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Income Inequality and Education from ECHP data

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Abstract

This paper analyses income inequality and its changes over the period 1993-2000 for a set of 13 Countries in European Community Household Panel (ECHP) survey. Focusing on wages and incomes of workers in general, inequality is related to education as a proxy of individual abilities, skills. Estimation of education premia is performed by quantile regressions to stress differences in income distribution and questioning the true impact of education. The same estimates are used to decompose income inequality and show the rise in residual inequality.

JEL Class.: D31, J24, J31
Keywords: Inequality, Education Premium, Quantile Regression

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1 Introduction

Since 70s in the US and UK, since 80s in many European Countries wage inequality increased, both between and within groups, defined by some observable individual characteristics, with respect to their 'skills'[1].

Education has been called in many analyses to explain new evidence. Facing with the increase in wage or income inequality, theories challenged to explain new findings with several models[2]. As a brief summary of the different theories engaged in explaining the rising inequality, three broad ideas can be tracked, namely trade, labor market institutions and technological change. On one extreme view, inequality pattern relates to trade growth, increasing inequality in developed countries and upward mobility in the developing ones are the two faces of the same coin, no concern should be expressed when considering the whole economy[3]. On the other extreme, inequality rises as the labor institutions (unions, employment protection laws, minimum wage level) have become weaker: hence, inequality - along with the diminishing labor share - can be related to the downfall of minimum wage or to the deunionization of labor force that worsened low-skilled incomes[4].

Some schumpeterian authors modeled technology resulting in skill-biased change, in order to explain the rising wage differentials between the educational groups. As the skill-biased technological change hypothesis (SBTC) gained growing consensus in coping with evidence on inequality, it should be useful to sum up the major findings of this branch of theory. In the simplest

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[1] See among others Murphy and Welch (1993) and Juhn et al. (1993), for an early debate on wage inequality trends for the US, and Machin (1996) for the UK.

[2] Income inequality and its components engaged economists in an intense debate, given its impact on economic growth; see for a recent contribution Voitchovsky (2005).

[3] See for example Wood (1995).

[4] See DiNardo et al. (1996).

end earliest contributions, models explained the increased inequality between skilled and unskilled workers through changes in relative demand and relative supply of skills: new technologies increased the demand for skilled workers, while the supply of skills went up at a lower rate (Juhn et al., 1993), ending with more skilled jobs and raising skill premium. In a more complex view, the technological change is skill-biased because is endogenously directed by the relative abundance of complement skills (Acemoglu, 1998) towards the skill-bias. Coping with the rising inequality among workers with similar observable skills - the residual or within-group inequality - some Authors also found the within groups inequality rise as an outcome of the more 'general' new technological paradigm[5]. All these contributions related to SBTC emphasized the role of education for the changes in technology and the new resulting skill premia.

European Countries have some differences with respect to the US labor market, in particular in the past European labor markets were less flexible. It has been argued that the same shift in the technology produced different outcomes with respect to the US and the European Countries. In the latter labor markets the technological shock had its main effects on quantity (unemployment) rather then price (inequalities)[6]. Nevertheless, also in Europe by the late 80s something changed, labor markets have became more flexible, employment protection legislation have become weaker and inequality rose (Glyn, 2001).

In this paper the link between inequality and education is exploited with a detailed look at differences throughout income distribution. Hence, Quantile Regression (QR) are used to get a wide picture of education premia over time and for each Countries. QR allows for the changes in shapes of income distribution and depicts an exhaustive description than mean estimates. Results are shown in an original way, fitted quantiles have been plotted over education experience and tenure, in order to get an easier comprehension of the changes in returns to education experience and tenure, so that the differences between Countries can be related to different effectiveness of the technological and institutional mechanisms. Moreover, a measure of QR-based residual inequality is proposed to stress that the role of unobservable characteristics grew for many Countries, driven by the changes in the upper tail of income distribution. Next section shows sample data and some figures about inequality and education. In section 3, the empirical model is presented as well the returns for education and the measure of residual inequality. Last section sums the results and concludes.

[5]Aghion, Howitt and Violante (2002) pointed out the role of luck in the labor market related to the increasing within-group inequalities, as a consequence of the major "generality" of knowledge in the new technological paradigm.

[6]See Ljunqvist and Sargent (1998) for some evidence.

2 Data

Sample data came from the European Community Household Panel (ECHP), an annual survey repeated from 1994 to 2001, based on a representative panel of households and individuals in 12 country [7]. In the following years other three Countries were added to the survey [8], so that ECHP in the end covered 15 Countries for slightly different periods[9].

A sub-sample of ECHP is used here: because of the availability of some key variables two Countries have been excluded, Netherlands and Sweden. Moreover, while in general the measures here refer to the period 1993-2000[10], there are three exceptions: Austria and Luxembourg start from 1994, Finland from 1995. Workers aged $16-64$ (employed and self-employed) are observed, personal net incomes[11] refer to the year prior to the survey and measured in real terms and in PPPs based on the starting year of the period 1993. In the ECHP data, education is classified in 3 broad levels, renamed here as low, middle and high skill[12].

Sample differs by Countries in population and income shares of each educational group (see figure 1 and table 1). Over the period, mean real income by educational group changed differently across Countries and educational groups. In general, mean income growth was slightly more effective for the high skilled group. Mean incomes figures can be summed up:

- high skilled workers mean income increased in Denmark, Belgium, Ireland, Greece, Finland and United Kingdom; it was almost stable in Germany and Luxembourg, slightly decreased in France, Italy, Spain, Portugal and Austria;

- medium skilled workers mean income increased in Denmark, Belgium, Ireland and United Kingdom, remained constant in Italy, Greece, Spain, Finland, Germany and Luxembourg, diminished in France, Portugal and Austria;

[7] At the beginning the Countries included in ECHP were: Denmark, Netherlands, Belgium, France, Ireland, Italy, Greece, Spain, Portugal, Germany, Luxembourg and United Kingdom.

[8] Austria joined in 1995 while Finland and Sweden in 1996, Sweden data were derived from the Swedish Living Conditions Survey.

[9] An exhaustive user guide as well other related documents for the ECHP data have been produced by the EPUNet team at Essex University.

[10] Incomes refer to the year prior the survey.

[11] Data on income differ for France and Finland with gross amount of personal incomes; there is no concern in the case of minor tax changes over the period.

[12] In particular, the three levels are quite similar to the primary, secondary an tertiary education with few differences across Countries; low-skilled stands for 0-2 ISCED codes (pre-primary; primary or first stage of basic education; lower secondary or second stage of basic education), medium skilled for the 3 ISCED code (upper secondary education), high skilled for the 4-6 ISCED codes (post secondary non tertiary; first stage of tertiary; second stage of tertiary).

Table 1: Mean Income, Sample and Income shares by educational levels

	Mean Real Income, PPPs					
	1993			*2000*		
	low-skill	medium-skill	high-skill	low-skill	medium-skill	high-skill
Denmark	10312.53	12606.05	15800.62	10227.93	13499.73	17328.10
Belgium	13268.84	14556.32	18349.89	12463.09	14915.81	19752.44
France	11966.43	14509.50	25051.20	12561.16	13100.09	19989.54
Ireland	13065.34	13406.81	22213.66	15113.67	16222.44	23324.79
Italy	11244.04	13242.93	18390.18	11497.96	13250.13	17571.57
Greece	8541.16	10762.47	13586.33	8876.91	10682.12	15368.24
Spain	10098.48	11912.55	17695.47	10504.25	11808.84	16484.59
Portugal	7063.89	10664.32	20442.83	7483.89	9628.30	17924.82
Austria	9942.67	15123.91	21146.21	8918.59	14308.68	19575.35
Finland	12297.14	14492.37	22917.71	13525.87	14428.73	25096.17
Germany	11235.56	13597.02	19538.43	9561.16	13532.51	19901.04
Luxembourg	18354.90	24766.83	37537.03	17390.27	25078.56	37441.18
United Kingdom	10416.11	11337.69	16083.46	11776.05	12852.60	17884.88
	Sample share					
	1993			*2000*		
	low-skill	medium-skill	high-skill	low-skill	medium-skill	high-skill
Denmark	0.23	0.41	0.36	0.15	0.53	0.32
Belgium	0.24	0.35	0.41	0.20	0.35	0.45
France	0.30	0.45	0.25	0.55	0.13	0.32
Ireland	0.37	0.43	0.20	0.32	0.45	0.23
Italy	0.50	0.40	0.10	0.42	0.46	0.13
Greece	0.46	0.28	0.26	0.40	0.37	0.22
Spain	0.57	0.19	0.24	0.46	0.22	0.32
Portugal	0.83	0.11	0.07	0.73	0.15	0.12
Austria	0.21	0.71	0.08	0.15	0.75	0.09
Finland	0.28	0.39	0.33	0.19	0.49	0.32
Germany	0.23	0.56	0.22	0.18	0.56	0.26
Luxembourg	0.42	0.41	0.17	0.36	0.37	0.27
United Kingdom	0.49	0.16	0.35	0.28	0.24	0.48
	Income share, PPPs					
	1993			*2000*		
	low-skill	medium-skill	high-skill	low-skill	medium-skill	high-skill
Denmark	0.18	0.39	0.43	0.11	0.50	0.39
Belgium	0.20	0.32	0.48	0.15	0.31	0.54
France	0.22	0.40	0.38	0.46	0.11	0.43
Ireland	0.33	0.38	0.29	0.27	0.42	0.31
Italy	0.44	0.41	0.15	0.37	0.46	0.17
Greece	0.38	0.29	0.33	0.33	0.36	0.31
Spain	0.47	0.18	0.35	0.38	0.20	0.41
Portugal	0.70	0.14	0.16	0.60	0.16	0.23
Austria	0.14	0.74	0.12	0.10	0.77	0.13
Finland	0.20	0.34	0.45	0.14	0.40	0.46
Germany	0.18	0.53	0.29	0.12	0.53	0.35
Luxembourg	0.32	0.42	0.26	0.24	0.37	0.39
United Kingdom	0.41	0.14	0.45	0.22	0.20	0.58

Figure 1: Mean Income by Educational Groups

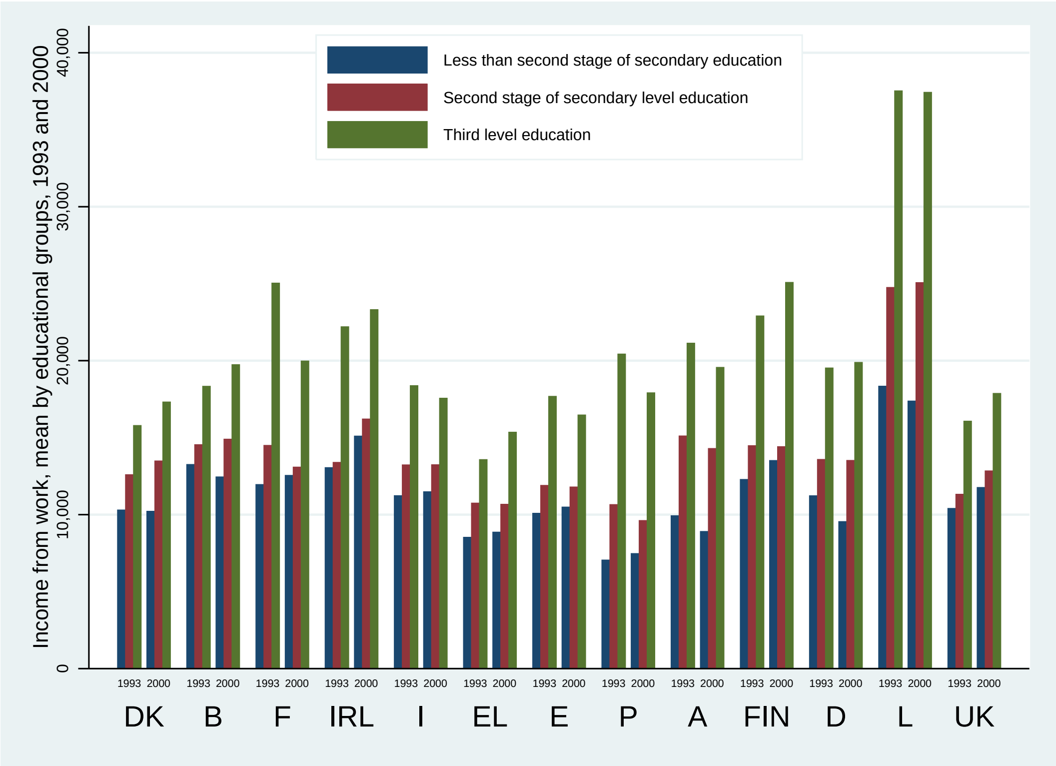


Table 3: Inequality decomposition by Education, between and within components

	Theil Index					
	total		*between*		*within*	
Country	1993	2000	1993	2000	1993	2000
Denmark	0.147	0.135	0.013	0.015	0.135	0.121
Belgium	0.172	0.266	0.009	0.016	0.163	0.249
France	0.309	0.233	0.045	0.025	0.264	0.209
Ireland	0.306	0.279	0.026	0.016	0.280	0.263
Italy	0.205	0.174	0.013	0.010	0.193	0.165
Greece	0.278	0.221	0.019	0.024	0.259	0.197
Spain	0.262	0.253	0.030	0.021	0.232	0.232
Portugal	0.284	0.239	0.063	0.056	0.220	0.183
Austria	0.222	0.185	0.019	0.018	0.202	0.167
Finland	0.241	0.255	0.035	0.040	0.206	0.215
Germany	0.193	0.215	0.019	0.029	0.174	0.186
Luxembourg	0.173	0.198	0.035	0.046	0.137	0.152
United Kingdom	0.242	0.245	0.021	0.018	0.221	0.227

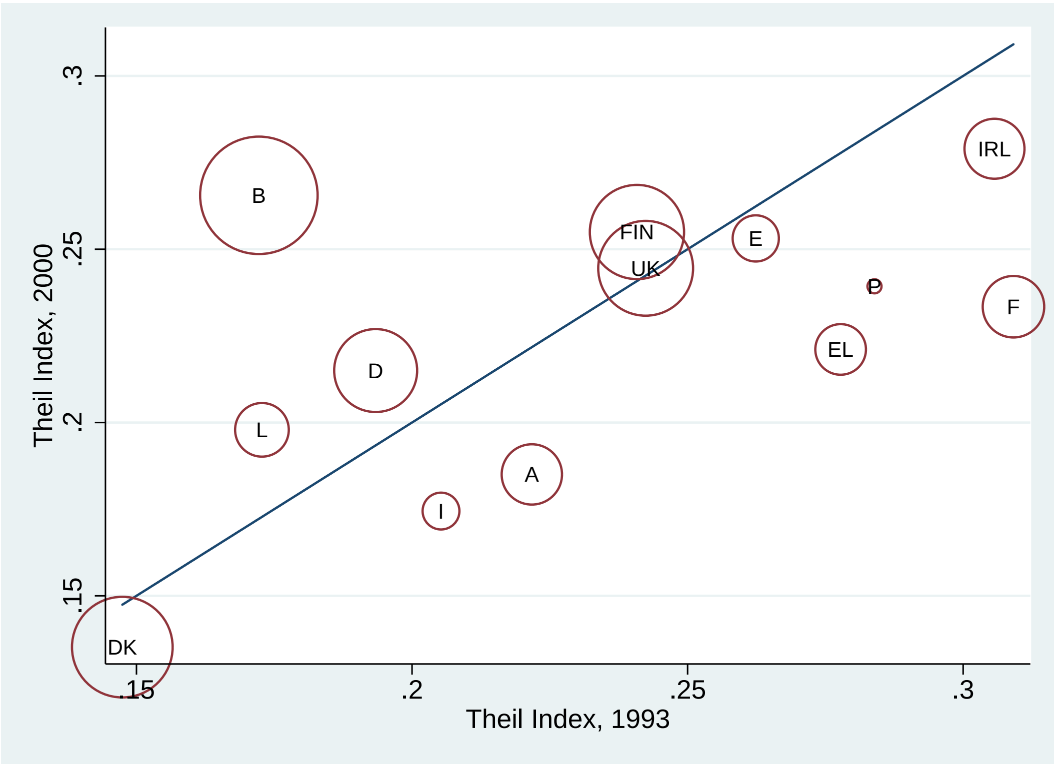
- low skilled workers mean income increased in France, Ireland, Italy, Greece, Spain, Portugal, Finland and United Kingdom, was stable in Denmark and decreased in Austria, Germany and Luxembourg.

Income inequality can be decomposed into the between-group and the within-group inequality components by the three educational groups, as it's shown in table 2 with respect to the Theil Index. Total inequality grew only for few Countries[13]: Belgium, Germany, Finland and Luxembourg. All of them were among the less unequal Countries in the sample at the starting year. Table 2 shows that education measured by the three broad levels explain only a negligible amount of total inequality, while differentials within each educational group play the major role. This is only a rough descriptive measure, where education is the only observable. Obviously, education should increase its role when accounted for other individual observables as age, sex, experience, tenure, occupation, industry and so on. Nevertheless, the link between higher inequality and education could be measured in several ways in order to get some different pictures (see figure 2, where the change in income inequality is related with the mean educational level of the Country, larger bubbles stand for higher mean educational level in the whole period).

What we need to better understand the role played by education in inequality patterns is to get not only a measure but a detailed range of

[13]It should be stressed that even if referred as Countries, samples here are not representative as summary measures at Country-level.

Figure 2: Change in Inequality and Educational level



Note: Circles are proportional to the mean educational level of the workers in the samples.

measures. In the next section, Quantile Regressions are used to consider the differences through incomes distribution in education premia between different groups of individuals.

3 Incomes and Education Premia through Quantile Regressions

3.1 Conditional Incomes by education and experience

The mean effect of education on income and inequality could be misleading. The changes in the shape of incomes distribution suggest to look for the differences between some points of such distribution[14]. Hence, the analysis is performed using quantile regression in some quantiles: estimation is performed at .10, .25, .50, .75 and .90 quantiles. Quantile regression model, also known as LAV model (Least Absolute Value), can be thought as a location model:

$$y_i = x_i'\beta_\theta + u_{\theta i}, \quad Q_\theta(y_i|x_i) = x_i'\hat{\beta}_\theta, \quad \theta \in (0,1) \tag{1}$$

with $Q_\theta(y_i|x_i)$ θ-quantile of y_i.

Quantile regressions allow for a detailed look to the premia structure, distinguishing the education impact on different segments of the labor market[15]. The income equation is:

$$\begin{aligned} Y_i = {} & \beta_0^\theta + \beta_1^\theta Edu_i + \beta_2^\theta Edu_i^2 + \beta_3^\theta Exp_i + \beta_4^\theta Exp_i^2 + \beta_5^\theta Ten_i + \\ & + \beta_6^\theta Ten_i^2 + \beta_7^\theta Edu_i * Exp_i + \beta_8^\theta Edu_i * Ten_i + \beta_9^\theta Edu_i * Sex_i + \\ & + \beta_{10}^\theta Exp_i * Sex_i + \beta_{11}^\theta Ten_i * Sex_i + \delta'^\theta D_i + u_i \end{aligned} \tag{2}$$

$$y_i = x_i'\beta^\theta + u_i^\theta, \tag{3}$$

$$Q_\theta(y_i|x_i) = x_i'b^\theta, \theta \in (0,1) \tag{4}$$

where: θ is the quantile, Edu means years of education and is measured as age in which the worker ended higher general education course *minus* starting education age, Exp means potential experience and is measured as age *minus* age in which the worker i ended higher general education course, Ten means tenure for the current job, D is a set of few controls for sex, industry[16] and occupation[17]. Age does not enter in the equation because of the collinearity, since it would be the sum of Edu and Exp variables.

The education premia structure has been easily measured from:

$$\frac{\delta Q_\theta(y|x)}{\delta Edu} = b_1^\theta + 2b_2^\theta Edu + b_7^\theta Exp + b_8^\theta Ten + b_9^\theta Sex \tag{5}$$

[14]See Lemieux (2007) for some evidence and explanations for the changes in inequality along the income distribution.

[15]See Koenker and Bassett (1978), Buchinsky (1998).

[16]The variable has three groups, agriculture, industry and services (variable PE007C in ECHP).

[17]Occupation is codified in nine levels (variable PE006C in ECHP).

Table 5: Conditional Quantiles, Results example

						Denmark 1993
QUANTILES	10Q	25Q	50Q	75Q	90Q	OLS
LS, Exp=0, Ten=0	3755.52	6144.85	8213.56	11132.63	12796.07	8802.87
	411.73	*346.86*	*279.95*	*263.47*	*431.02*	*471.68*
LS, Exp=15, Ten=0	8448.77	10972.45	14209.12	17803.15	21990.75	15364.88
	313.64	*180.03*	*342.89*	*249.58*	*506.92*	*388.45*
LS, Exp=15, Ten=10	12651.59	14269.66	16458.99	19151.63	22680.27	17148.22
	289.11	*192.60*	*188.62*	*352.17*	*402.13*	*256.06*
LS, Exp=30, Ten=10	13172.57	15115.93	17796.45	21604.09	26848.05	19226.94
	336.08	*235.46*	*241.75*	*305.51*	*549.45*	*375.22*
LS, Exp=30, Ten=20	8367.32	10223.54	12672.15	14049.78	18002.01	13857.39
	753.05	*733.84*	*875.67*	*880.98*	*1396.99*	*1292.60*
MS, Exp=0, Ten=0	5656.17	8673.10	11038.77	13926.22	15876.67	11148.71
	506.13	*364.23*	*312.65*	*452.37*	*557.77*	*502.91*
MS, Exp=15, Ten=0	9505.20	12692.02	16417.67	20722.73	25313.69	17579.23
	472.74	*263.79*	*468.78*	*470.11*	*779.57*	*470.59*
MS, Exp=15, Ten=10	13873.42	15622.72	18200.77	21295.32	25255.06	19113.93
	292.35	*204.60*	*238.07*	*458.40*	*554.35*	*349.44*
MS, Exp=30, Ten=10	13550.19	15660.33	18921.58	23873.77	29665.17	21061.16
	405.65	*364.94*	*412.17*	*598.62*	*856.06*	*612.42*
MS, Exp=30, Ten=20	8910.33	10401.43	13330.50	15543.57	20070.97	15442.98
	797.51	*735.40*	*785.33*	*963.27*	*1245.65*	*1479.49*
HS, Exp=0, Ten=0	7182.03	10844.40	13598.80	16663.77	19031.06	13221.57
	753.88	*427.09*	*429.22*	*819.28*	*1052.23*	*625.80*
HS, Exp=15, Ten=0	9975.80	13852.49	18206.88	23617.77	28770.99	19487.71
	841.99	*487.83*	*674.72*	*876.68*	*1393.40*	*714.33*
HS, Exp=15, Ten=10	14550.76	16325.05	19406.52	23220.50	27777.16	20711.64
	297.23	*217.08*	*409.16*	*616.39*	*984.87*	*521.63*
HS, Exp=30, Ten=10	13172.26	15351.83	19356.50	25956.44	32490.19	22494.49
	605.28	*616.45*	*733.64*	*1160.21*	*1483.57*	*1015.52*
HS, Exp=30, Ten=20	8739.16	9634.79	13181.96	16656.38	21960.80	16565.53
	870.58	*760.27*	*863.32*	*1197.17*	*1598.81*	*1798.43*

and an example of the results of such estimation are shown in table 5, with reference to the male workers.

As premia structure can add a degree of confusion given its derivative nature, conditional quantiles (CQ) have been plotted in figures 3-15[18]. Such figures are arranged in the way that each column refers to different educational level (from right: low, middle and high skills) while each row refers to different combinations of potential experience and job tenure, starting from the young unexperienced workers in top boxes and ending with high-tenure old workers in the bottom boxes. The red lines stand for the 2000 conditional quantiles, ending year of the period, while the black dashed ones stand for the initial year, different for some Countries (see section 2). The figures show also two points for the conditional OLS income.

Theories could suggest some general patterns in the figures, mainly with

[18]Similar figures with respect to the education premia can be sent by the author on request.

respect to the SBTC (see section 1)[19]:

- CQ should be increasing with education and over time for the SBTC hypothesis (in the figures: from the left to the right and from dashed to red lines);
- CQ should be increasing also with experience, given the major generality of the new technological paradigm which allows higher transferability of skills between jobs (in the figures: moving down along each column);
- incomes over time reflect at least economic growth and the changes in the supply of skills: while the former should rise the overall distribution no matter the group (differences in general between the dashed black and the red lines), the latter should impact negatively on the younger unskilled workers incomes (implying minor changes or negative ones over time for the top-left boxes[20]).

Moreover, going back to the inequality-education link, one should note that the differences explained by education can be thought as the differences between columns in the figures (between-group inequality), while flatter lines could be seen as lower unequal returns within each educational level (within-group inequality)[21].

Countries can be grouped on the similar patterns of incomes over time[22]:

a) In many Countries experience had an effective value in determining the changes over the 90s, with also upward shifts related to the older cohorts: this is the case of Denmark, Belgium, France, Italy, Greece, Spain, Germany and United Kingdom, while in Ireland it was true only for low-skilled workers and in Portugal only for low-paid workers (the lower tail of distribution). Note also that in Belgium also unexperienced workers entering the labor market had a real premium and that Austria and Ireland moved in the opposite direction with respect to experience.

b) Education explained part of the shifts in other Countries, where the changes in incomes were also related to more educated individuals: France, Greece, Portugal, Luxembourg, Belgium for the upper tail of distribution, Ireland and Finland for the younger workers. In these labour markets the

[19]Note that trade hypothesis should be tested in a different way, e.g. relating wage and trade openness by occupation and industry; institutional analyses focus on the impact on wages of changes in institutions.

[20]Young unskilled workers in the rich economies should pay for the increased competition from developing Countries and minor demand for unskilled jobs.

[21]A QR-based measure of between and within inequality components is shown in the next section.

[22]For other results on some European Countries in previous years see Pereira and Martins (2004); See Buchinsky (1994) for an application to US data, Lilla (2005) for an QR analysis of Italian labor market.

changes can be related to the SBTC, relative demand for high-skilled over-grew relative supply.

3.2 The case of Italy

This brief comment about Italy can also help to understand the figures on the other Countries. Figure 7 shows the QR estimates for Italy, a quite different evidence in the sample. As a first step, we can look at the role played by education through differences among the three columns of the figure. Supposing that younger worker should face the major impact of the new technologies, let us concentrate on the top boxes in the figure, i.e. the top two rows. Differences between skill groups did not significantly changed over the period: young unexperienced or little experienced workers in the 2000 had similar wage structure than at the beginning of the period, no matter the skill groups. There has been just a minor change in the shape of the wage structure, with a little increase for the less paid for all the skill groups, which made a flatter structure[23].

Moving towards workers with some tenure, consider the third and fourth rows of the figure. Even in this case there are negligible differences between columns, with a common slight diminishing trend for the whole wage structure. In this case, there have been minor changes to the wage structure and the most relevant ones concentrated on the last row of the panel, i.e. experienced high-tenure workers who gained more and no matter the skill group.

Summing up the Italian picture, while education does not relate to the wages changes in the period, experience and tenure can be called in support of the institutional theories: some workers received a major premium for their skills, experience and tenure, maybe for the institutional Italian framework that preserve more the insider than the outsider workers.

4 Residual inequality by quantile regression

The estimates from quantile regression can be used to construct a measure of the relevance of the model and, conversely, of the changing role of residual inequality over time.

Following Angrist et al (2004), let us define the Inter-Quantile Range as difference in conditional income between two points of income distribution: $IQR_{\theta_2,\theta_1}(Y \backslash X) = X'\beta^{\theta_2} - X'\beta^{\theta_1}$ [24]. Hence, we can define a measure of within-group (residual) inequality (RI) from the IQR:

[23] This evidence is independent from the skill group and is related to the new jobs (tenure in the top two rows is set equal to 0).

[24] Note that IQR should be 0 if there is no within inequality.

$$RI_{\theta_2,\theta_1} = Median(IQR_{\theta_2,\theta_1}(Y \backslash X)) = Median[X'(\beta^{\theta_2} - \beta^{\theta_1})] \quad (6)$$

Similarly, the conditional median of the IQR could be used to sum up the between-group inequalities:

$$BI_{\theta_2,\theta_1} = IQR_{\theta_2,\theta_1}(X'\beta^{0.5}) \quad (7)$$

Finally, a relative measure of the residual inequality can be defined as the Residual-to-Total Ratio (RTR):

$$RTR_{\theta_2,\theta_1} = \frac{RI^2_{\theta_2,\theta_1}}{RI^2_{\theta_2,\theta_1} + BI^2_{\theta_2,\theta_1}} \quad (8)$$

RTR is positive by construction and bounded between 0 (no within inequalities) and 1 (no between inequalities). Figure 16 shows some RTR, in particular with reference to the differences between the 90th and the 10th quantiles, the 90th and the 50th quantiles, the 50th and the 10th quantiles. The measures show that RTR was major when the upper tail is taken into consideration. While there is no general trend for the within and between absolute measures of inequality (RI and BI) across Countries over time, the relative weight of residual inequality increased over time for many Countries, with the major rise when to the bottom of the income distribution is considered.

5 Concluding Remarks

Education has been called to explain the pattern of income inequality over time and across different economies. As the relative income of skilled workers grew more than the supply of skill, it was argued that a skill-biased technological change was occurring, i.e. labour markets demanding more and more educated workers.

Many Countries experienced the increase in education premium in its mean level, but differences arise when we consider the whole income distribution and different groups of workers based on their sex, experience, tenure and so on. Education had a real value especially for the younger high-skilled workers in some Countries, while the change in technology was not-so-easy for the older cohorts, with increasing within-group differences. Experience in many Countries played an important role, determining major changes in conditional incomes. The role of the unobservables has been measured by quantile regression to complete the picture.

In this paper some evidence has been shown for thirteen European Countries, from the ECHP data. Analysing a period of quite stable or declining inequality, many Countries presented a more unequal premia structure. This is true especially for some segments of the labor markets. Policies aimed at targeting these workers and facilitate their adjustment should be encouraged.

Figure 3: DENMARK

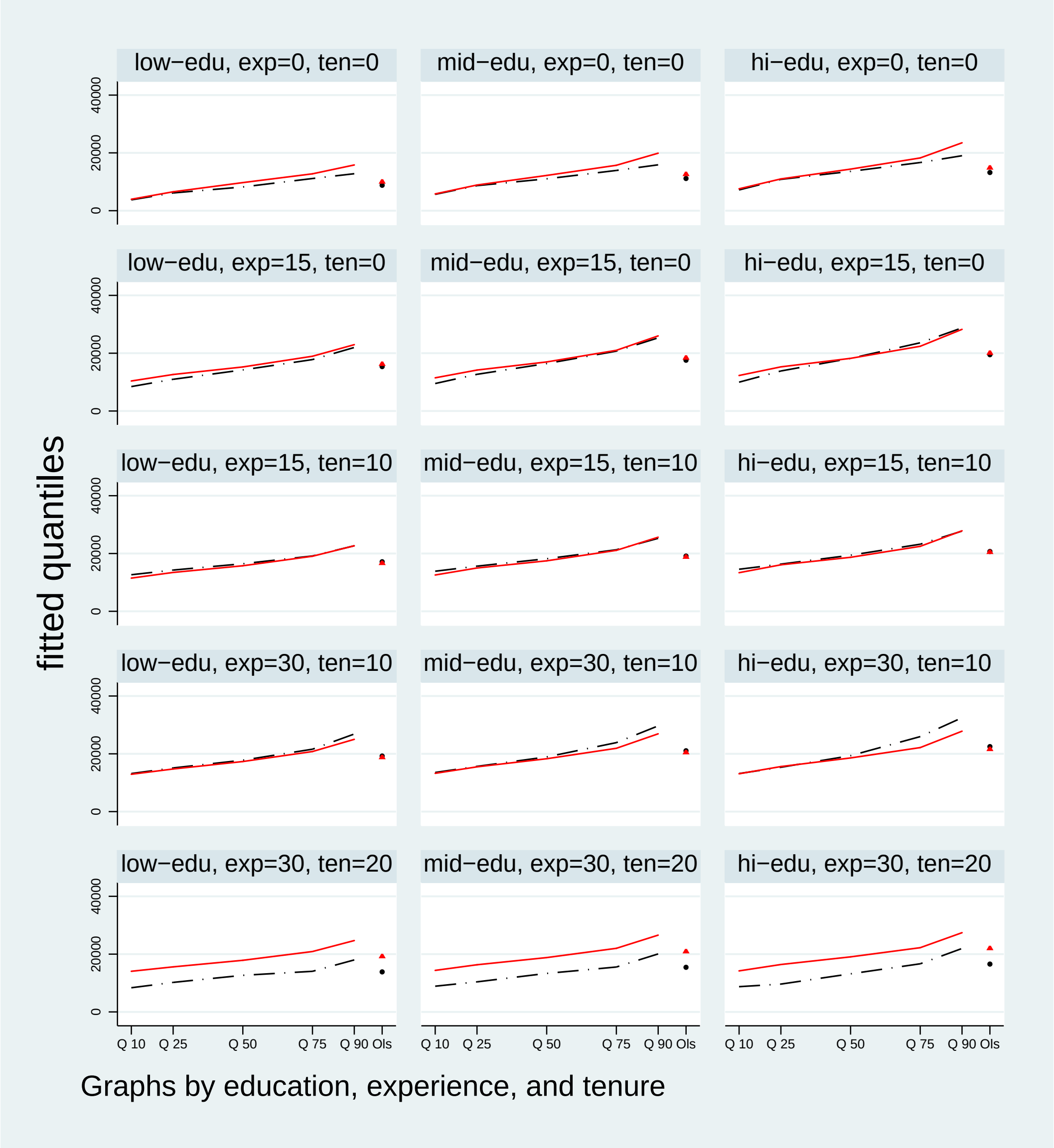
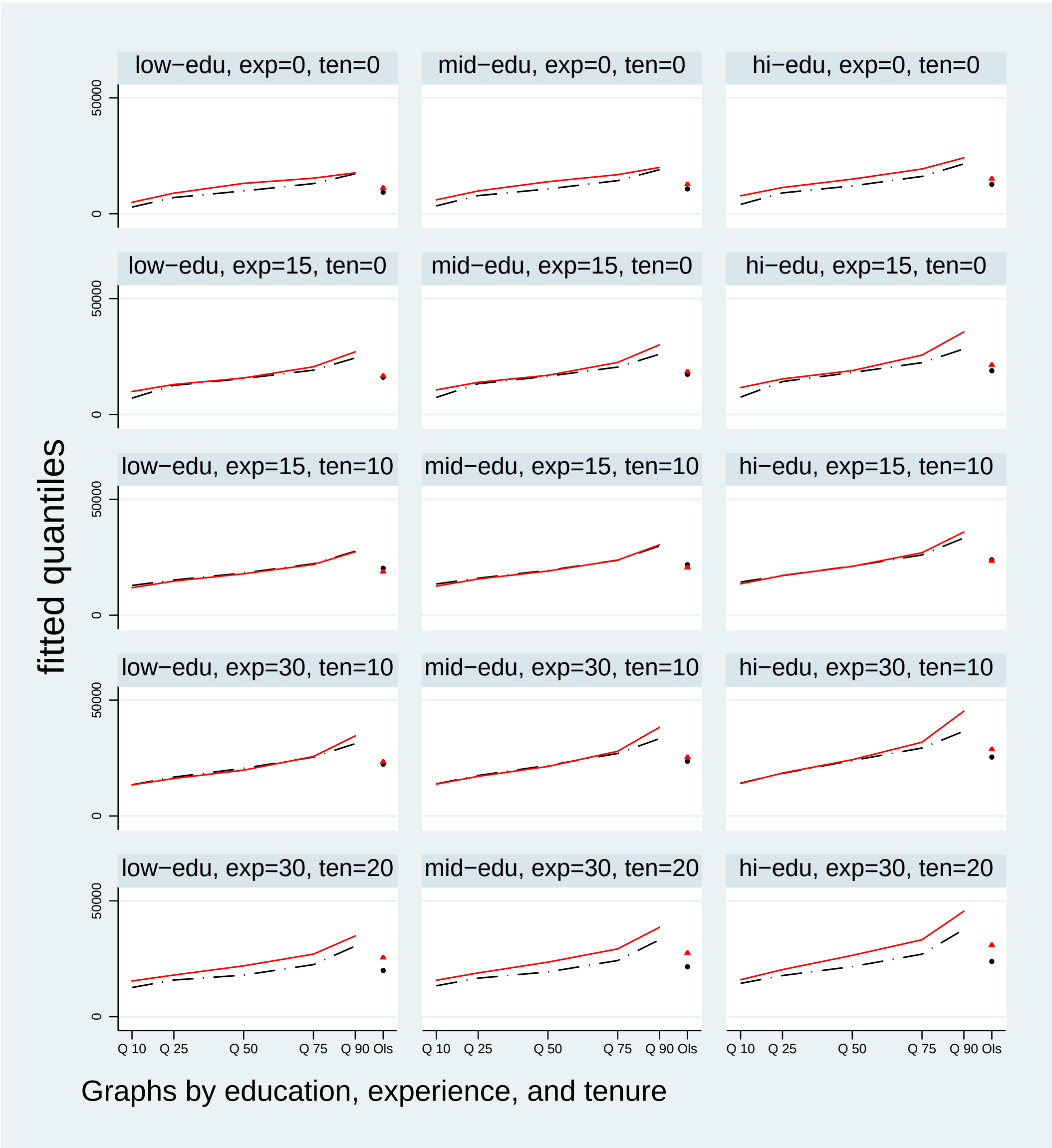
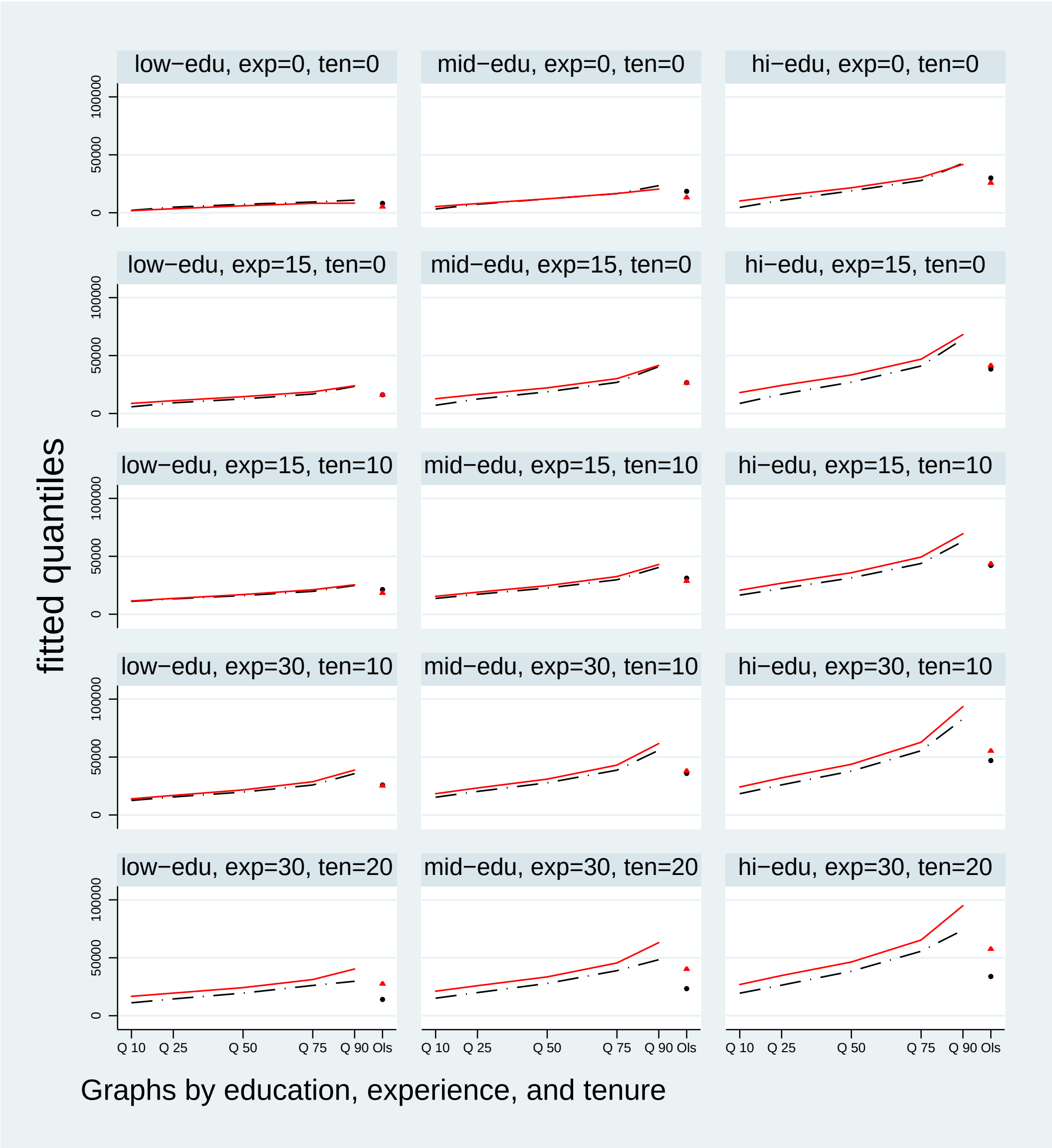


Figure 4: BELGIUM



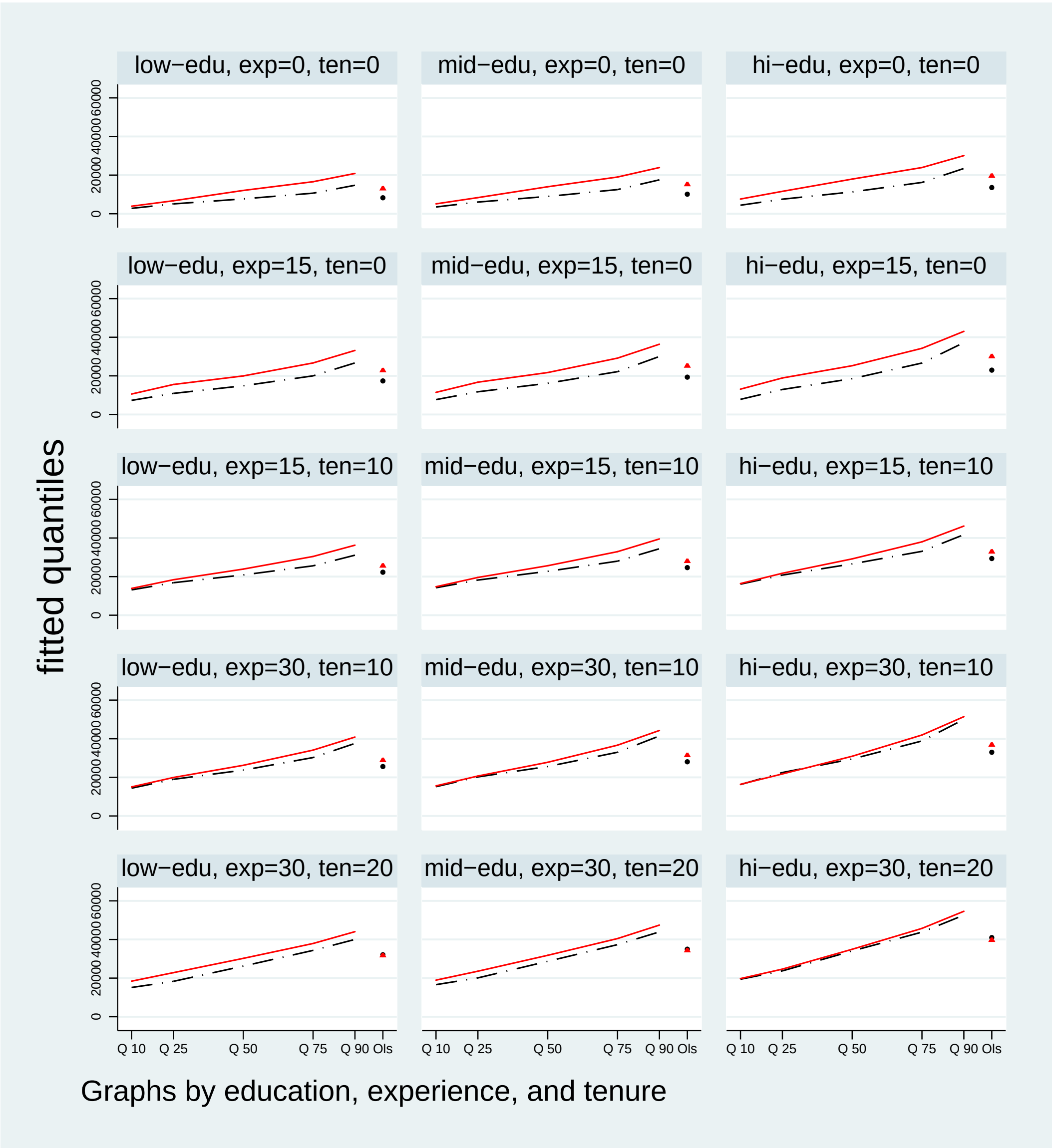
Source: ECHP

Figure 5: FRANCE



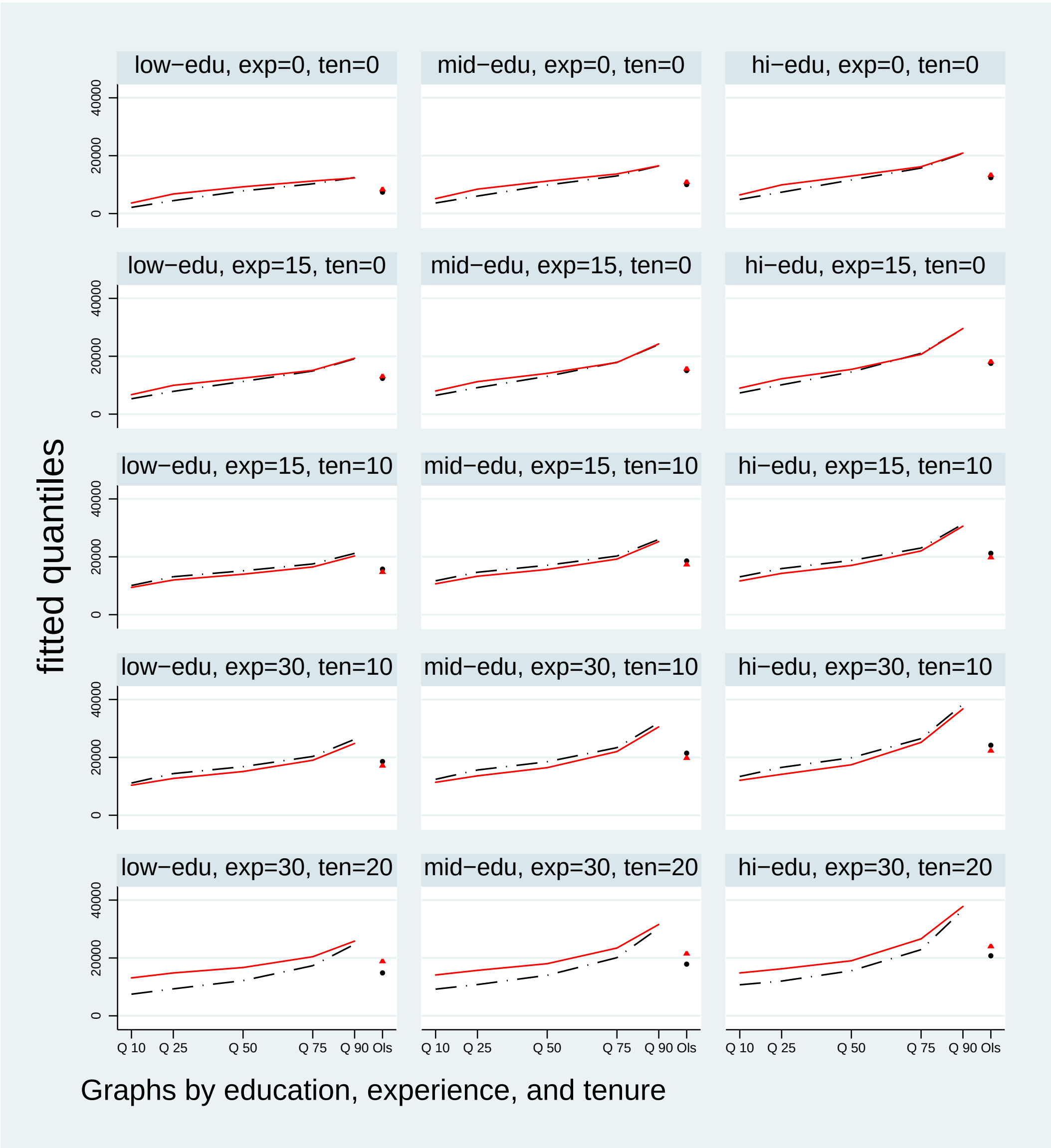
Source: ECHP

Figure 6: IRELAND



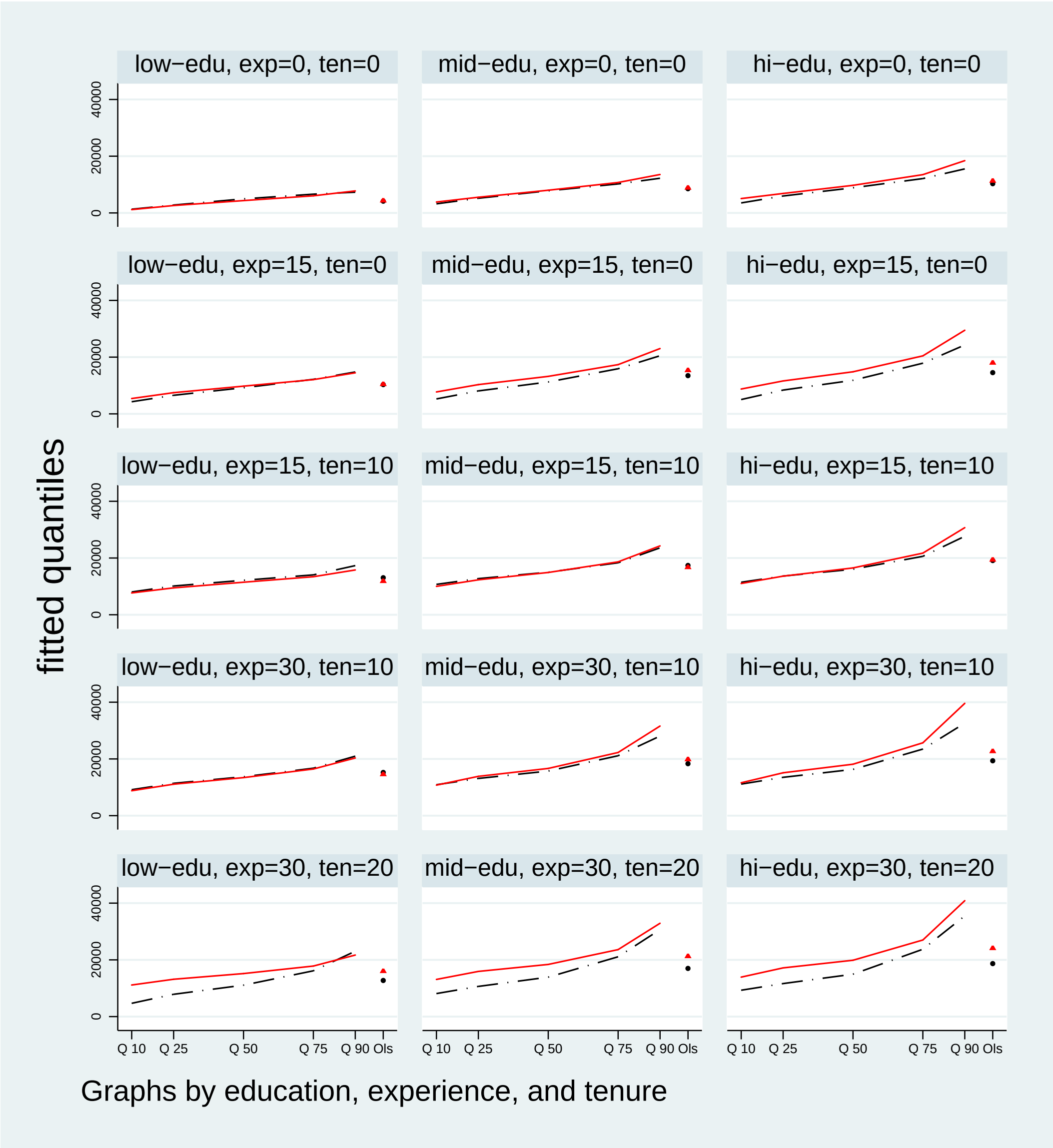
Source: ECHP

Figure 7: ITALY



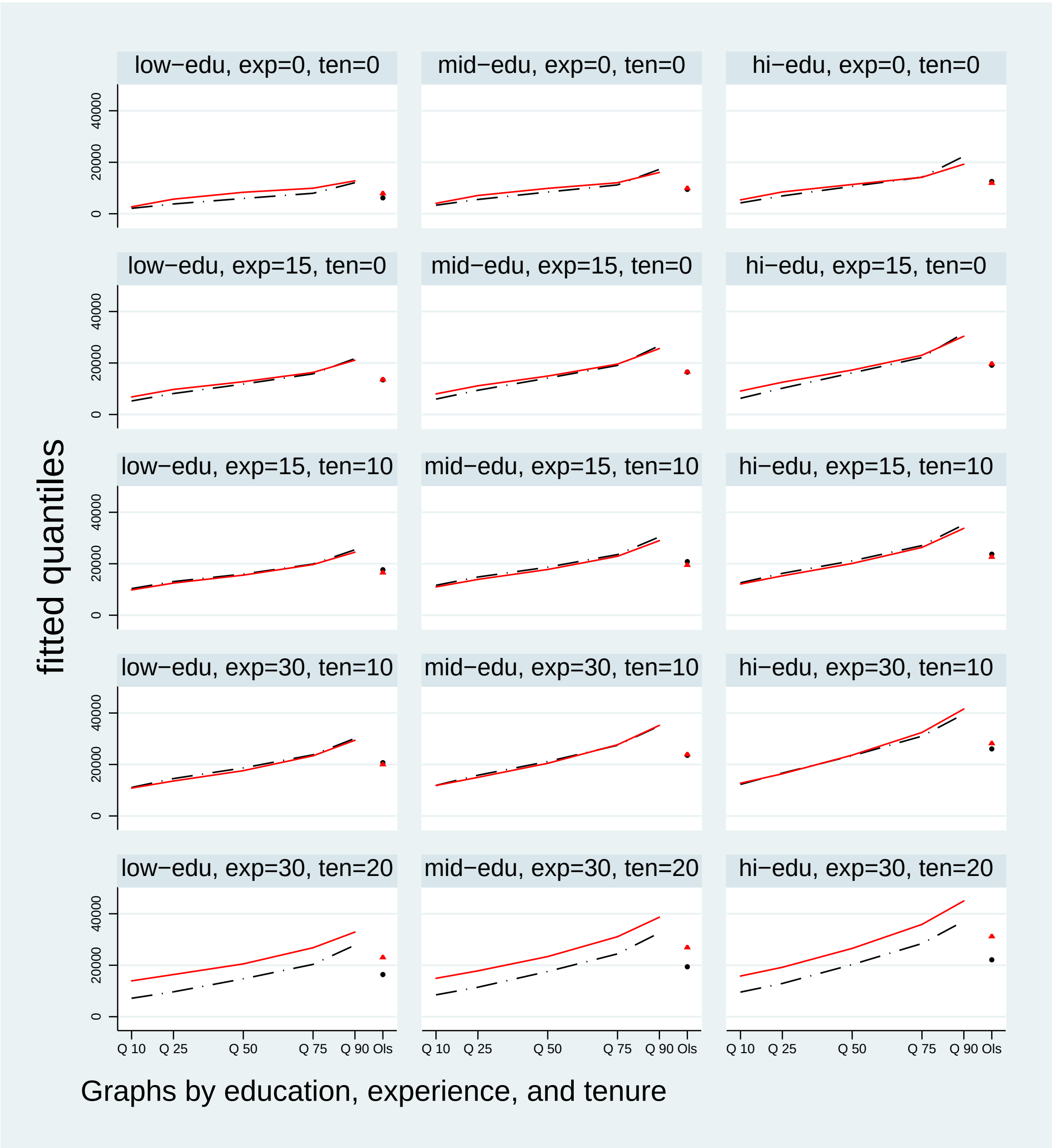
Source: ECHP

Figure 8: GREECE



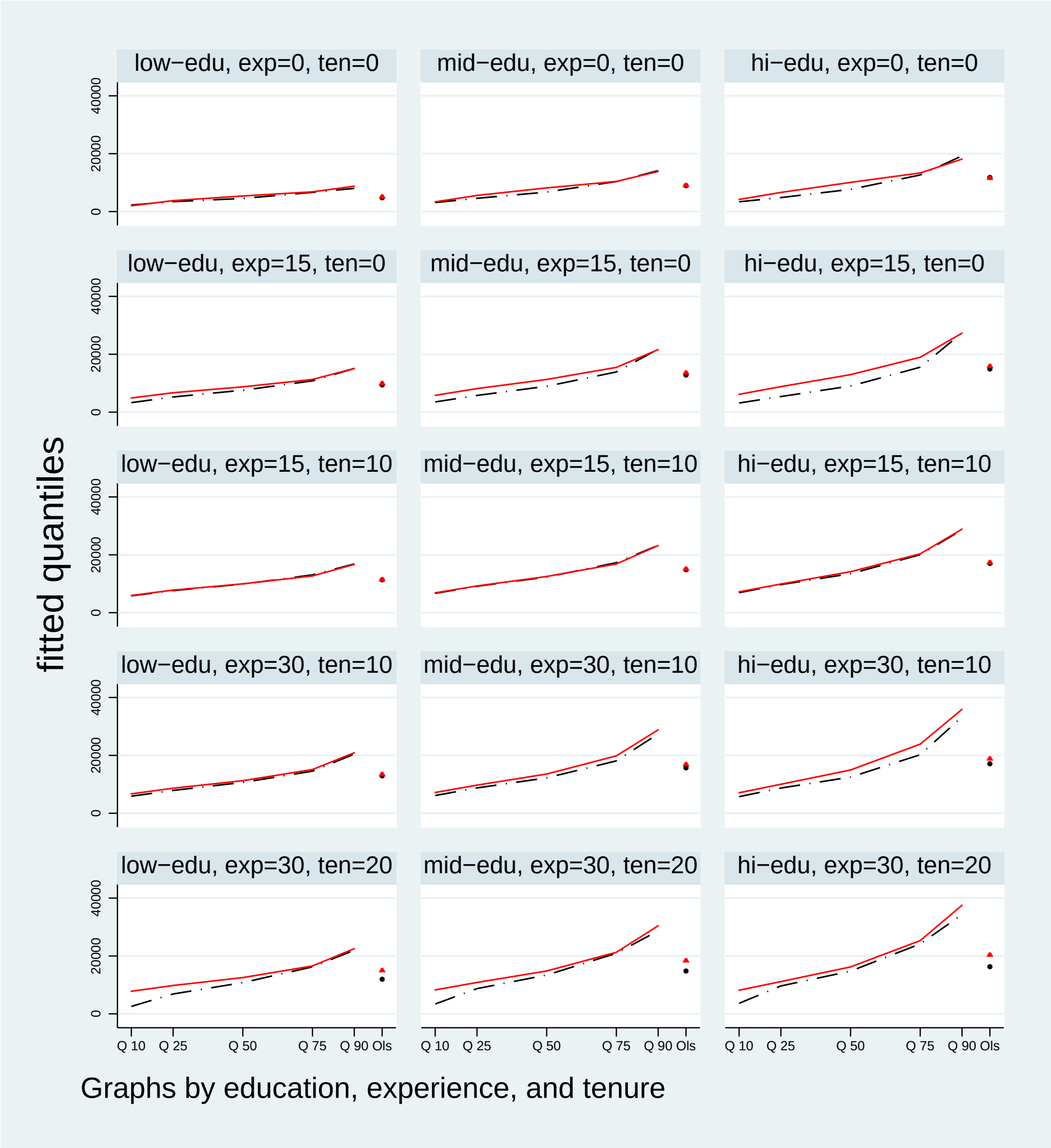
Source: ECHP

Figure 9: SPAIN



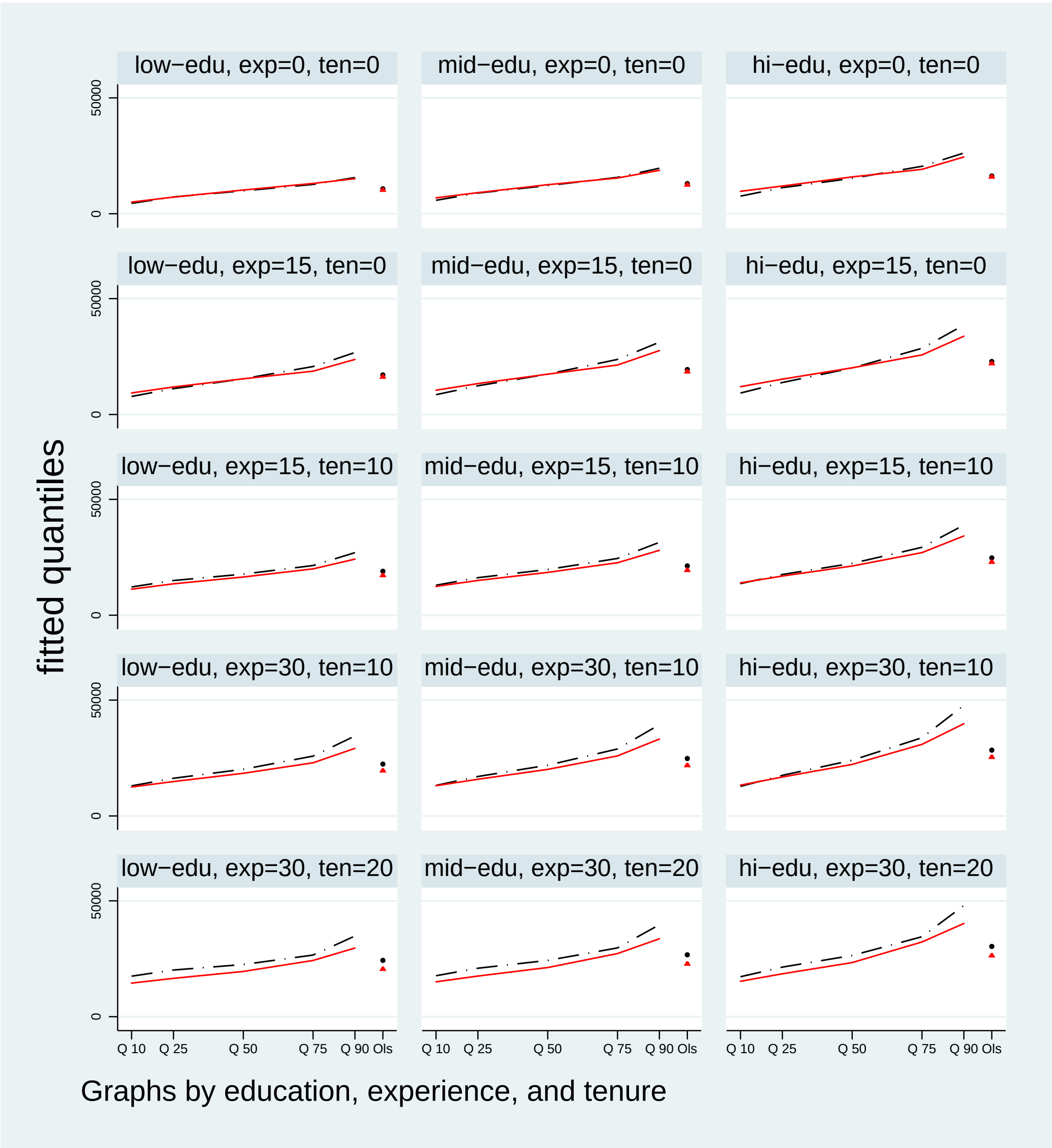
Source: ECHP

Figure 10: PORTUGAL



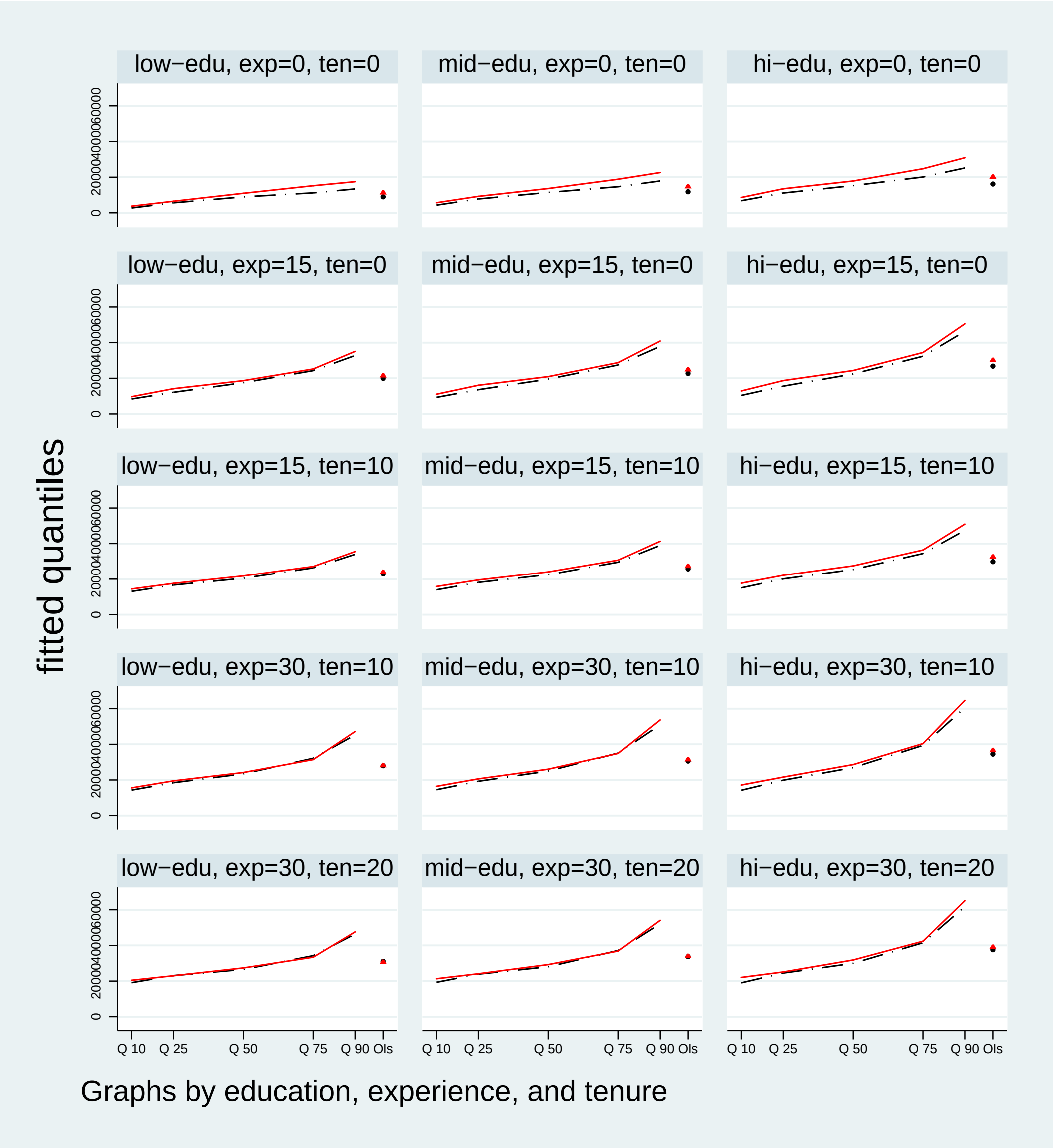
Source: ECHP

Figure 11: AUSTRIA



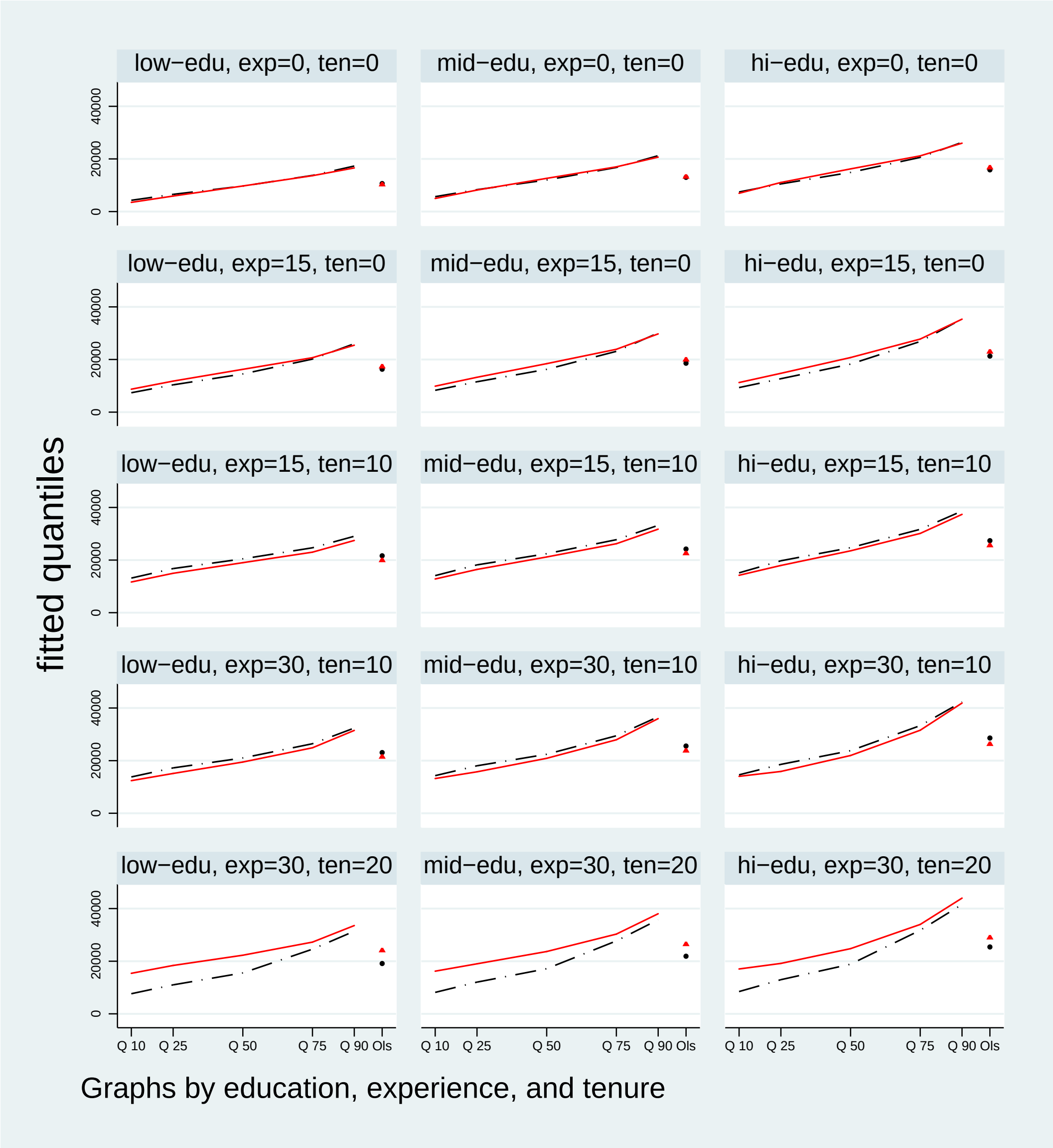
Source: ECHP

Figure 12: FINLAND



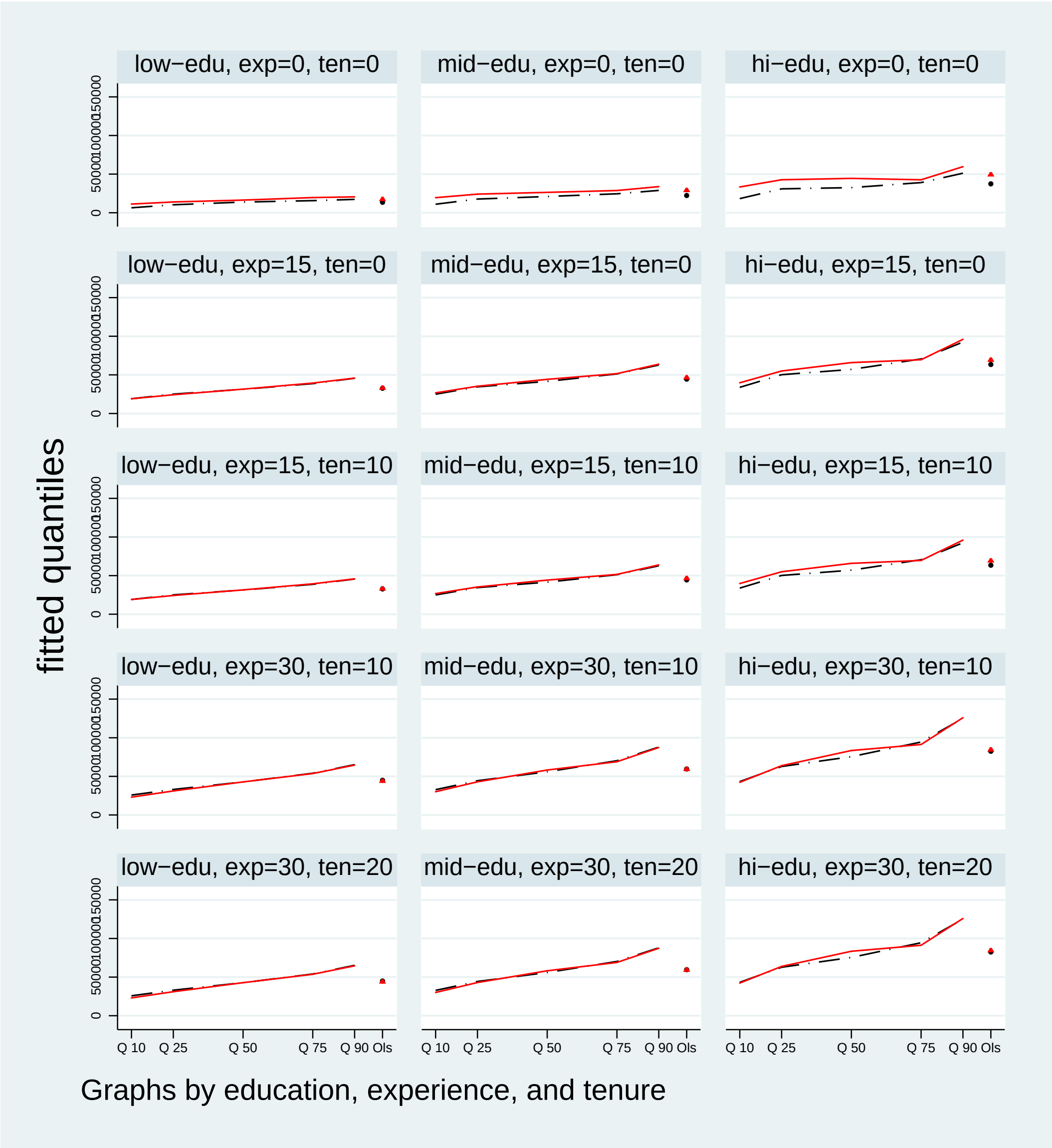
Source: ECHP

Figure 13: GERMANY



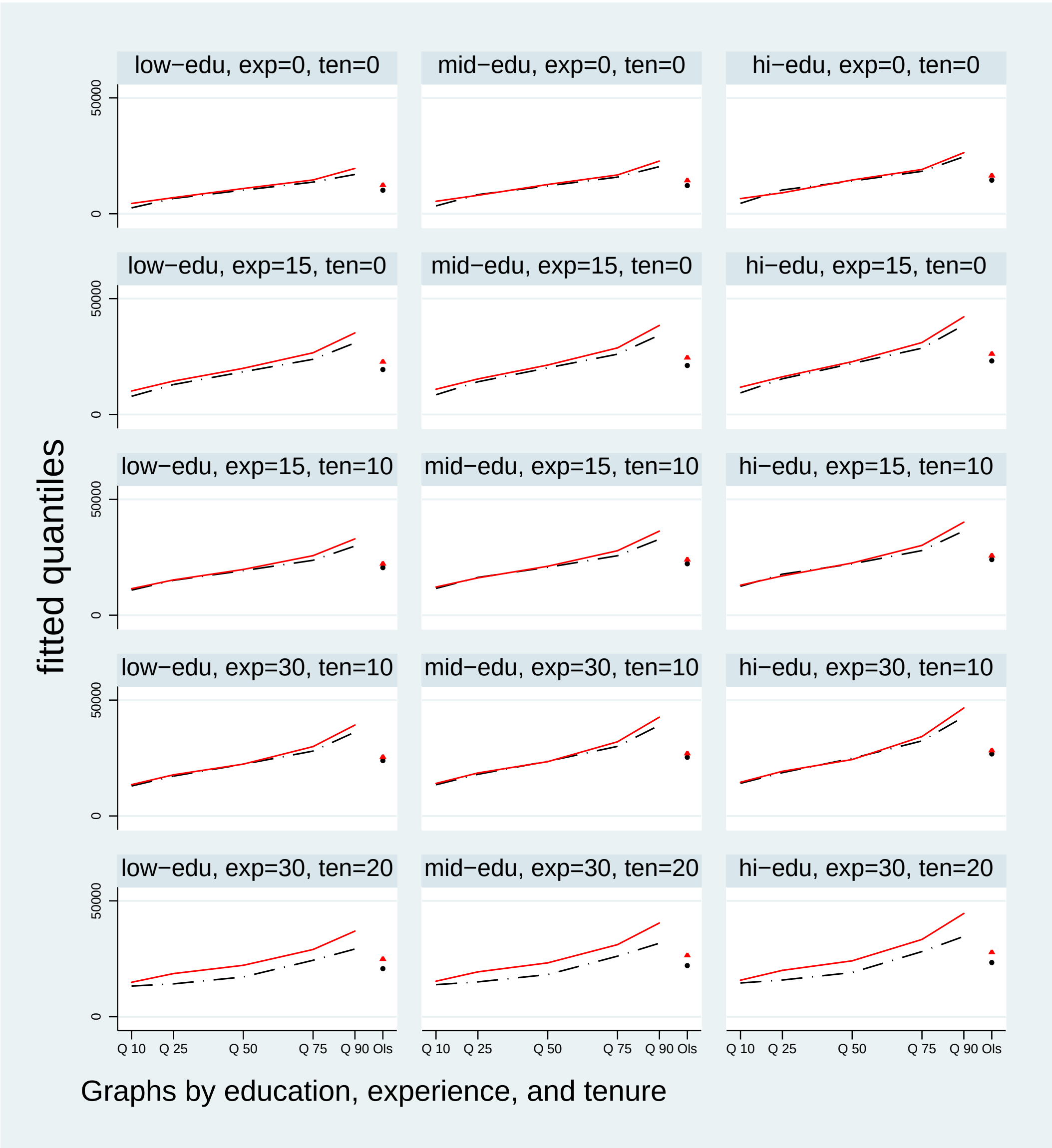
Source: ECHP

Figure 14: LUXEMBOURG



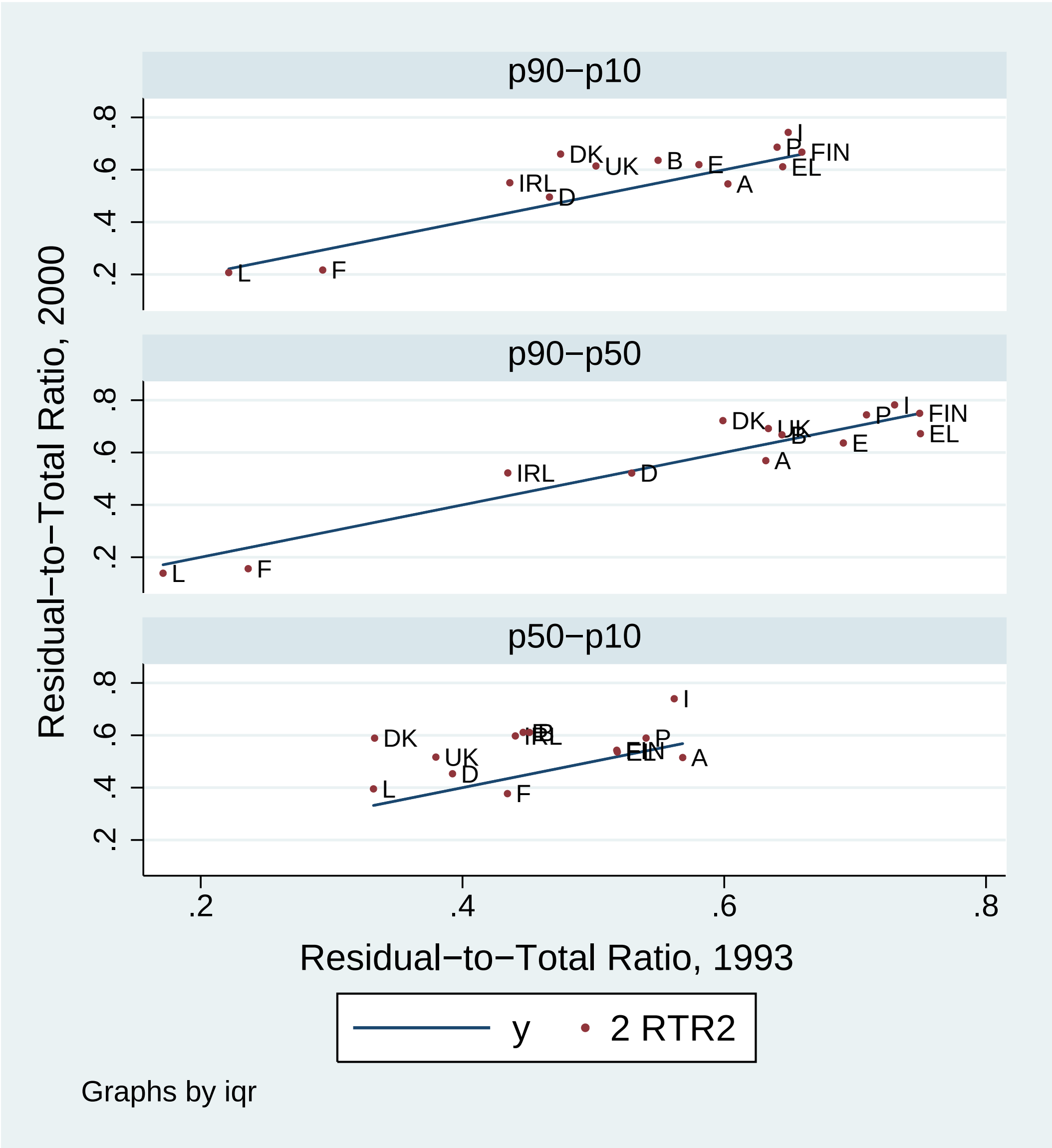
Source: ECHP

Figure 15: UNITED KINGDOM



Source: ECHP

Figure 16: QR-based Inequality Decomposition



Source: ECHP

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