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Wage inequality and Returns to Schooling in Europe: a Semi-Parametric Approach Using EU-SILC Data

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Abstract

In this paper we apply a semi-parametric approach (quantile regression - QR) to the last 2007 wave of the EU-SILC data set, in order to explore the connection between education and wage inequality in 8 European countries. We find that wages increase with education and this holds true across the whole distribution. Furthermore, this effect is generally more important at the highest quantiles of the distribution than at the lowest, implying that schooling increases wage dispersion. This evidence is found to be rather robust as showed through tests of linear hypothesis. We also corroborate the idea that, although OLS coefficients estimates are substantially in line with the QR's, the former technique really misleads relevant information about cross-countries heterogeneity in the impact of education on within group inequality at different points of the wage distribution. Hence this paper confirms that a semi-parametric QR approach is more interesting, as well as more appropriate, because it measures the wage effect of education at different quantiles, thus describing relevant cross-countries changes or bounces not only in the location, but also in the shape of the distribution.

Keywords: Returns to education; Wage inequality; Quantile regression; Europe
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1. Introduction[1]

There is a wide consensus that schooling has a relevant impact on wage inequality across countries. In particular returns to education tend to be increasing over the wage distribution: this evidence is interpreted as a direct effect of education on within-groups inequality.

As a matter of fact, some empirical analysis have explored the gain effects of schooling over the entire wage distribution, by using not only different specifications of the mincerian equation, but several econometric procedures as well. In particular, since the seminal paper by Koenker and Basset (1978), quantile regression (QR) was adopted by many authors. It has been exploited both in surveys concerning single countries and in comparative studies. As to the former strand of empirical literature, Buchinsky (1994) for the US, Budría and Moro-Egido (2008) for Spain, Machado and Mata (1997, 2005) Hartog *et al.* (2001), Martins (2004) and Andini (2007, 2008) for Portugal, Gosling *et al.* (2000) for UK, McGuinness et al. (2009) for Ireland, are only some examples.

As to the latter strand, just a few papers have explored comparable cross-countries differences. This in-depth examination has been constrained by the use of older homogenized data sets, but has been also due to the greater availability of diverging data sets, as argued by Budria and Pereira (2005). With regard to the former point Barros, Prieto-Rodríguez and Vieira (2008) have examined the connections between education and wage across 14 European countries by using the European Community Household Panel data-set.

With regard to the latter, on the one hand, Budria and Pereira (2005) have evaluated how the impact of education on wage inequality has evolved over time in 9 European countries, covering a period ranging from 26 years in the case of

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Sweden (1974-2000) to 7 years in the case of Portugal (1993-2000) and by distinguishing for educational qualification. On the other hand, Martins and Pereira (2004, MP henceforth), using cross sectional data sets which refer to different years, ranging from 1991 in the case of Sweden to 1996 in the case of Netherlands, have shown that in 16 European countries higher education is associated with higher wage dispersion. Both these papers were completed under a framework of research projects[2] where each country team analyzed their own country different data set. However, they "assure that these data sources were as similar and thus comparable as possible" (MP, 2004 p.356). In this paper we apply a similar approach to 8 European countries, using the European Union Statistics on Income and Living Conditions inquiry (EU-SILC), the new European homogenized panel survey, widely considered an attractive source of information, as it adopts the same "community" questionnaire, thus obviously making comparisons across nations easier. More specifically, our primary purpose is to explore the potential for EU-SILC data to shed some light on the relationship between wage inequality and returns to schooling in Europe.

In particular, a couple of questions are relevant here: 1) to what extent can education be called to explain the behaviour of income inequality across European countries? 2) Is a semi-parametric approach – i.e. QR - more appropriate than the standard Ordinary Least Squared (OLS) in order to clear up this issue?

As outlined above, we try to answer these questions through the use of the last 2007 wave of the EU-SILC data set, available since march 2009 and which has succeeded the European Community Household Panel (ECHP) since 2005[3]. The

[2] The projects are the "Education and Wage Inequality in Europe" (EDWIN) for Budria and Pereira (2005) and the "Public Funding and Private Returns to Education" (PuRE) for MP.

[3] EU-SILC was launched gradually between 2003 and 2005 in all EU Member States and has become the source of data for the analysis of income distribution and social inclusion at EU level. More precisely, EU-SILC was first brought out in 2003 on the basis of a gentlemen's agreement in six Member States (Belgium, Denmark, Greece, Ireland, Luxembourg and Austria) as well as in Norway. In 2004, under Regulation N° 1177/2003 of the EP and the European Council, EU-SILC

EU-SILC data set firstly provides two advantages with respect to the ECHP, namely: a) an update of indicators, and b) a larger cover of European countries. Secondly, it keeps the main advantage that ECHP had on other data sets: attaining comparability by exploiting common guidelines, definitions and procedures. Thus, through EU-SILC, one is able to evaluate possible similarities between a much higher number of European countries whose educational systems and labour market institutions are quite different.

To address these issues we apply the QR semi-parametric approach which seems more interesting, as well as more suitable, for it allows us to get a more precise picture of the dynamics of the dependent variable at different points of the distribution, rather than at the conditional mean. We also compare QR with OLS, in order to provide a cross countries comparable view. The paper demonstrates that there is a high cross-country heterogeneity in returns to education at different points of the wage distribution, which OLS modelling of conditional average of a dependent variable completely fails to account for.

This empirical paper is organized as follows. The next section describes the data. Section 3 illustrates our econometric specification. Section 4 reports the results of the returns to education across European countries, both in terms of OLS and QR as well as a robustness check. In the Section 5 we show the robustness check, while the final section presents our main conclusions.

2. Data selection

was implemented in 12 EU-15 countries (Germany, Netherlands and the United Kingdom delayed the launch for one year) as well as in Estonia, Iceland and Norway. In 2005, EU-SILC was operating in all EU-25 countries, plus Iceland and Norway, all with available cross-sectional data. Bulgaria, Turkey and Romania launched EU-SILC in 2006, and Switzerland followed suit in 2007. Also Former Yugoslav Republic of Macedonia and Croatia are evaluating its start.

Data are collected from the 2007 European Union Statistics on Income and Living Conditions (EU-SILC) wave for 6 out of our 8 countries[4], the only ones having available data for our interest variables. EU-SILC is the new homogenized panel survey that has replaced ECHP, and actually covers EU-25 (old and new) member states. Similarly to ECHP, EU-SILC is an attractive source of information because it adopts the same "community" questionnaire used by the national data collection units in each included country, which obviously makes comparisons across nations easier. Furthermore, EU-SILC actually covers a larger and increasing number of European countries with respect to the ECHP.

We have focused our analysis on the personal file of EU-SILC[5]. In the 2007 wave 387,170 individuals from EU-25 countries were interviewed. 184,879 of them were males, 202,287 females. The two countries for which we extract data from the 2005 wave have interviews for 22,355 individuals, 10,793 of which are men. We chose to concentrate the survey on males aged between 25 and 65 working full-time: women were disregarded on account of potential selectivity biases[6]. Younger males were dropped because they are still in the "almost exclusively" educational period of their life, i.e. they are very likely enrolled in a secondary or tertiary course and at the same time do not perform any work activity. People who had missing or NA data on the educational variable were also dropped. Our dependent variable is the hourly (logarithmic) gross wage, available for 24,118 full-time working males aged between 25 and 65 for the 6 countries of the 2007 wave and 3,621 Belgian and Greek men of the 2005 wave. Thus our analysis focuses on 27,739 individuals altogether.

[4] For Greece and Belgium we used the 2005 wave. The time mismatch is not supposed to greatly weaken international comparisons as we deal with structural variables, i.e. values changing slowly between years.

[5] A household data file is also available together with two more register file for household and individuals as well.

[6] See Buchinsky (1998) to have an insight on methods developed to deal with selectivity biases.

EU-SILC does have data for the highest educational attainment from which we have built up our first independent variable (schooling years) following the usual framework, i.e. by making use of the highest ISCED level of education attained by a male worker, and for each level assigning the legal minimum number of years typically required to achieve it[7]. Our second and third regressors are respectively the number of years spent in paid work and its squared: the former is regarded as being a proxy for individual experience while the latter takes account of possible non linearities. The summary statistics of these variables are shown in table 1, while in the appendix the figures concerning the link between ISCED levels and monthly gross income for all of our 8 countries are reported educ.

[Table 1 here]

3. Econometric specification: OLS versus quantile regression

The first equation has the following simple form:

$$\ln w_i = \alpha_i + \beta_i \text{edu} + \gamma_i \exp + \delta_i \exp^2 + \varepsilon_i \qquad (1)$$

The equation (1) is solved through a classic OLS method, based on the mean of the conditional distribution of the dependent variable. As is well known, it implicitly assumes that the impact of the regressors along that conditional distribution are irrelevant. This fact is referred to as a pure location shift. In other words, the x's are unable to cause a scale effect or any other consequence on the distributional shape. But as covariates may influence the conditional distribution

[7] Those who reached only an ISCED 1 grade have been given 5 years of schooling; 8 years of school have been assigned to those with an ISCED 2 grade; 13 years to those with an ISCED 3; 14 to people who attained an ISCED 4 grade and 18 years to those who reached an ISCED 5.

of the response in many other ways, we are willing to estimate the whole distribution of the conditional quantiles of the dependent variable, and to be able to study the influence of the regressors on its shape, We do this performing a quantile regression (QR), which has the following functional form (Koenker & Basset, 1978):

$$Quant_{\theta}\left\{\begin{array}{l}\sum_{i:\ln w_i \geq x_i\beta} \theta \mid \ln w_i - \left(\alpha_\theta + \beta_\theta \mathrm{edu}_i + \gamma_\theta \exp_i + \delta_\theta \exp_i^2\right) \mid + \\ + \sum_{i:\ln w_i \leq x_i\beta} (1-\theta) \mid \ln w_i - \left(\alpha_\theta + \beta_\theta \mathrm{edu}_i + \gamma_\theta \exp_i + \delta_\theta \exp_i^2\right) \mid \end{array}\right\} \qquad (2)$$

The equation (2) is normally written as:

$$\min_{\beta \in R^k} \sum_i \rho_\theta \left(\ln w_i - \alpha_\theta - \beta_\theta \mathrm{edu}_i - \gamma_\theta \exp_i - \delta_\theta \exp_i^2\right) \qquad (3)$$

where $\varrho_\theta(z) = \theta z$ if $z \geq 0$ or $\varrho_\theta(z) = (\theta - 1)z$ if z<0.

This problem is solved using linear programming methods. Standard errors for the vector of coefficients are obtainable by using a bootstrap procedure described in Buchinsky (1998).

The quantile regression has other advantages which can be summarized as the following (Buchinsky, 1998): i) it provides robust estimates of the coefficient vector, i.e. estimates insensitive to outliers of the dependent variable; ii) when error terms are not normally distributed, estimators provided by the quantile regression can be more efficient than OLS estimators; iii) if different estimates for several quantiles are observed, the influence change of the covariates on the y variable along the whole conditional distribution can be easily understood.

4. Results

In table 2 we show OLS returns as well as conditional returns at 19 representative quantiles: 0.05, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75, 0.80, 0.85, 0.90 and 0.95, which are denoted θ5, θ10, θ15, θ20 θ25, θ30, θ35, θ40, θ45, θ50, θ55, θ60, θ65, θ70, θ75, θ80, θ85, θ90 and θ95 henceforth.

[Table 2 here]

Both OLS and QR estimated coefficients are positive and significant at the 1% level in every country. Differences between percentiles of the wage distribution computed for 6 different extremes taken by twos (θ95-θ5, θ90-θ10 and θ75-θ25) are also reported. In fig. 1 we rank countries by their OLS estimates and compare each country both in terms of OLS coefficients and of differences between percentiles at the levels of the wage distribution specified above. In terms of OLS returns of education, Portugal – in line with previous studies - shows the highest coefficient (8%), while Austria, Poland, Ireland, Belgium and Spain exhibit values respectively equal to 6.7%, 6.3%, 5.5%, 4.9% and 4.6%. At the bottom of the wage distribution Greece displays the lowest value (3.5%), while Italy shows a slightly higher coefficient (4.3%).

[Figure 1 here]

In terms of differences between percentiles computed at the 6 considered extremes, it seems useful to us to remind and make clear that, in every country, they are decreasing with the distance between percentiles: in other words, in all of the countries inspected θ95-θ5 (θ75-θ25) is higher (lower) than θ90-θ10. Similarly to MP which found that Portugal was top ranked both in terms of OLS and difference between the ninth and the first decile, our estimates show that the country having the greatest OLS coefficient and the largest spreads between percentiles, for all of the 3 comparisons, is still Portugal (0.0513 for θ95-θ5, 0.0447 for θ90-θ10 and 0.0193 for θ75-θ25). The same situation occurs for Greece at the bottom of the distribution, which is also the only country with no difference between the 75^{th} and 25^{th} quantiles (2.1% for θ95-θ5, 1.3% for θ90-θ10 and 0.0% for θ75-θ25). Austria has a particular evidence: in fact, it displays a high OLS returns on education but quite low differences between the percentiles of the wage distribution. Poland shows both relatively high return on education and high inter-quantiles differences, while in Italy a low OLS coefficient is associated to a relatively high inequality between different percentiles of the wage distribution.

It should be also noted that coefficients obtained by QR estimates resemble those obtained by OLS. That is also confirmed when the correlation matrix between OLS estimates and the 3 differences of the QR estimated coefficients at the chosen percentiles is computed (see tab. 3). Of course the smallest inter-quantile difference (θ75-θ25) is more correlated with its nearest neighbour difference (θ90-θ10). When the OLS estimates are considered, evidence is found that the larger the difference between quantiles and their associated estimates the stronger the correlation with OLS: 0,533 for θ75-θ25, 0,697 for θ90-θ10 and 0,783 for θ95-θ5.

[Table 3 here]

Nevertheless, OLS technique really misleads relevant information about cross-counties differences in the impact of education on within group inequality at different points of the wage distribution. This arises from the fig 2 a-c which compares the OLS results with the QR estimates at different points of the wage distribution. There is a clear evidence that wages increase with education and this is true across the whole distribution. Furthermore, this effect is generally more important at the highest quantiles of the distribution than at the lowest, implying that schooling increases wage dispersion. Also Greece, which was found the only exception by MP, follows the same pattern. It can be further noted that in MP the data for Austria, Greece and Italy were based on net wages, "which troubles a full comparison with the remaining countries" (MP, p. 365).

[Figure 2 a-c here]

Despite this common pattern across countries, fig. 2a-c puts also on different paths across countries from the bottom to the top of the distribution. As to Portugal, it can be noted an increasing distance from Spain when passing from the lowest to the highest percentiles. This gap decreases in the last 4 quantiles. Indeed in Portugal highest returns to education are obtained at the 80th percentile (9.2%), and after that they slightly decrease. On the other hand Spain shows a more bounceless (and weaker) growth. Belgium follows a path similar to that of Spain, with a small decrease from the 5th to the 10th quantile.

Fig 2-b makes clear that Poland has a changing path over the wage distribution: returns to education of Polish adult male workers trace a curve which is concave in the lower half of it and then convex, with a couple of jumps (around 1%) from the 5th to the 10th quantile and from the 90th to the 95th. Ireland displays a similar but somewhat flatter path, with the same jumps at the two extremes of the wage distribution. In Austria, returns to schooling of adult full-time working men are on the contrary decreasing in the first 4 quantiles of the distribution and after that almost always increasing.

In fig 2-c a flat path all around the OLS returns to schooling is found for Greece: similarly to Poland and Ireland, on the left half QR estimates lay on a concave curve, while on the right half they lay on a convex one, but unlike them they are much more lower: indeed, Greece shows the lowest return to schooling, at the first quantile (2.3%). As for Italy, after a decreasing in returns from the first to the second percentile, the values are almost always increasing. It is also evident a convex path since the 50th quantile.

5. Robustness check

Further, in addition to MP and similarly to Budrìa and Pereira (2005) who applied an F test to the differences between quantiles in terms of education levels, in table 4 we test whether gaps between quantile coefficients estimated in our QR are statistically significant.

[Table 4 here]

The test has been carried out with respect to the three spreads considered in the paper (θ95-θ5=0, θ90-θ10=0 and θ75-θ25=0) and to all quantiles. More specifically, p-values are obtained through a bootstrapped variance-covariance matrix that includes between quantiles blocks. The results indicate that the first linear hypothesis (θ95-θ5=0) is found to be significant at all levels of confidence for almost each of the 8 countries. Only Austria displays a weaker difference, as the associated p-value is not significant at the 1% confidence level. As to the second linear hypothesis (θ90-θ10=0), overall significance is found. As expected, significance decreases when the third linear hypothesis (θ75-θ25=0) is analysed: in particular it is detected not significant at the 1% confidence level for Ireland and Poland, while it is not significant for any confidence level in Greece. This result is absolutely straightforward if one observes the precise equality between the θ75 and θ25 estimated coefficients of returns to education for greek full-time working males (3.4% at both percentiles). Finally, the joint equality of coefficients at all quantiles is rejected as well.

6. Conclusions

In this paper we have applied a QR technique to the last 2007 wave of the EU-SILC data set, in order to explore the connection between education and wage inequality in 8 European countries. Our comparative study gives a contribution to the "little comparable evidence for Europe" (Budria and Pereira 2005, p.1). We found that wages increase with education and this is true across the whole distribution. Furthermore, this effect is generally more important at the highest quantiles of the distribution than at the lowest, implying that schooling increases wage dispersion. This evidence is found to be rather robust as showed through tests of linear hypothesis carried out on 3 particular differences between estimated quantile coefficients of the returns to education, as well as through a joint test of equivalence for all of the estimated quantile coefficients.

We have so corroborated the idea that, although coefficients obtained by OLS estimates are substantially in line with the those achieved through QR, OLS technique really misleads relevant information about cross-countries differences in the impact of education on within group inequality at different points of the wage distribution.

Hence we confirm that a semi-parametric QR approach is more interesting, as well as more appropriate, because it measures the wage effect of education at different quantiles, thus describing relevant cross-countries changes or bounces not only in the location, but also in the shape of the distribution.

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Tables and figures

Tab. 1. Summary statistics

Country	Year	Variable	Obs	Mean	Std. Dev.	Std. Err.	[95% Conf. Interval]	
Austria	2007	Log hourly wage	2774	2.72	0.44	0.01	2.704103	2.737159
		edu	3280	13.90	2.72	0.05	13.80358	13.98971
		exp	3259	23.54	10.14	0.18	23.19081	23.88744
Belgium	2005	Log hourly wage	1754	2.78	0.37	0.01	2.76343	2.79843
		edu	2234	13.91	4.10	0.09	13.74191	14.08172
		exp	2232	20.23	10.62	0.22	19.78489	20.66672
Greece	2005	Log hourly wage	1867	2.03	0.41	0.01	2.009044	2.046668
		edu	3038	11.25	4.80	0.09	11.08325	11.42498
		exp	3038	19.69	11.26	0.20	19.29304	20.09405
Ireland	2007	Log hourly wage	1574	3.06	0.54	0.01	3.033858	3.086896
		edu	2172	12.49	4.79	0.10	12.28793	12.69089
		exp	2100	25.76	11.87	0.26	25.25386	26.26995
Italy	2007	Log hourly wage	7324	2.45	0.38	0.00	2.437701	2.454926
		edu	10512	11.58	3.83	0.04	11.51043	11.657
		exp	10512	19.59	10.48	0.10	19.39296	19.79369
Poland	2007	Log hourly wage	5273	1.13	0.52	0.01	1.116841	1.144935
		edu	6862	13.12	3.21	0.04	13.03968	13.19174
		exp	6819	19.70	10.93	0.13	19.4437	19.96266
Portugal	2007	Log hourly wage	1735	1.68	0.55	0.01	1.650772	1.702105
		edu	2204	8.08	4.37	0.09	7.898257	8.263268
		exp	2197	24.39	12.33	0.26	23.87838	24.90997
Spain	2007	Log hourly wage	5438	2.37	0.45	0.01	2.356271	2.38029
		edu	7181	11.56	5.00	0.06	11.44659	11.67805
		exp	7076	22.63	11.75	0.14	22.35731	22.90498

Tab. 2. Conditional returns to schooling - OLS and QR.

Quantile	Austria	Belgium	Spain	Greece	Irland	Italy	Poland	Portugal
θ=.05	0.055	0.035	0.031	0.023	0.036	0.030	0.033	0.036
	9.3	*8.49*	*11.5*	*6.22*	*2.75*	*10.2*	*3.63*	*5.9*
θ=.10	0.050	0.033	0.030	0.028	0.042	0.027	0.042	0.044
	11.74	*10.12*	*15.16*	*7.87*	*7.2*	*14.35*	*9.27*	*11.06*
θ=.15	0.049	0.034	0.032	0.028	0.047	0.029	0.048	0.058
	19.58	*26.06*	*18.62*	*9.07*	*6.71*	*19.09*	*15.99*	*12.35*
θ=.20	0.048	0.036	0.035	0.034	0.047	0.029	0.051	0.061
	16.29	*20.37*	*17.84*	*15*	*9.05*	*23.15*	*22.87*	*31.93*
θ=.25	0.052	0.037	0.037	0.034	0.049	0.030	0.054	0.069
	20.44	*22.73*	*18.62*	*15.82*	*15.32*	*22.51*	*24.52*	*25.75*
θ=.30	0.057	0.040	0.040	0.036	0.049	0.031	0.057	0.073
	27.21	*21.67*	*22.79*	*15.98*	*10.74*	*20.87*	*19.46*	*38.47*
θ=.35	0.060	0.044	0.041	0.036	0.051	0.030	0.060	0.078
	24.14	*19.41*	*23.47*	*15.74*	*12.64*	*20.05*	*24.28*	*74.1*
θ=.40	0.061	0.046	0.042	0.035	0.054	0.032	0.062	0.078
	17.6	*27.95*	*28.27*	*16.75*	*17.41*	*24.48*	*27.7*	*60.3*
θ=.45	0.062	0.046	0.043	0.036	0.053	0.034	0.064	0.081
	17.32	*20.98*	*34.32*	*14.36*	*21.83*	*31.22*	*48.01*	*48.01*
θ=.50	0.063	0.049	0.044	0.034	0.054	0.035	0.065	0.082
	18.96	*21.21*	*30.35*	*13.08*	*19.25*	*30.82*	*24.95*	*64.62*
θ=.55	0.065	0.051	0.046	0.035	0.055	0.036	0.064	0.083
	24.04	*25.8*	*37.99*	*13.32*	*17.24*	*33.09*	*23.52*	*50.22*
θ=.60	0.067	0.052	0.047	0.034	0.057	0.038	0.065	0.086
	24.14	*29.55*	*35.14*	*12.91*	*12.94*	*26.51*	*32.33*	*24.17*
θ=.65	0.068	0.051	0.048	0.035	0.057	0.040	0.064	0.089
	22.01	*26.57*	*46.05*	*17.25*	*15.9*	*27.56*	*31.08*	*31.09*
θ=.70	0.072	0.054	0.050	0.035	0.057	0.043	0.064	0.089
	15.6	*25.07*	*41.52*	*16.17*	*18.97*	*32.15*	*23.51*	*36.99*
θ=.75	0.071	0.054	0.051	0.034	0.058	0.047	0.064	0.092
	16.44	*30.3*	*25.35*	*17*	*13.41*	*25.36*	*26.99*	*37.79*
θ=.80	0.074	0.055	0.054	0.035	0.058	0.050	0.063	0.093
	13.77	*27.52*	*23.65*	*11.05*	*16.02*	*29.98*	*31.54*	*21.03*
θ=.85	0.077	0.055	0.055	0.036	0.060	0.053	0.065	0.087
	17.9	*29.08*	*38.36*	*13.35*	*14.65*	*23.84*	*27.77*	*27.41*
θ=.90	0.078	0.057	0.055	0.041	0.066	0.059	0.068	0.088
	13.26	*19.97*	*31.01*	*9.6*	*20.53*	*29.08*	*16.57*	*29.32*
θ=.95	0.085	0.061	0.061	0.044	0.075	0.067	0.076	0.088
	17.8	*11.52*	*39.97*	*7.95*	*12.54*	*24.86*	*19.31*	*12.13*
OLS	0.067	0.049	0.045	0.035	0.055	0.043	0.063	0.079
	22.34	*26.33*	*40.93*	*19.54*	*20.44*	*40.34*	*29.19*	*31.26*
θ95-θ5	0.030	0.026	0.030	0.021	0.039	0.037	0.043	0.052
θ90-θ10	0.028	0.024	0.025	0.013	0.024	0.032	0.026	0.044
θ75-θ25	0.019	0.017	0.014	0.000	0.009	0.017	0.010	0.023
Obs.	2756	1744	5350	1867	1522	7324	5236	1702

Note. Data for Austria, Spain, Irland, Italy, Poland and Portugal are from cross sectional UDB SILC 2007 – version 1 of March 2009; Belgium and Greece from EU-SILC 2005. All coefficent significants at $p<0.001$, *t-statistics* in italics.

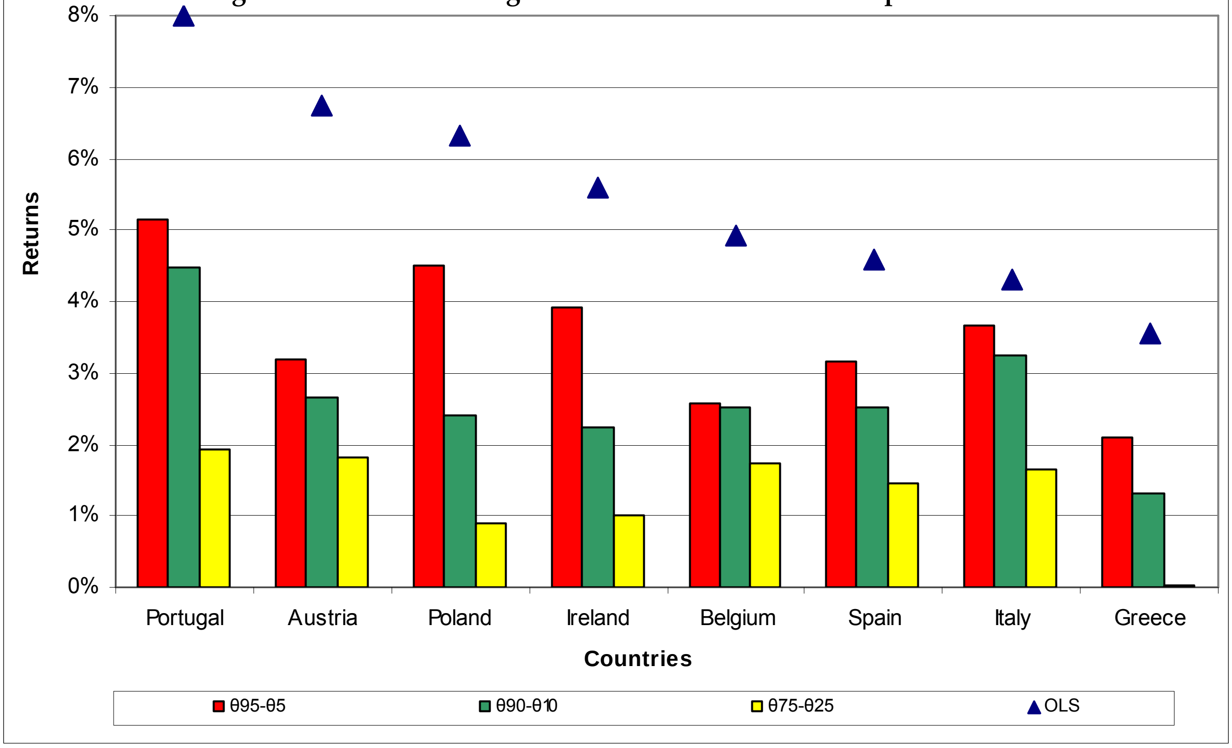


Fig 1: Returns to schooling: OLS and difference between percentiles

Tab 3. Correlation between OLS and inter-quantile differences

	θ95-θ5	θ90-θ10	θ75-θ25	OLS
θ95-θ5	1			
θ90-θ10	0.747	1		
θ75-θ25	0.379	0.787	1	
OLS	0.783	0.697	0.533	1

Fig 2 a-c: Returns to schooling

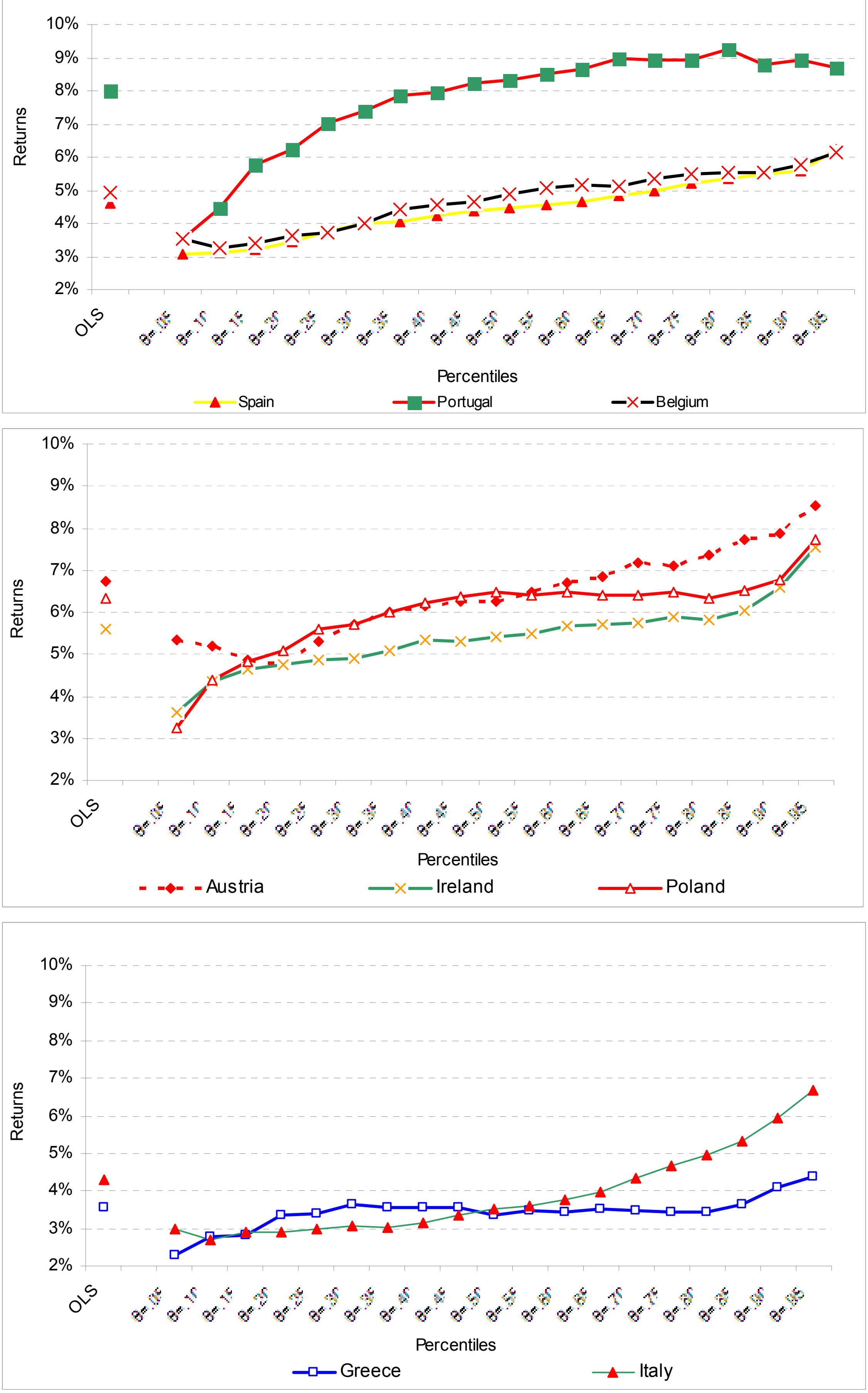
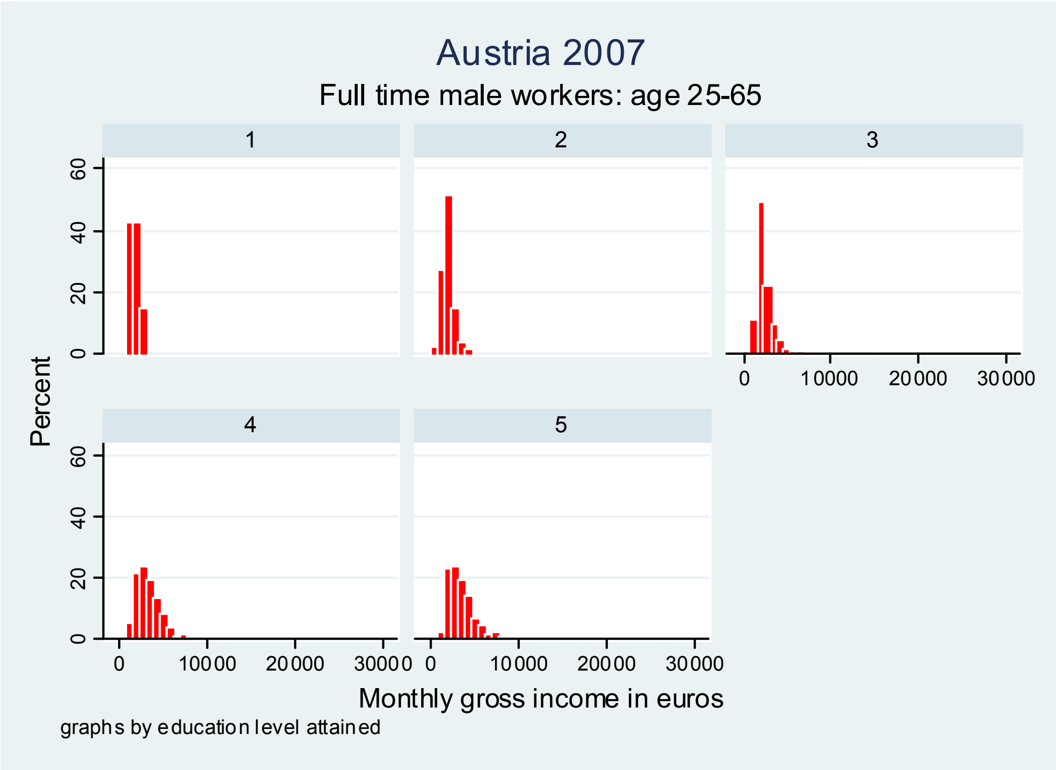
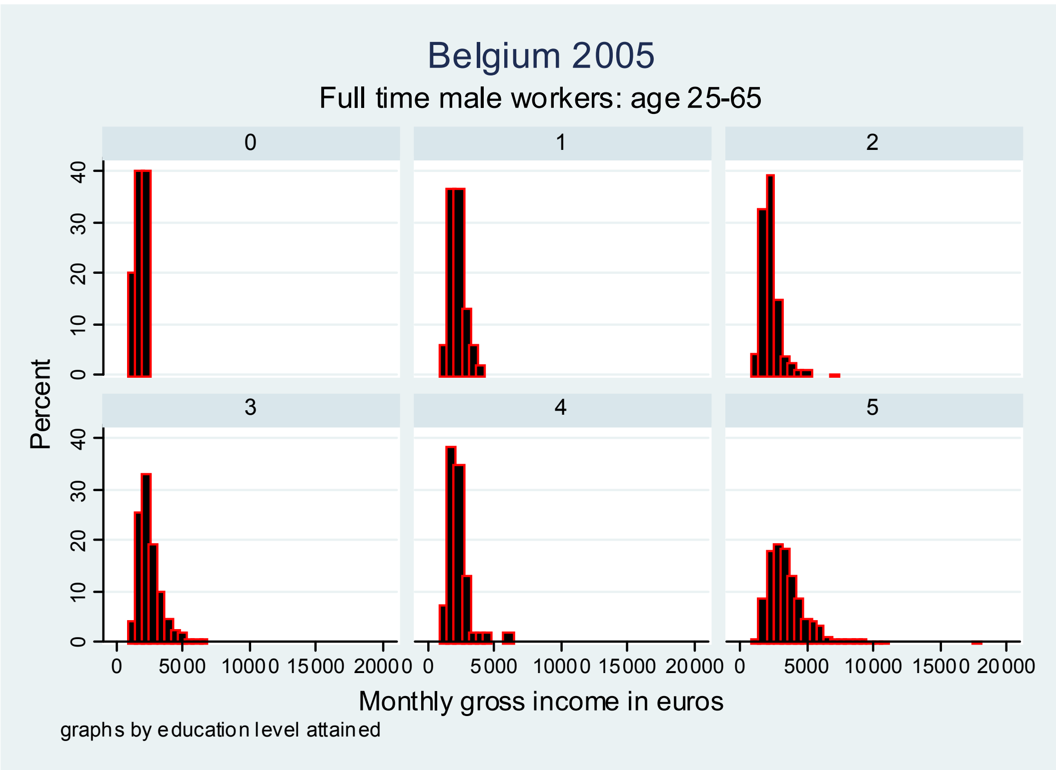


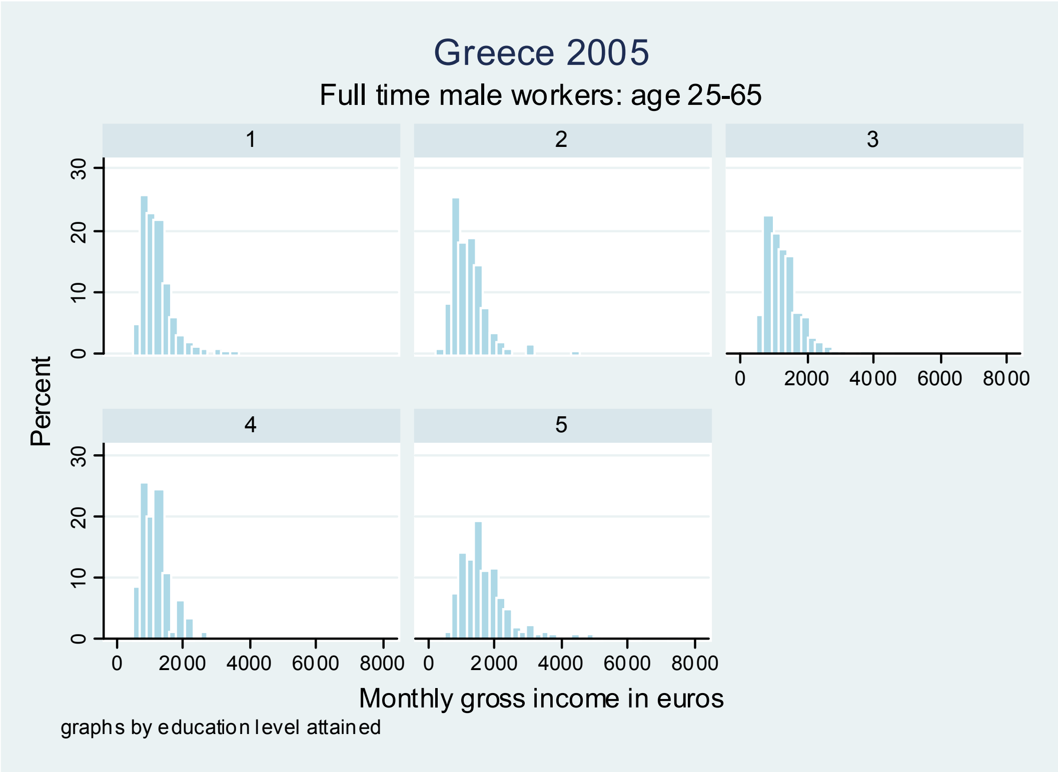
Table 4: Null Inter-quantile differences and joint equality: hypothesis testing by country

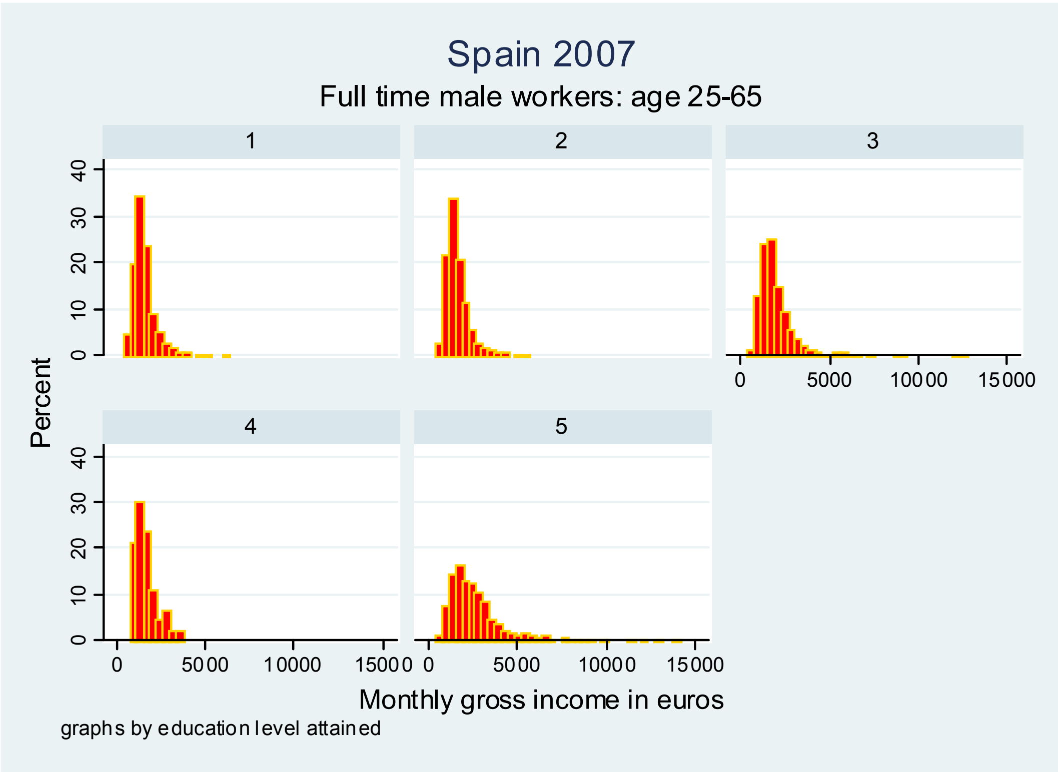
Countries	θ95-θ5=0	θ90-θ10=0	θ75-θ25=0	All quantiles equal
Austria	F(1, 2752) = 6.34 *Prob > F = 0.0119*	F(1, 2752) = 34.46 *Prob > F = 0.0000*	F(1, 2752) = 12.67 *Prob > F = 0.0004*	F(9, 2752) = 32.94 *Prob > F = 0.0000*
Belgium	F(1, 1740) = 15.16 *Prob > F = 0.0001*	F(1, 1740) = 39.17 *Prob > F = 0.0000*	F(1, 1740) = 33.59 *Prob > F = 0.0000*	F(9, 1740) = 6.86 *Prob > F = 0.0000*
Spain	F(1, 5346) = 96.45 *Prob > F = 0.0000*	F(1, 5346) = 115.77 *Prob > F = 0.0000*	F(1, 5346) = 74.07 *Prob > F = 0.0000*	F(9, 5346) = 217.83 *Prob > F = 0.0000*
Greece	F(1, 1863) = 17.30 *Prob > F = 0.0000*	F(1, 1863) = 23.38 *Prob > F = 0.0000*	F(1, 1863) = 0.08 *Prob > F = 0.7801*	F(9, 1863) = 20.11 *Prob > F = 0.0000*
Irland	F(1, 1518) = 10.53 *Prob > F = 0.0012*	F(1, 1518) = 14.89 *Prob > F = 0.0001*	F(1, 1518) = 6.08 *Prob > F = 0.0138*	F(9, 1518) = 18.01 *Prob > F = 0.0000*
Italy	F(1, 7320) = 34.76 *Prob > F = 0.0000*	F(1, 7320) = 52.74 *Prob > F = 0.0000*	F(1, 7320) = 57.28 *Prob > F = 0.0000*	F(9, 7320) = 15.86 *Prob > F = 0.0000*
Poland	F(1, 5232) = 16.69 *Prob > F = 0.0000*	F(1, 5232) = 29.37 *Prob > F = 0.0000*	F(1, 5232) = 6.52 *Prob > F = 0.0107*	F(9, 5232) = 44.87 *Prob > F = 0.0000*
Portugal	F(1, 1698) = 76.85 *Prob > F = 0.0000*	F(1, 1698) = 38.26 *Prob > F = 0.0000*	F(1, 1698) = 16.04 *Prob > F = 0.0001*	F(9, 1698) = 56.87 *Prob > F = 0.0000*

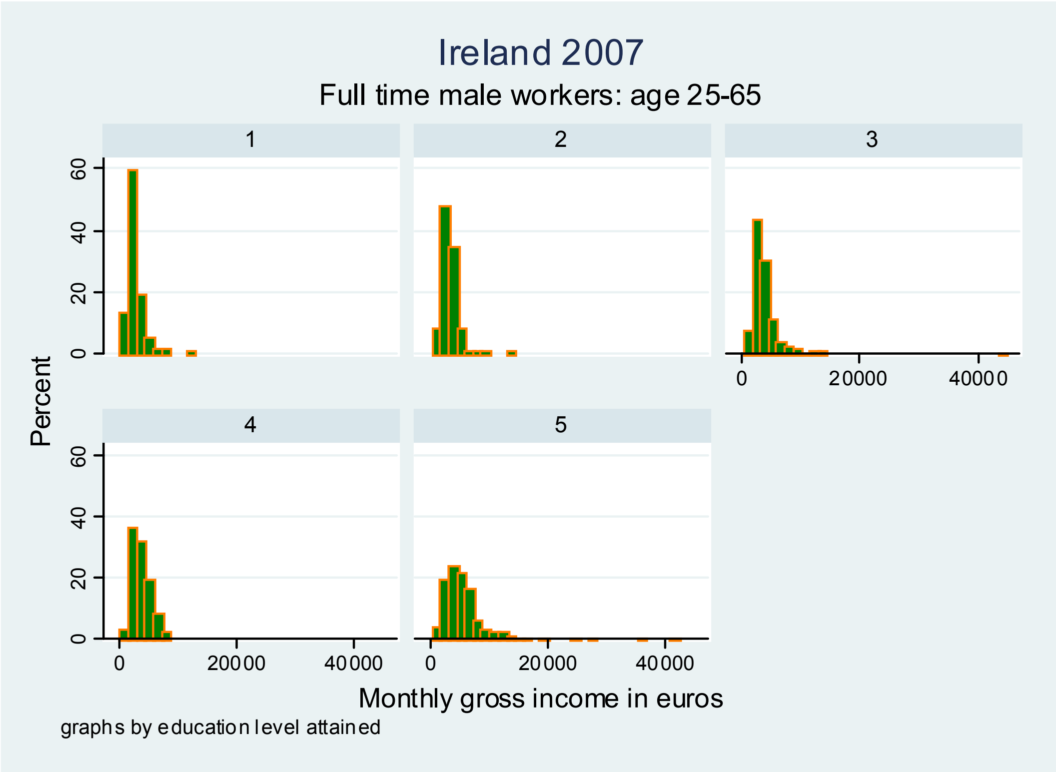
Appendix

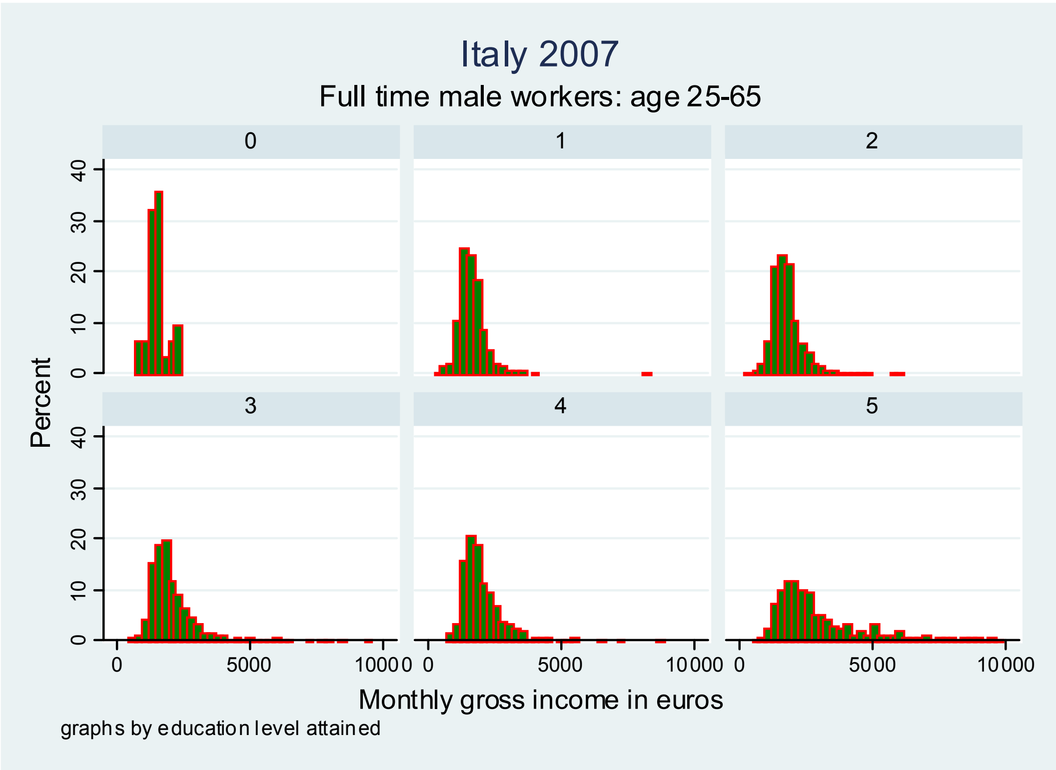

Austria 2007
Full time male workers: age 25-65
1
2
3
4
5
Percent
0
20
40
60
0
10000
20000
30000
Monthly gross income in euros
graphs by education level attained

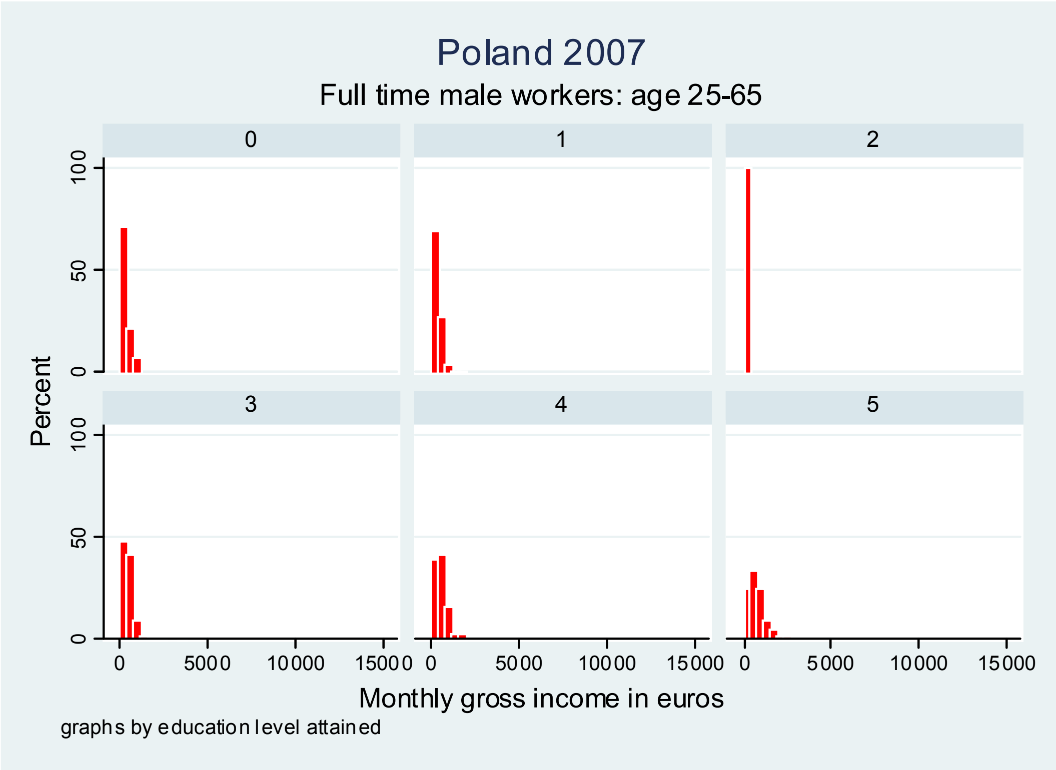

Belgium 2005
Full time male workers: age 25-65
0
1
2
3
4
5
Percent
0
10
20
30
40
0
5000
10000
15000
20000
Monthly gross income in euros
graphs by education level attained


Greece 2005
Full time male workers: age 25-65
1
2
3
4
5
Percent
0
10
20
30
0
2000
4000
6000
8000
Monthly gross income in euros
graphs by education level attained

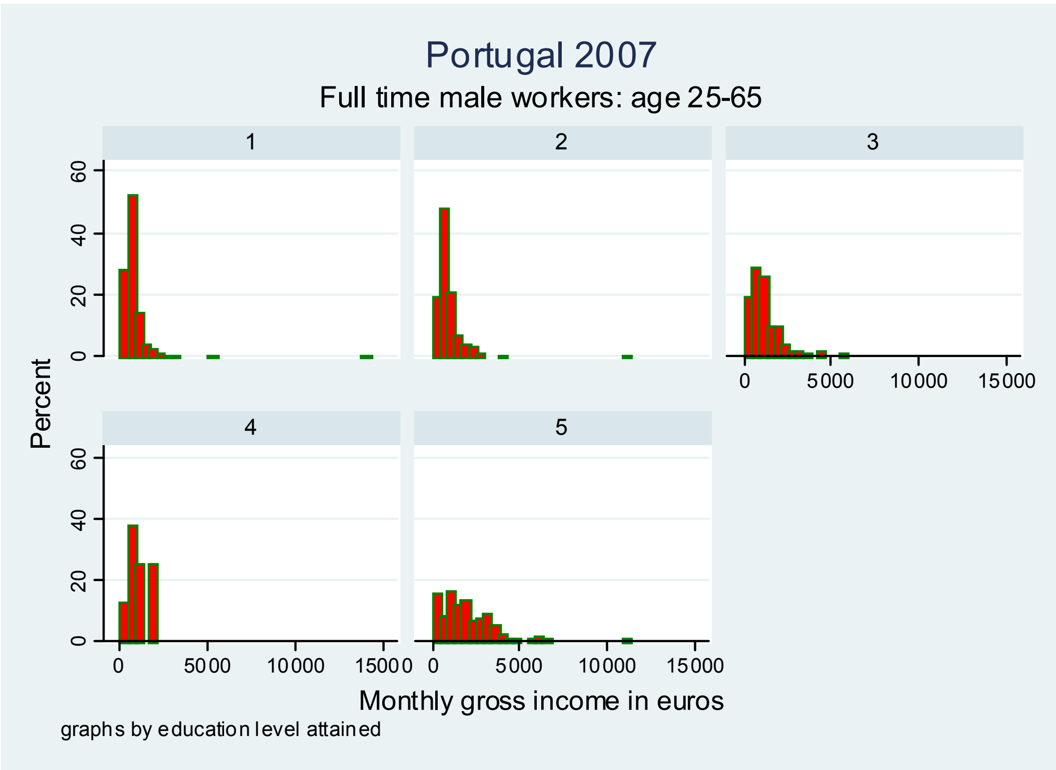

Spain 2007
Full time male workers: age 25-65
1
2
3
4
5
Percent
0
10
20
30
40
0
5000
10000
15000
Monthly gross income in euros
graphs by education level attained


Ireland 2007
Full time male workers: age 25-65
1
2
3
4
5
Percent
0
20
40
60
0
20000
40000
Monthly gross income in euros
graphs by education level attained


Italy 2007
Full time male workers: age 25-65
0
1
2
3
4
5
Percent
0
10
20
30
40
0
5000
10000
Monthly gross income in euros
graphs by education level attained



Poland 2007
Full time male workers: age 25-65
0
1
2
3
4
5
Percent
0
50
100
0
5000
10000
15000
Monthly gross income in euros
graphs by education level attained



Portugal 2007
Full time male workers: age 25-65
1
2
3
4
5
Percent
0
20
40
60
0
5000
10000
15000
Monthly gross income in euros
graphs by education level attained