5]. However for simplicity when discussing differences across different states/models change is reported in percentage terms.

5.1) Model (I)

Table 2 (Appendix 1, Section 8.1, pp.21-22) reports results for schooling coefficients for Model (I). As one can see there is a big cross country heterogeneity – it ranges from -13.52% (Lithuania) to 32.43% (Poland) for males and -8.53% (Netherlands) to 30.14% (South Korea) for females.

However reason for such variation becomes apparent very quickly – since we have negative values it means that Model (I) is misspecified. It is further confirmed by t-statics since majority of countries are not statistically significant. In some extreme cases like China coefficients of schooling are very high, equal to 23.39%/28.75% (males/females), and standard errors are very low, equal to 1.57%/2.04% (males/females). It is explained by goodness of fit (R^2 statistics) which for many countries is lower than 2%. It is an extremely bad fit considering that some Mincerian models explain even up to 90% of variation in endogenous variable. The only results that seem reasonable are for pooled equation where schooling coefficient is equal to 8.82% for males and 7.95% for females which is broadly consistent with literature (e.g. Psacharopolous & Patrinos, 2004). Yet it suffers from the same problem as countries with significant coefficient - R^2 is equal to 1.22% and 0.82% for males and females respectively.

5.2) Model (II)

Model (II) is an augmented Model (I), with added year (and country for pooled equation) fixed effects and robust standard errors, but it makes huge difference as we can see in *Table 3* (Appendix 2, Section 8.2, pp.23-24).

All regressions are significant at least at 90% significance level, except for Portugal and India (both with relatively small samples), and most countries are significant at 99% significance level. Outside of insignificant countries group Iceland has the lowest goodness of fit – 9% for males and 8.51% for females. Overall majority of countries have the fit above 50% with above third of them having R^2 above 90%.

There is a lot of cross country variation. The highest returns to education are found in Northern Ireland (19.46%) for males and in Chile for females (19.93%). While the lowest returns are noted in Denmark (3.04%) for males and in Venezuela (2.82%) for females. However there is no particular pattern irrespectively whether we examine developed or developing economy e.g. Norway have schooling coefficient equal to 3.83%/3.48% (males/females), while its neighbouring Finland has a return to education equal to 13.16%/9.86% (males/females). Pooled coefficients are equal to 6.51% and 6.85% for males and females respectively. They are between Trostel's *et al.* (2002, p.5) and

[5] $exp^{\beta_{1,n}} - exp^{\beta_{1,n+1}}$, where β_1 is schooling coefficient

Montenegro and Patrinos's (2014, p.7) results. The coefficients are consistent considering the former examines sample covering period between 1985-1995 and the latter between 2005-2011 (Trostel *et al.*, 2002; Montenegro & Patrinos, 2014).

Differences between males and females shape very interestingly – for pooled equation there is barely any difference for return to education (0.34%). If we exclude insignificant regression coefficients, they are higher for females in 32 countries out of 49. That is true even for countries known stereotypically for high female discrimination like Mexico (United Nation Development Programme, 2013). The biggest difference in favour of males equal to 4.85% is recorded in Japan and the converse statistics for females is true in Estonia and it is equal to 4.77%.

5.3) Model (III)

Model (III) is exactly the same as Model (II) with added controls proposed by Trostel *et al.* (2002), namely union and marital status dummies. The biggest objective here was to check whether adding more subjective controls is positive for modelling returns to education. All results are summarized in *Table 4* (Appendix 3, Section 8.3, pp.25-26)

Schooling coefficient wise the biggest difference between Model (II) and (III) is equal to 3.2% and for majority of countries it is much more modest – below 1%. All results described in Section 5.2 hold approximately as well; that includes comparable goodness of fit, lack of trend and discrimination. However both controls are not significant for many countries. What is more pooled results are even lower than before. Meaning that they are less consistent with most recent research (Montenegro & Patrinos, 2014). And they are just over 1% and under 1% bigger for males and females respectively than pooled results of Trostel *et al.* (2002, p.5) for exactly the same model and the same dataset that covers only 1985-1995. All in all those results are a slight indication that additional controls crowd out schooling coefficient on average and their addition should be based on merit of theoretical underpinnings and area of focus.

5.4) Model (IV)

Model (IV) is essentially Model (II) but it replaces years of schooling with dummies for education categories. Meaning that the interpretation of coefficients is considerably different e.g. 1% PRIM coefficient means that whole primary education increase earnings by 1% (non-linearly as noted before). As one can see from *Table 5* (Appendix 4, Section 8.4, pp.27-31) this model seem to be performing rather poorly.

Dummies for primary (PRIM) and secondary (SECO) education are insignificant for majority of countries and have opposite sign to what we would expect. Furthermore for many countries they are fully omitted due to severe collinearity. It suggest that in all those regressions dummies are not significantly different from zero. However the specification is not particularly different to what is usually applied in this kind of situation. Meaning that fault most likely lies within the way dataset was compiled or with raw data itself because there is significant heterogeneity in the ISSP surveys, not only among the years but even countries within the same year.

Before dismissing this model altogether it should be mentioned that the samples are much smaller since ISSP categorize education in more than just three categories e.g. they include incomplete primary education, incomplete secondary education etc. The fit of the model is also not particularly different for pooled equation than Model (II) or (III). Another issue is that primary and secondary education is a compulsory staple for most countries. So we might actually expect it having no effect. And big returns to tertiary education (26.19%/11.30% in pooled equations for males/females) can be attributed to the fact that in here we cannot tell apart undergraduate degree from postgraduate which makes huge difference as suggested by Walker and Zhu (2011). Unfortunately all those consideration still does not explain why the primary and secondary dummies are negative in pooled regressions where they are both significant. All in all the results might be a mix of those deliberations, mistakes in compilation code and/or raw data.

5.5) Pre- and post-crisis model

Table 6 - Pre- and post-crisis regressions using Model (I)						
Period	**Males**			**Females**		
	β_1	**SE**	**t**	**β_1**	**SE**	**t**
1985-2006	0.0780	0.0025	31.47	0.0665	0.0029	23.29
2007-2012	0.0889	0.0039	23.04	0.0717	0.0042	17.06
Table reports schooling coefficients (β_1) following Model (I). SE and t stands for standard error and t-statistic respectively.						

Table 6 is a casual test to check how 2007-08 crisis affected returns to schooling. Coefficients actually increased by 1.09% and 0.52% for males and females respectively which indicates that crisis had no effect on returns to schooling. However that is not a full picture as we should take into account shortcomings of Model (I) discussed before and lack of controls for technological growth. It might also represent the fact the crisis actually increased return to schooling. Since firms are more interested in high ability, high productivity labour that would by default have higher schooling due to signalling and ability bias. Furthermore average returns to schooling tend to decrease overtime (Montenegro & Patrinos, 2014, p.10). Thus it is very interesting issue for further research but impossible to elaborate further using ISSP dataset because there is not enough instruments in IV estimations for equations to be identified.

5.6) OLS models: replacing experience with age variable

Main goal here is to check whether replacing years of potential job experience and its square with age and its square make any empirical difference. Since there are theoretical underpinnings (Mincer, 1974) – as we do not earn any experience during first six years of our lives and during education. What is more literature is largely indifferent between the two. So it would aid the theory and provide more homogeneity in this line of research.

Table 7 – OLS models: replacing experience variable with age variable								
Pooled regressions using EXP and EXP^2								
Variable	**Model (I)**		**Model (II)**		**Model (III)**		**Model (IV)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
β_1	0.0882	0.0795	0.0651	0.0685	0.0595	0.0649	-0.2540	-0.2945
SE/RSE	0.0022	0.0025	0.0017	0.0019	0.0017	0.0020	0.0285	0.0368

β_2	0.0222	0.0095	0.0338	0.0229	0.0246	0.0207	-0.0878	-0.1005
SE/RSE	0.0032	0.0033	0.0023	0.0024	0.0025	0.0025	0.0342	0.0389
β_3	-0.0002	0.0000	-0.0004	-0.0003	-0.0003	-0.0002	0.2619	0.1130
SE/RSE	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	0.0146	0.0157
β_4							0.0350	0.0208
SE/RSE							0.0029	0.0031
β_5							-0.0005	-0.0004
SE/RSE							0.0000	0.0001
R^2	0.0122	0.0082	0.5117	0.4971	0.5092	0.4957	0.5852	0.5529
Pooled regressions using AGE and AGE^2								
Variable	**Model (I.I)**		**Model (II.I)**		**Model (III.I)**		**Model (IV.I)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
β_1	0.0788	0.0706	0.0564	0.0608	0.0537	0.0581	-0.2524	-0.3122
SE/RSE	0.0020	0.0023	0.0016	0.0018	0.0016	0.0018	0.0284	0.0367
β_2	0.0488	0.0188	0.0478	0.0321	0.0347	0.0296	-0.0738	-0.0916
SE/RSE	0.0057	0.0060	0.0040	0.0043	0.0042	0.0045	0.0341	0.0389
β_3	-0.0005	-0.0001	-0.0005	-0.0003	-0.0004	-0.0003	0.2633	0.1261
SE/RSE	0.0001	0.0001	0.0000	0.0001	0.0001	0.0001	0.0144	0.0154
β_4							0.0540	0.0340
SE/RSE							0.0050	0.0055
β_5							-0.0006	-0.0004
SE/RSE							0.0001	0.0001
R^2	0.0124	0.0082	0.5116	0.4970	0.5091	0.4957	0.5857	0.5531
SE, RSE and R^2 stands for standard error, robust standard error and goodness of fit (R^2 statistic) respectively.								

If we look for differences in goodness of fit between our original models and their counterparts utilizing age (I-IV.I) there is no major difference (approx. 0.0005). However if we set Model IV and IV.I aside, due to their problems described in section before, there are two significant trends. Firstly, all models utilizing experience have higher schooling coefficients than their counterpart – up to 0.94% difference between Model (I) and (I.I). Secondly, counterpart models have higher values for age. That suggest that in Models (I-III.I) some explanatory power is absorbed from schooling and attributed to experience measured by age. It is anticipated as age variable is always higher than experience for the same individuals since we calculate it by subtracting years of education and first six years of our lives. It suggests the experience should be used instead of age.

5.7) Model (V.I)

Table 8 presents results for IV counterpart of Model (I) and it has the same problems but much more severe.

Due to a large cross-country and time variation schooling coefficients are negative when instrumented by parents' education. When we use spouse's schooling as an instrument they are far more robust – 8.43% for males and 12.17% for females. However IV estimates tend to be at least

20% higher than OLS estimates (e.g. Trostel *et al.,* 2002) whilst here there are almost exactly the same for males. Again it shows importance of controlling for country and year fixed effects.

Table 8 - Model (V.I): Pooled Regressions						
Instrument	**Males**			**Females**		
	β_1	**SE**	**z**	**β_1**	**SE**	**z**
Spouse's schooling	0.0843	0.0085	9.98	0.1217	0.0153	7.96
Father's schooling	-0.1581	0.0511	-3.09	-0.1653	0.0527	-3.14
Mother's schooling	-0.1317	0.0505	-2.61	-0.1082	0.0456	-2.37
Table reports schooling coefficients (β_1) following Model (V.I). SE and z stands for standard error and z-statistic respectively.						

5.8) Model (V.II)

Further proving the point of last section, by adding fixed effects we obtain Model (V.II) which, as can be seen from *Table 9*, cause all coefficients to be strongly significant and have the right sign.

Table 9 - Model (V.II): Pooled Regressions						
Instrument	**Males**			**Females**		
	β_1	**RSE**	**z**	**β_1**	**RSE**	**z**
Spouse's schooling	0.1034	0.0087	11.89	0.1218	0.0147	8.26
Father's schooling	0.1276	0.0188	6.78	0.1788	0.0235	7.61
Mother's schooling	0.1490	0.0217	6.87	0.1656	0.0215	7.72
Table reports schooling coefficients (β_1) following Model (V.II). RSE and z stands for robust standard error and z-statistic respectively.						

Variation across returns to education, depending on instruments, is rather high but it is broadly consistent with the literature (Trostel *et al.*, 2002). However return to schooling is considerably higher for females than males, irrespectively of instrument used. And with father's schooling it is as high as 5.12%. Which is difficult to explain unless we assume that ability bias is actually much higher for women.

5.9) Model (V.III)

Table 10 - Model (V.III): Pooled Regressions						
Instrument	**Males**			**Females**		
	β_1	**SE**	**z**	**β_1**	**SE**	**z**
Spouse's schooling	0.1039	0.0087	11.95	0.1209	0.0148	8.17
Father's schooling	0.1250	0.0186	6.74	0.1772	0.0235	7.55
Mother's schooling	0.1497	0.0214	6.98	0.1643	0.0214	7.67
Table reports schooling coefficients (β_1) following Model (V.III). RSE and z stands for robust standard error and z-statistic respectively.						

As one can see from *Table 10* results for Model (V.III) are roughly the same as for Model (V.II). The difference is even smaller than between their counterpart models – (II) and (III). It might suggest that marital status and union status are highly correlated with schooling. So when we instrument the schooling those controls do not cause any significant variation between the two specifications. Meaning that after controlling for crucial variables like experience, its square and fixed effects less controls is better, at least as long as they are highly correlated with schooling and endogeneity bias is not accounted for.

5.10) IV models: replacing experience with age variable

Table 11 presents differences between all IV models and their counterparts that use age and its square instead of potential years of job experience.

Table 11 – IV models: replacing experience variable with age variable

Pooled regressions using EXP and EXP^2 with all three instruments						
Variable	**Model (V.I)**		**Model (V.II)**		**Model (V.III)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
β_1	0.1101	0.1415	0.1020	0.1364	0.1355	0.1670
SE/RSE	0.0109	0.0177	0.0118	0.0185	0.0189	0.0204
β_2	0.0463	0.0534	0.0525	0.0554	0.0505	0.0494
SE/RSE	0.0107	0.0124	0.0099	0.0142	0.0055	0.0051
β_3	-0.0005	-0.0008	-0.0006	-0.0008	-0.0006	-0.0006
SE/RSE	0.0002	0.0002	0.0002	0.0003	0.0001	0.0001
R^2	0.1861	0.1646	0.2726	0.1884	0.8537	0.8602
Pooled regressions using AGE and AGE^2 with all three instruments						
Variable	**Model (V.I)**		**Model (V.II)**		**Model (V.III)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
β_1	0.0889	0.1304	0.0807	0.1252	0.1119	0.1412
SE/RSE	0.0100	0.0162	0.0106	0.0175	0.0147	0.0167
β_2	0.0711	0.0868	0.0795	0.0908	0.0703	0.0719
SE/RSE	0.0172	0.0217	0.0169	0.0235	0.0093	0.0084
β_3	-0.0007	-0.0009	-0.0008	-0.0010	-0.0007	-0.0007
SE/RSE	0.0002	0.0003	0.0002	0.0003	0.0001	0.0001
R^2	0.1900	0.1653	0.2761	0.1893	0.8545	0.8615
SE, RSE and R^2 stands for standard error, robust standard error and goodness of fit (R^2 statistic) respectively.						

If we were to compare goodness of fit it is all in favour of specification with age but the differences are too small to be significant. Other than that, the differences discussed in Section 5.6 follow the same pattern but are considerably magnified. The difference for schooling coefficients are as high as 2.58% for females between Model (V.III) and its counterpart utilizing age. And difference is bigger than 1% across all models and genders. That further aids previous conclusions that years of potential job experience are more correct variable not only theoretically but empirically as well.

5.11) IV instruments validity test

Table 12 - Instrument validity tests						
F-tests for exclusion of instruments in first (1) stage equations						
Instrument	**Model (V.I)**		**Model (V.II)**		**Model (V.III)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Spouse's Schooling	447.71	311.74	76.98	68.23	68.32	60.57
Father's Schooling	224.19	240.28	29.43	34.70	27.80	32.66
Mother's Schooling	223.70	269.67	26.68	35.49	24.95	33.55
F-tests for exclusion of instruments in second (2) stage equations						
Instrument	**Model (V.I)**		**Model (V.II)**		**Model (V.III)**	
	Male	**Female**	**Male**	**Female**	**Male**	**Female**
Spouse's Schooling	the214.10	86.34	832.50	402.30	869.17	419.17
Father's Schooling	28.79	28.35	46810.04	41746.02	45753.58	40681.39
Mother's Schooling	25.62	25.34	42808.90	44356.07	41413.45	43068.72

Table 12 presents F-test for exclusions of instruments used in IV models in both first and second stage equations (where it is known as Cragg-Donald Wald F-statistic).

By the rule of thumb F-statistics higher than 10 indicate relatively strong instrument. Evidently that is true for all statistics included in *Table 11*. It is even better since all corresponding p-values are equal to 0 up to four decimal places meaning that they are all highly significant.

It suggests that IV estimates for Model (V.II) and (V.III) are consistent with previous literature. Whilst Trostel *et al.* (2002, p.15) talked about IV estimates being higher than OLS estimates by at least 20%. It is in line with results of this paper since more countries were added and sample increased considerably. In addition there is a suggestion that ability bias is much bigger for female population.

6) Conclusion

Summing up, the analyses of different specification both for OLS and IV estimators shows importance of year and country fixed effects. As we could see from comparing Models (I-II) and (V.I-V.II) omitting them can turn schooling coefficients to be insignificant for single countries and bias the coefficients even for pooled equations. However adding other controls should be carefully considered since it causes downward bias as we could see by comparing Models (II-III). Though the problem seem to exist only if the controls are considerably correlated with schooling. Primarily because if we instrument it, the results for Model (V.II), without additional controls, and Model (V.III), with marital and union dummies, are almost identical. What is more, experience and its square should be considered a basic control in Mincerian style models over age, which seem to absorb considerable explanatory power that belongs to schooling variable. It is particularly significant for IV models where use of age can cause downward pressure of approximately 15%.

Similarly to previous literature, especially Trostel *et al.* (2002, p.15), a large cross-country variation in schooling is found. Yet there are no obvious trends that could explain it. According to models tested on ISSP 1985-2012 dataset mean schooling is approximately equal to 7% for OLS models and approximately to 10-18% for IV models depending on instrument used. Those results are consistent with literature, particularly Trostel *et al.* (2002) and Montenegro and Patrinos (2014), considering the sample. However for some reason coefficients of IV estimator are always higher for females by approximately 18% to 40%. It might suggest that ability bias is more pronounced for female population. Even though parents' education and spouse's education seem to be equally strong predictor of schooling for either sex. Casual test for impact of crisis on returns to schooling is inconclusive and highly subjective therefore it requires further research.

In terms of policy prescription Model (IV) using education categories instead of schooling suggest that there is biggest return to tertiary education. Meaning that countries should consider expansion of bills tackling universities. Furthermore it also shows that labour market seem to be very discriminative of individuals with just primary or secondary education. So depending on equality stance some transfer taxes should be considered. However one should treat those results with caution due to the issues that this particular model had.

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8) Appendices

8.1) Appendix 1

Table 2 - Model (I)

Country	Males			Females		
	β_1	SE	t	β_1	SE	t
Australia	0.0416	0.0057	7.30	0.0709	0.0075	9.42
West Germany	0.0458	0.0023	20.06	0.0450	0.0029	15.69
Great Britain	-0.0328	0.0064	-5.12	-0.0433	0.0063	-6.88
USA	0.0813	0.0086	9.48	0.0935	0.0092	10.22
Austria	-0.0192	0.0087	-2.20	-0.0349	0.0098	-3.57
Hungary	0.0975	0.0087	11.19	0.1037	0.0081	12.83
Netherlands	-0.0827	0.0071	-11.58	-0.0853	0.0101	-8.44
Italy	0.0855	0.0098	8.75	0.1294	0.0119	10.87
Ireland	0.0982	0.0103	9.54	0.1300	0.0099	13.08
Norway	0.0124	0.0122	1.02	-0.0022	0.0129	-0.17
Switzerland	0.0563	0.0029	19.47	0.0598	0.0040	14.89
Slovenia	0.0811	0.0280	2.89	0.1697	0.0286	5.94
Sweden	0.0803	0.0120	6.70	0.0922	0.0129	7.13
Czech Republic	0.0535	0.0045	11.83	0.0989	0.0048	20.77
Poland	0.3243	0.0245	13.23	0.2882	0.0246	11.73
New Zealand	0.0032	0.0083	0.39	0.0083	0.0084	0.99
Bulgaria	0.0370	0.0167	2.22	0.0526	0.0145	3.64
Russia	0.1598	0.0179	8.93	0.2244	0.0175	12.83
Canada	0.1323	0.0212	6.23	0.1455	0.0251	5.80
Philippines	0.1012	0.0136	7.43	0.0816	0.0223	3.66
Israel	0.0858	0.0091	9.39	0.1099	0.0101	10.91
Japan	0.2281	0.0218	10.44	0.2310	0.0317	7.28
Spain	-0.0201	0.0081	-2.48	-0.0135	0.0089	-1.51
Latvia	0.1684	0.0338	4.98	0.2420	0.0323	7.50
Slovak Republic	0.1943	0.0266	7.30	0.2160	0.0242	8.91
East Germany	0.0449	0.0065	6.88	0.0459	0.0074	6.19
Northern Ireland	0.2043	0.0136	14.99	0.1710	0.0136	12.60
France	0.0563	0.0041	13.82	0.0575	0.0034	16.79
Cyprus	0.0871	0.0110	7.94	0.1127	0.0163	6.89
Portugal	0.0058	0.0163	0.36	-0.0318	0.0143	-2.23
Denmark	0.0201	0.0115	1.74	0.0386	0.0135	2.87
Bangladesh	0.0393	0.0167	2.35	0.0726	0.0205	3.55
Chile	0.1943	0.0149	13.02	0.2162	0.0174	12.39
Finland	0.1564	0.0038	40.75	0.1101	0.0040	27.51
Mexico	0.0577	0.0278	2.07	0.0071	0.0353	0.20
South Africa	0.0970	0.0080	12.13	0.1098	0.0092	11.99
Belgium	0.0500	0.0035	14.10	0.0527	0.0044	12.00
Taiwan	0.1259	0.0130	9.69	0.1476	0.0153	9.66

Venezuela	0.1364	0.0486	2.80	0.1662	0.0622	2.67
South Korea	0.1933	0.0294	6.58	0.3014	0.0398	7.57
Uruguay	0.0503	0.0067	7.49	0.0941	0.0070	13.43
Dominican Republic	0.1084	0.0062	17.60	0.1169	0.0080	14.65
Croatia	0.0751	0.0051	14.79	0.1018	0.0047	21.45
Argentina	0.0835	0.0059	14.20	0.0918	0.0078	11.77
Turkey	0.0865	0.0077	11.19	0.1034	0.0132	7.80
Ukraine	0.0495	0.0137	3.62	0.0629	0.0095	6.62
China	0.2339	0.0157	14.93	0.2875	0.0204	14.08
Estonia	0.0542	0.0197	2.76	0.1018	0.0160	6.36
Iceland	0.0547	0.0135	4.06	0.0477	0.0147	3.24
Lithuania	-0.1352	0.1106	-1.22	0.2037	0.0976	2.09
India	0.0097	0.0177	0.55	0.0233	0.0277	0.84
Pooled	0.0882	0.0022	39.80	0.0795	0.0025	31.92

Table reports schooling coefficients (β_1) following Model (I). SE and t stands for standard error and t-statistic respectively.

8.2) Appendix 2

Table 3 - Model (II)						
Country	**Males**			**Females**		
	β_1	**RSE**	**t**	**β_1**	**RSE**	**t**
Australia	0.0392	0.0047	8.31	0.0555	0.0065	8.52
West Germany	0.0589	0.0020	29.12	0.0592	0.0028	20.92
Great Britain	0.0905	0.0043	20.95	0.0869	0.0040	21.92
USA	0.1006	0.0040	24.87	0.1199	0.0041	29.46
Austria	0.0446	0.0033	13.72	0.0630	0.0038	16.51
Hungary	0.0779	0.0058	13.40	0.0803	0.0052	15.30
Netherlands	0.0508	0.0020	25.05	0.0430	0.0033	13.01
Italy	0.0499	0.0038	13.19	0.0722	0.0051	14.08
Ireland	0.0819	0.0051	16.11	0.0638	0.0048	13.16
Norway	0.0383	0.0024	16.24	0.0348	0.0022	15.84
Switzerland	0.0536	0.0026	20.90	0.0528	0.0036	14.66
Slovenia	0.0774	0.0036	21.25	0.0852	0.0033	25.60
Sweden	0.0418	0.0023	17.83	0.0307	0.0026	11.95
Czech Republic	0.0583	0.0047	12.47	0.0870	0.0044	19.69
Poland	0.1020	0.0050	20.40	0.1004	0.0042	24.08
New Zealand	0.0563	0.0034	16.71	0.0515	0.0040	13.03
Bulgaria	0.0583	0.0054	10.70	0.0757	0.0048	15.84
Russia	0.0685	0.0051	13.30	0.0776	0.0043	18.17
Canada	0.0578	0.0043	13.56	0.0589	0.0047	12.43
Philippines	0.1035	0.0043	24.23	0.1250	0.0070	17.74
Israel	0.0715	0.0032	22.15	0.0880	0.0034	26.12
Japan	0.1020	0.0082	12.40	0.0535	0.0169	3.16
Spain	0.0513	0.0021	24.52	0.0586	0.0029	20.54
Latvia	0.0556	0.0050	11.09	0.0539	0.0037	14.50
Slovak Republic	0.0866	0.0071	12.17	0.0806	0.0057	14.09
East Germany	0.0505	0.0055	9.16	0.0461	0.0074	6.24
Northern Ireland	0.1946	0.0122	15.90	0.1719	0.0117	14.69
France	0.0808	0.0029	28.30	0.0722	0.0029	24.89
Cyprus	0.0589	0.0039	15.29	0.0734	0.0058	12.59
Portugal	-0.0403	0.0121	-3.33	-0.0216	0.0101	-2.14
Denmark	0.0304	0.0018	16.79	0.0310	0.0021	14.42
Bangladesh	0.0393	0.0195	2.01	0.0726	0.0189	3.83
Chile	0.1655	0.0091	18.16	0.1993	0.0096	20.70
Finland	0.1316	0.0040	33.15	0.0986	0.0042	23.56
Mexico	0.0779	0.0045	17.51	0.0832	0.0055	15.10
South Africa	0.0879	0.0082	10.66	0.1076	0.0091	11.77
Belgium	0.0496	0.0042	11.89	0.0511	0.0044	11.67
Taiwan	0.0522	0.0069	7.60	0.0637	0.0076	8.41
Venezuela	0.0414	0.0079	5.27	0.0282	0.0092	3.08
South Korea	0.1002	0.0046	21.71	0.1341	0.0070	19.26

Uruguay	0.0857	0.0058	14.89	0.1021	0.0059	17.19
Dominican Republic	0.1060	0.0062	17.05	0.1157	0.0073	15.91
Croatia	0.0732	0.0058	12.68	0.1012	0.0051	19.67
Argentina	0.0841	0.0056	15.16	0.0910	0.0075	12.14
Turkey	0.0886	0.0071	12.53	0.1025	0.0149	6.89
Ukraine	0.0495	0.0127	3.89	0.0625	0.0105	5.97
China	0.1038	0.0109	9.48	0.1246	0.0163	7.64
Estonia	0.0542	0.0190	2.85	0.1018	0.0153	6.65
Iceland	0.0425	0.0144	2.94	0.0339	0.0146	2.32
Lithuania	0.0385	0.0103	3.74	0.0652	0.0079	8.26
India	0.0097	0.0190	0.51	0.0233	0.0310	0.75
Pooled	0.0651	0.0017	38.47	0.0685	0.0019	35.23

Table reports schooling coefficients (β_1) following Model (II). RSE and t stands for robust standard error and t-statistic respectively.

8.3) Appendix 3

Table 4 - Model (III)

Country	Males			Females		
	β_1	RSE	t	β_1	RSE	t
Australia	0.0375	0.0048	7.74	0.0543	0.0069	7.91
West Germany	0.0567	0.0020	28.30	0.0600	0.0028	21.09
Great Britain	0.0925	0.0046	20.16	0.0824	0.0043	19.01
USA	0.0973	0.0041	23.73	0.1143	0.0042	27.01
Austria	0.0437	0.0033	13.40	0.0617	0.0038	16.04
Hungary	0.0769	0.0059	12.95	0.0803	0.0053	15.26
Netherlands	0.0504	0.0020	24.77	0.0429	0.0033	12.87
Italy	0.0490	0.0038	12.93	0.0699	0.0051	13.61
Ireland	0.0775	0.0053	14.59	0.0575	0.0050	11.55
Norway	0.0368	0.0024	15.61	0.0349	0.0023	15.38
Switzerland	0.0542	0.0026	20.86	0.0527	0.0036	14.50
Slovenia	0.0757	0.0037	20.70	0.0848	0.0033	25.60
Sweden	0.0409	0.0023	17.50	0.0305	0.0026	11.80
Czech Republic	0.0581	0.0047	12.26	0.0868	0.0045	19.30
Poland	0.0978	0.0051	19.27	0.0990	0.0043	23.30
New Zealand	0.0540	0.0034	15.81	0.0498	0.0041	12.27
Bulgaria	0.0562	0.0055	10.24	0.0737	0.0048	15.20
Russia	0.0690	0.0052	13.32	0.0782	0.0043	18.26
Canada	0.0566	0.0043	13.27	0.0557	0.0047	11.80
Philippines	0.1028	0.0043	23.78	0.1211	0.0072	16.82
Israel	0.0702	0.0033	21.00	0.0824	0.0037	22.57
Japan	0.1032	0.0088	11.75	0.0545	0.0174	3.13
Spain	0.0495	0.0021	23.28	0.0573	0.0029	19.44
Latvia	0.0536	0.0051	10.49	0.0540	0.0038	14.13
Slovak Republic	0.0836	0.0071	11.80	0.0804	0.0057	14.09
East Germany	0.0486	0.0056	8.62	0.0440	0.0074	5.91
Northern Ireland	0.1927	0.0122	15.80	0.1593	0.0117	13.66
France	0.0799	0.0029	27.81	0.0712	0.0030	23.96
Cyprus	0.0576	0.0038	14.97	0.0701	0.0060	11.64
Portugal	-0.0161	0.0120	-1.34	-0.0103	0.0101	-1.02
Denmark	0.0279	0.0018	15.23	0.0306	0.0022	14.22
Bangladesh	0.0317	0.0187	1.69	0.0718	0.0193	3.73
Chile	0.1643	0.0092	17.77	0.2024	0.0097	20.94
Finland	0.0996	0.0045	22.34	0.0710	0.0040	17.72
Mexico	0.0756	0.0045	16.74	0.0819	0.0056	14.60
South Africa	0.0831	0.0085	9.80	0.1111	0.0095	11.72
Belgium	0.0495	0.0044	11.26	0.0500	0.0046	10.86
Taiwan	0.0549	0.0071	7.70	0.0881	0.0076	11.64
Venezuela	0.0403	0.0081	5.01	0.0285	0.0095	3.00
South Korea	0.0996	0.0049	20.49	0.1350	0.0066	20.42

Uruguay	0.0848	0.0062	13.75	0.0940	0.0065	14.43
Dominican Republic	0.1035	0.0072	14.34	0.1178	0.0086	13.63
Croatia	0.0724	0.0057	12.60	0.1016	0.0052	19.60
Argentina	0.0802	0.0056	14.23	0.0850	0.0077	11.00
Turkey	0.0843	0.0074	11.45	0.0964	0.0159	6.05
Ukraine	0.0520	0.0129	4.03	0.0632	0.0104	6.07
China	0.0982	0.0116	8.49	0.1128	0.0177	6.36
Estonia	0.0471	0.0202	2.33	0.0986	0.0158	6.24
Iceland	0.0344	0.0151	2.28	0.0260	0.0149	1.75
Lithuania	0.0384	0.0106	3.64	0.0639	0.0079	8.07
India	0.0078	0.0192	0.40	0.0041	0.0287	0.14
Pooled	0.0595	0.0017	34.05	0.0649	0.0020	32.28

Table reports schooling coefficients (β_1) following Model (III). RSE and t stands for robust standard error and t-statistic respectively.

8.4) Appendix 4

Table 5 - Model (IV)						
Country	**Males**			**Females**		
	β_{1-3}	**RSE**	**t**	**β_{1-3}**	**RSE**	**t**
Australia						
PRIM	-0.0900	0.1383	-0.65	0.1107	0.2385	0.46
SECO	-0.0834	0.0879	-0.95	0.0502	0.0819	0.61
TERT	0.1922	0.0476	4.04	0.2567	0.0628	4.09
West Germany						
PRIM	-0.2221	0.0223	-9.95	-0.1502	0.0417	-3.60
SECO	-0.0952	0.0566	-1.68	-0.0030	0.0715	-0.04
TERT	0.2849	0.0232	12.31	0.2581	0.0306	8.43
Great Britain						
PRIM	-0.3072	0.0233	-13.17	-0.3495	0.0266	-13.12
SECO	-0.0625	0.0233	-2.69	-0.0693	0.0269	-2.58
TERT	0.1921	0.0184	10.45	0.2636	0.0208	12.70
USA						
PRIM	-0.2599	0.0375	-6.94	-0.2813	0.0434	-6.48
SECO	-0.0313	0.0339	-0.93	-0.0049	0.0353	-0.14
TERT	0.3301	0.0360	9.16	0.3392	0.0325	10.45
Austria						
PRIM	-0.2051	0.0357	-5.74	-0.2841	0.0461	-6.17
SECO	0.1011	0.0287	3.52	0.0214	0.0422	0.51
TERT	0.2066	0.0218	9.48	0.2368	0.0296	8.01
Hungary						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1857	0.0578	3.21	0.1784	0.0553	3.23
Netherlands						
PRIM	-0.1621	0.0252	-6.43	-0.1214	0.0579	-2.09
SECO	-0.0289	0.0239	-1.21	0.0322	0.0430	0.75
TERT	0.2014	0.0214	9.42	0.1155	0.0260	4.43
Italy						
PRIM	-0.1613	0.0488	-3.30	-0.3406	0.0829	-4.11
SECO	0.0302	0.0486	0.62	-0.0180	0.0855	-0.21
TERT	0.1348	0.0463	2.91	0.2189	0.0644	3.40
Ireland						
PRIM	-0.1632	0.0647	-2.52	-0.4146	0.1194	-3.47
SECO	0.1154	0.0558	2.07	-0.2305	0.0742	-3.11
TERT	0.1990	0.0357	5.57	0.0823	0.0308	2.67
Norway						
PRIM	-0.0863	0.0504	-1.71	-0.1611	0.0517	-3.11
SECO	-0.0864	0.0229	-3.77	-0.1024	0.0290	-3.53
TERT	0.0577	0.0198	2.92	0.0937	0.0219	4.29

Switzerland						
PRIM	-0.1850	0.0545	-3.39	-0.1809	0.1464	-1.24
SECO	-0.0978	0.0454	-2.15	0.1003	0.0873	1.15
TERT	0.2174	0.0258	8.43	0.2339	0.0346	6.76
Slovenia						
PRIM	-0.2767	0.1474	-1.88	-0.2372	0.0765	-3.10
SECO	0.1166	0.0767	1.52	0.2275	0.0626	3.64
TERT	0.2068	0.0281	7.37	0.2704	0.0267	10.12
Sweden						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1455	0.0183	7.96	0.1164	0.0171	6.81
Czech Republic						
PRIM	-0.0925	0.1788	-0.52	-0.1719	0.1755	-0.98
SECO	0.0438	0.0568	0.77	0.3357	0.0620	5.41
TERT	0.1569	0.0187	8.41	0.2743	0.0217	12.61
Poland						
PRIM	-0.2735	0.1497	-1.83	-0.0795	0.1306	-0.61
SECO	0.0167	0.0854	0.20	0.0276	0.0738	0.37
TERT	0.2631	0.0315	8.34	0.2706	0.0295	9.18
New Zealand						
PRIM	0.0171	0.0844	0.20	-0.1653	0.0781	-2.11
SECO	0.0407	0.0518	0.79	-0.1653	0.0781	-2.11
TERT	0.2115	0.0272	7.79	0.1986	0.0310	6.40
Bulgaria						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	-0.3420	1.0943	-0.31	0.3452	0.9989	0.35
TERT	0.0080	0.0491	0.16	0.0025	0.0459	0.06
Russia						
PRIM	0.6400	0.1117	5.73	-0.3090	0.0425	-7.26
SECO	-0.3310	0.0788	-4.20	-0.3136	0.0761	-4.12
TERT	0.1618	0.0320	5.05	0.1545	0.0257	6.01
Canada						
PRIM	-0.2498	0.2780	-0.90	0.2302	0.2683	0.86
SECO	0.0907	0.1055	0.86	0.0083	0.1090	0.08
TERT	0.2283	0.0559	4.08	0.0756	0.0519	1.46
Philippines						
PRIM	-0.4921	0.1370	-3.59	-0.5730	0.2370	-2.42
SECO	0.1870	0.1128	1.66	0.1356	0.1716	0.79
TERT	0.2788	0.0350	7.97	0.4163	0.0574	7.26
Israel						
PRIM	-0.1422	0.0704	-2.02	-0.7302	0.1531	-4.77
SECO	-0.0423	0.0633	-0.67	-0.3212	0.0757	-4.25
TERT	0.2033	0.0270	7.53	0.1786	0.0292	6.13

Japan						
PRIM	-0.4260	0.1108	-3.85	-0.4920	0.1783	-2.76
SECO	-0.2255	0.0594	-3.80	-0.1342	0.1237	-1.09
TERT	0.1875	0.0391	4.80	0.0669	0.0454	1.47
Spain						
PRIM	-0.3668	0.0883	-4.15	-0.4848	0.1138	-4.26
SECO	-0.1872	0.1269	-1.47	-0.2374	0.1430	-1.66
TERT	0.2573	0.0228	11.29	0.1796	0.0257	6.99
Latvia						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1465	0.0391	3.75	0.0646	0.0329	1.97
Slovak Republic						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1978	0.0217	9.13	0.1551	0.0233	6.67
East Germany						
PRIM	-0.0114	0.0652	-0.17	-0.0540	0.1010	-0.53
SECO	0.1086	0.1127	0.96	0.6569	0.5599	1.17
TERT	0.3583	0.0966	3.71	0.3052	0.0861	3.54
Northern Ireland						
PRIM	-0.5712	0.0534	-10.69	-0.5545	0.0588	-9.43
SECO	-0.3424	0.0577	-5.93	-0.2580	0.0554	-4.66
TERT	0.0531	0.0521	1.02	0.1085	0.0560	1.94
France						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.2932	0.0218	13.42	0.2012	0.0169	11.92
Cyprus						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1303	0.0275	4.73	0.1073	0.0354	3.03
Portugal						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.3200	0.0552	5.80	0.3777	0.0420	8.99
Denmark						
PRIM	-0.2165	0.0845	-2.56	-0.4098	0.1820	-2.25
SECO	-0.0321	0.0632	-0.51	-0.1447	0.0706	-2.05
TERT	-0.0169	0.0188	-0.90	0.0589	0.0172	3.43
Bangladesh						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0975	0.2656	0.37	-0.0180	0.2845	-0.06
TERT	0.4072	0.2164	1.88	0.4320	0.3067	1.41

Chile						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.3589	0.0629	5.71	0.2387	0.0711	3.36
Finland						
PRIM	1.0326	0.2424	4.26	0.5086	0.2343	2.17
SECO	1.6069	0.1529	10.51	0.9175	0.1430	6.41
TERT	0.4394	0.0483	9.10	0.3054	0.0353	8.64
Mexico						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.3838	0.0397	9.67	0.3509	0.0537	6.53
South Africa						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.6278	0.0534	11.75	0.3623	0.0578	6.27
Belgium						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.0002	0.0200	0.01	-0.0608	0.0208	-2.93
Taiwan						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1294	0.0214	6.04	0.1670	0.0273	6.12
Venezuela						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1504	0.0498	3.02	0.1323	0.0578	2.29
South Korea						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1406	0.0276	5.09	0.1735	0.0348	4.98
Uruguay						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.5851	0.0671	8.71	0.6522	0.0649	10.05
Dominican Republic						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.5881	0.0571	10.30	0.5600	0.0626	8.94
Croatia						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1392	0.0257	5.42	0.2364	0.0266	8.90

Argentina						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.2880	0.0450	6.40	0.2674	0.0589	4.54
Turkey						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.4892	0.0516	9.47	0.7104	0.1086	6.54
Ukraine						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.0649	0.0662	0.98	0.0947	0.0470	2.01
China						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.4398	0.0696	6.32	0.5787	0.0911	6.35
Estonia						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.2173	0.0987	2.20	0.1463	0.1019	1.44
Iceland						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	-0.0506	0.0837	-0.60	0.0043	0.0836	0.05
Lithuania						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	0.1745	0.0431	4.05	0.1888	0.0293	6.43
India						
PRIM	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
SECO	0.0000	(omitted)	(omitted)	0.0000	(omitted)	(omitted)
TERT	-0.1110	0.1303	-0.85	0.1364	0.2528	0.54
Pooled						
PRIM	-0.2540	0.0285	-8.91	-0.2945	0.0368	-8.01
SECO	-0.0878	0.0342	-2.57	-0.1005	0.0389	-2.58
TERT	0.2619	0.0146	17.91	0.1130	0.0157	7.22

Table reports education categories coefficients ($\beta_{1\text{-}3}$) following Model (IV). RSE and t stands for robust standard error and t-statistic respectively. When coefficients are equal to zero and statistics are omitted it means that they were removed from the regression due to collinearity.