THE DETERMINANTS OF EARNINGS INEQUALITY – EVIDENCE FROM QUANTILE REGRESSIONS

by
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Unconditional and conditional quantile regressions are used to explore the determinants of labour earnings at different parts of the distribution and, hence, the determinants of overall labour earnings inequality. The analysis combines several household surveys to provide comparable estimates for 32 countries. The empirical work suggests that, in general, a rise in the share of workers with an upper-secondary or post-secondary non-tertiary degree and a rise in the share of workers on permanent contracts are associated with a narrowing of the earnings distribution. By contrast, a shift in the sector composition of the economy is not found to have a large impact on overall earnings inequality. As for tertiary education, the impact remains ambiguous as there are several offsetting forces.

JEL classification codes: D31, C21, I24, J41, J45

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Although many countries have seen labour earnings inequality rise over the past decade, there are marked cross-country differences with respect to both the extent and timing of this increase. In addition, there are notable cross-country differences in the current level of earnings inequality. Since all OECD economies face the same global environment and have essentially benefited from the same technological advances, globalisation and skill-biased technological change should have led to broadly similar shifts in labour demand. Even though countries have differed with respect to supply shifts, a relative supply-demand shift story is unlikely to fully account for the marked cross-country differences in both the level and the evolution of labour earnings inequality. This hints at a possible role for differences in policy and institutional settings.

Against this background, this article aims at shedding further light on the factors that shape the distribution of labour earnings. Specifically, it tries to answer questions such as: How does the educational composition of the workforce influence the distribution of labour earnings? Does the sector composition of employment matter for the distribution of labour earnings? Do the share of fixed-term work contracts and the share of self-employment play a role in shaping the distribution of labour earnings? Since many of the factors that are found to be relevant for how labour earnings are distributed among the working population can be influenced by policy makers, the article also draws some tentative policy conclusions from the empirical results.

The analysis is carried out for a cross-section of 32 countries using household survey data. As far as possible, the analysis is based on comparable individual data for this wide set of countries, providing a unique country-by-country assessment of the drivers of earnings inequality. The empirical analysis mainly makes use of the unconditional quantile regression technique proposed by Firpo *et al.* (2009). This method allows estimating the effect of the potential determinants on all parts of the earnings distribution and is thus better suited to answer questions about the drivers of earnings inequality than standard least squares techniques that only allow estimating effects on mean earnings. The unconditional quantile regressions are complemented by conditional quantile regressions (Koenker and Basset, 1978). While this technique has been widely used in empirical applications—in contrast to the unconditional quantile regression technique which is still fairly new—it does not allow drawing conclusions about the impact of a variable on overall earnings inequality but rather provides insights about the dispersion of earnings within different subgroups of the population. To complete the analysis, the unconditional quantile regression results are used to decompose cross-country differences in the level of earnings inequality into differences in population characteristics (*e.g.* education) and differences in the returns to these characteristics (*e.g.* returns to education). This decomposition helps to get a better understanding of cross-country differences in earnings inequality.

This article is structured as follows. Section 1 presents the empirical methodology, focusing on the specification of the earnings equation, the estimation and interpretation of conditional and unconditional quantile regressions and the methods used to decompose differences in earnings inequality across countries. Section 2 briefly discusses the benefits and drawbacks of the dataset that is employed in the empirical analysis before presenting the estimation results.[1] The article is complemented by an annex which provides further details on the dataset and the empirical results.

1. The empirical methodology

1.1. The earnings equation

The empirical analysis makes use of household survey data for 32 countries.[2] It relates individual gross labour earnings to personal and employer characteristics, focusing on individuals aged between 15 and 64 who work either part-time or full-time and have positive labour earnings during the reference year.[3,4] The choice of explanatory variables is inspired by the seminal work of Mincer (1958, 1974), who developed a parsimonious model of labour earnings, first using only schooling and later also age and working time as explanatory factors. Mincer-type earnings functions have since been estimated by a large number of studies, including, among others, Fortin (2006), Heckman *et al.* (2006) and Firpo *et al.* (2009) in more recent years. Numerous supplementary variables have since been added to earnings functions, including gender, ethnicity and union membership, among others (*e.g.* Polachek, 2007). Following this literature and keeping the model simple to ensure comparability across countries, this article starts by estimating a baseline model which relates the logarithm of an individual's gross monthly labour earnings to the logarithm of working hours, gender, age and age squared, and the highest education level attained. The level of education is captured by two dummy variables, the first one being equal to one for individuals who have *at least* finished upper-secondary education, and the second one being equal to one for individuals who have finished tertiary education.[5] While this measure is rather simple, it is the only measure that is available for all countries covered in the study.[6] Hence, the coefficient on the first dummy variable gives the impact of an upper-secondary or post-secondary non-tertiary education relative to lower-secondary education or less, and the coefficient on the second dummy variable gives the impact of tertiary education relative to upper-secondary or post-secondary non-tertiary education.[7]

Several additional drivers of labour earnings are of interest but are excluded from the baseline because they exist only for a subset of countries and/or cause potential endogeneity bias.[8] These are dummy variables for the sector of employment and the occupation, the number of years of work experience, the number of years of education, and dummy variables for having a temporary as opposed to a permanent work contract, for being self-employed, for having foreign citizenship, for being born in a foreign country, and for having a PhD. These variables are added on top of the baseline in a number of alternative specifications, the details of which are set out in Section 2.

1.2. Going beyond mean effects with quantile regressions

The impact on earnings of the variables listed above is likely to differ across individuals. For example, a tertiary degree may be more valuable for high-income workers as their jobs require such an education, whereas it goes beyond the needs of most jobs of low-income workers (*e.g.* Hartog *et al.*, 2001). Standard OLS techniques ignore this heterogeneity and only provide an estimate of the mean effect of a given variable. As this would severely weaken the analysis (Koenker and Bassett, 1978), this article makes use of two alternative techniques that allow estimating the impact of explanatory variables on different parts of the earnings distribution (nonetheless simple OLS results are also shown for the sake of comparison). These are the conditional quantile regression (hereafter CQR) technique proposed by Koenker and Bassett (1978) and the unconditional quantile regression (hereafter UQR) technique proposed by Firpo *et al.* (2007a, 2009). While the former has been widely used in the literature, the latter is fairly new and applications are thus still scarce. In general, the estimation of the effects of a given set of variables on the distribution of another variable is still an active area of research and no preferred method has yet emerged from the literature. The choice made here of the methodology by Firpo *et al.* (2007a, 2009) over alternative techniques such as the non-parametric approach proposed by Rothe (2010) is mainly motivated by its ease of computation.

Conditional quantile regressions focus on the conditional quantile of an individual, which is his/her position in a virtual distribution in which all individuals are assumed to have the same observed characteristics. For example, if individuals differ only with respect to their education level, the conditional quantile of a low-educated person would be his/her earnings quantile among all low-educated individuals, whereas the conditional quantile of a highly-educated person would be his/her earnings quantile among all highly-educated persons. Unconditional quantile regressions, by contrast, focus on the unconditional quantile of an individual, which is his/her earnings quantile in the overall earnings distribution, abstracting from (*i.e.* not controlling for) observed and unobserved characteristics. In the example above, the unconditional quantiles of the two individuals with respectively low and high education would be their earnings quantiles among all individuals in the population.

Given the different focus of the two approaches, the types of questions they can answer differ. Conditional quantile regressions—which have often been simply referred to as “quantile regressions”—provide an estimate of the return to a certain characteristic (such as having a tertiary degree), where the return varies across individuals based on the conditional quantile into which they fall (Koenker and Hallock, 2001). The method can thus be used to answer questions such as: what is the impact on an individual’s earnings of increasing the education level by one year, holding everything else constant? The technique assumes in particular, that the conditional quantile of an individual remains the same when his/her characteristics change. Since this assumption may well not hold in practice, the results of conditional quantile regressions must be interpreted with caution (Koenker, 2005). Unconditional quantile regressions, by contrast, allow estimating the effect of a small change in workers’ characteristics on each quantile of the *overall* distribution. They thus provide answers to questions such as: what is the impact on median earnings (or the earning of any particular quantile) of increasing everybody’s education by one year, holding everything else constant?[9,10]

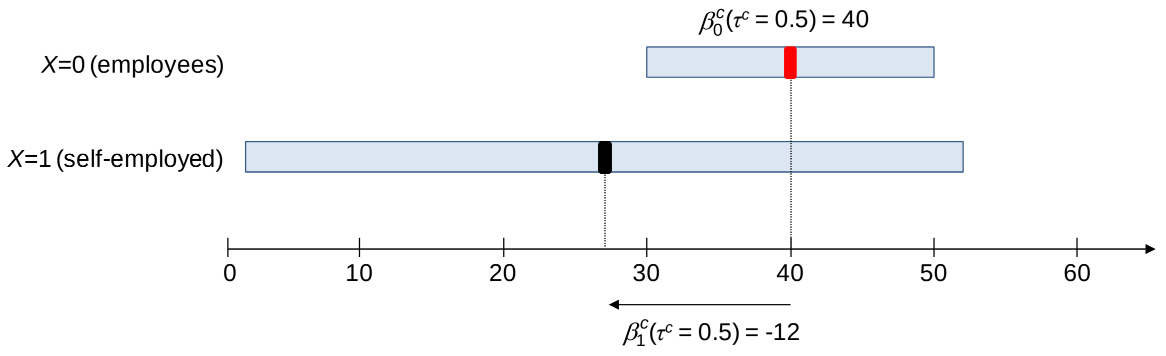
Since the unconditional quantile of an individual is simply the share of individuals in the sample population whose earnings are lower than the earnings of the individual of interest, the results of UQRs are easier to interpret than those of CQRs. Since UQRs allow assessing the impact of a particular variable on *overall* earnings inequality, they are also more suitable than CQRs in the context of this article and are thus used as the baseline method. CQRs are computed for two purposes. First, this widely used method remains a robustness check *if* the unconditional quantile is likely to remain quite close to the quantile conditional on the variable of interest. Many results are indeed relatively similar with these two methods. Second, it provides insights about the comparison of the dispersion of earnings within different groups, which helps to understand the mechanisms at work. Further details on how to interpret conditional and unconditional quantile regressions are provided in Box 1.

Box 1. **How to interpret the results of conditional and unconditional quantile regressions**

To illustrate the interpretation of conditional and unconditional quantile regressions, assume that there are only two explanatory variables, a constant and a dummy variable *X*, which takes value one if an individual is self-employed and zero otherwise. Assume further that earnings are higher on average and less dispersed among employees. In Figures 1 and 2 below, the grey rectangles show the distribution of earnings in the two sectors, with the length of the rectangles indicating the range of earnings and their thickness – assumed here to be the same across the whole distribution for simplicity – indicating the number of persons with a certain earnings level.

The coefficient $\beta_1^c(\tau^c)$ on the union membership dummy obtained from a *conditional quantile regression* gives the change in earnings associated with becoming self-employed, assuming that the position of the individual among all individuals with the same characteristics does not change. For example, if the individual had the median earnings among all employees before the job change (τ^c = 0.5), he will have the median earnings among self-employed after the job change, so that his earnings rise by 12 units in Figure 1. The constant β_0^c (τ^c) obtained from a CQR gives the quantile of the individual among the subsample of individuals with a 0-value for the dummy variable, *i.e.* among all employees, which here is 40 for the median.

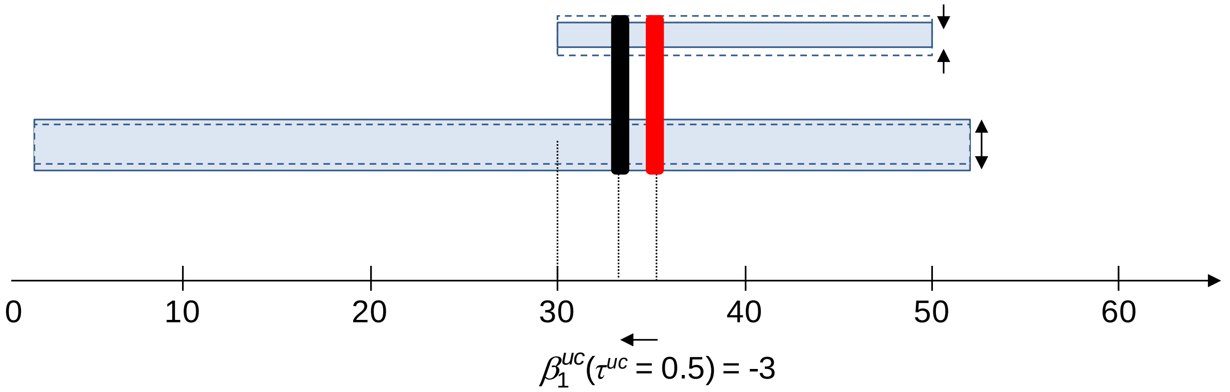
Figure 1. **Interpreting conditional quantile regressions**



The CQR results can also be used to draw conclusions about the dispersion of earnings within certain subgroups of individuals. In the example above, the coefficient of the dummy variable increases along the earnings distribution. This reflects that earnings are more dispersed among self-employed than among employees.[1] While conclusions about the dispersion of earnings among certain subgroups of workers could also be derived from simple summary statistics such as the variance, CQRs have the advantage that they can control for other determinants of earnings.

The coefficient $\beta_1^{uc}(\tau^{uc})$ on the self-employment dummy obtained from an *unconditional quantile regression* gives the change in a certain earnings quantile of the observed distribution – say, the median – associated with an increase in the share of self-employed by 1 percentage point. As shown in Figure 2, the size of the two groups is affected by such a change with the group of self-employed increasing and the group of employees shrinking in size.[2] As there are now more individuals in the economy that earn the lower earnings of self-employed, the median earnings of the entire population decrease. In the example shown in Figure 2, median earnings decrease by 3, from 36 to 33. The constant cannot easily be interpreted in the case of UQRs and is therefore not shown in the figure.

Figure 2. **Interpreting unconditional quantile regressions**



1. This is strictly true when there are no control variables. As soon as control variables are added (*e.g.* a dummy variable that takes value one if an individual is highly educated and value zero otherwise) the interpretation is slightly different. Let's assume for the sake of demonstration that earnings depend not only on self-employement and education dummies, but also on an unobserved determinant. If the coefficient on the self-employment dummy increases along the earnings distribution, this solely reflects that the dispersion that is due to the unobserved determinant is higher among self-employed since the impact of education is picked up by the education dummy.
2. In the CQR example, the size of the two sectors was hardly affected as only one person was assumed to change employment status.

Both conditional and unconditional quantile regressions are estimated by breaking up the [0,1] interval of quantiles into 10 intervals of equal length so as to be able to simultaneously estimate nine quantile regressions for the quantiles 0.1 to 0.9. As a result, for each year and country, the estimation procedures do not yield a single coefficient for each variable of interest, but nine different coefficients, one for each conditional or unconditional quantile in the range 0.1 to 0.9.[11] In the estimation each observation is weighted by the sampling weight of the individual to correct for imperfections in the representativeness of the sample.[12] The standard errors around the estimated parameter values are obtained using a bootstrap procedure with 200 replications in the case of UQRs, whereas for CQRs an analytical solution exists and is used.[13] The homogeneity hypothesis is rejected in most cases for both CQRs and UQRs, confirming the need to go beyond the mean and the usefulness of quantile regressions.

1.3. Decomposing labour earnings inequality

Earnings differences between two individuals can have two main sources: *i*) differences in personal characteristics such as the level of education and *ii*) differences in the returns to these characteristics. Similarly, cross-country differences in earnings inequality can be decomposed into: *i*) differences in the *composition* of the population (for example, inequality should be higher in countries with a more unequal distribution of education endowment) and *ii*) differences in *rates of return* (for example, inequality should be higher in countries with a larger wage gap between highly- and low-educated workers).

Several methods have been developed to decompose cross-country differences in inequality which go beyond the decomposition of mean effects proposed by Oaxaca (1973) and Blinder (1973) (for a recent survey, see Fortin *et al.*, 2011). This article adopts a methodology that is close to the one proposed by Firpo *et al.* (2007*b*) and builds on the UQRs discussed above.[14] The United States is used as the reference country so that each country's level of earnings inequality is compared with the level of inequality in the United States.[15]

An important choice is the measure of earnings inequality to be decomposed. Many studies use the Gini index of the logarithm of earnings because their underlying models consider the logarithm of earnings as the dependent variable. A major drawback of this measure is that the scale independence assumption does not hold, meaning that the value of the measure changes when all earnings are multiplied by a certain scale factor. In addition, by putting less weight on the upper part of the earnings distribution, the Gini index of the logarithm of earnings may yield a country ranking that differs from that of the Gini index. The logarithm of the 90/10 percentile ratio does not have these two weaknesses and is therefore preferred in this article. The main limitation of this measure is that it only builds on the estimated effect of explanatory variables at the 10th and 90th percentiles, and leaves aside effects on the middle class.

For each explanatory variable *k*, the composition effect $C_k^{90/10}$ relies on a comparison of the estimated effects in the two countries (*i.e.* the United States and the country of interest *i*) at the 10th percentile and the estimated impact at the 90th percentile. If the rise of, say, the proportion of tertiary-educated workers from the US level to the level observed in country *i* is relatively small, the effect can be linearized. To get the effect on the 90/10 percentile ratio, the variation of the 90th percentile, *i.e.* $(E(X_{k,i}) - E(X_{k,USA}))\beta_{k,i}^{90}$, is compared with that of the 10th percentile, *i.e.* $(E(X_{k,i}) - E(X_{k,USA}))\beta_{k,i}^{10}$:

$$C_k^{90/10} = (E(X_{k,i}) - E(X_{k,USA}))\left(\beta_{k,i}^{90} - \beta_{k,i}^{10}\right) \qquad (1)$$

where $\beta_{k,i}^{90}$ ($\beta_{k,i}^{10}$) is the coefficient estimate on the variable k at the 90th (10th) unconditional quantile for the country of interest i (the country to be compared with the United States) and $E(X_{k,i})$ is the expectation of the variable X_k conditioned on the fact that the worker belongs to country i (proxied here by the empirical mean within the country).[16]

The rate-of-return effect $R_k^{90/10}$ for variable k is computed by running two separate UQRs—one on the United States and another on the country of interest—and then comparing the coefficients at the 10th and 90th percentiles obtained from the two regressions:

$$R_k^{90/10} = E(X_{k,USA})\left[\left(\beta_{k,i}^{90} - \beta_{k,i}^{10}\right) - \left(\beta_{k,USA}^{90} - \beta_{k,USA}^{10}\right)\right] \tag{2}$$

This rate-of-return effect can also be regarded as the difference between the rate-of-return effect for high-income earners $E(X_{k,USA})\left(\beta_{k,i}^{90} - \beta_{k,USA}^{90}\right)$ and the rate-of-return effect for low-income earners $E(X_{k,USA})\left(\beta_{k,i}^{10} - \beta_{k,USA}^{10}\right)$. The method yields more accurate results for the size of the composition effects than for the size of the rate-of-return effects. In fact, the composition effects strongly rely on differences between the means of the explanatory variables which are known with relatively high precision. By contrast, the rate-of-return effects strongly rely on differences between the estimated rates of return which are intrinsically less accurate. For this reason, solely qualitative conclusions are drawn below regarding the rate-of-return effects.

2. Empirical results: labour earnings inequality and its main determinants

2.1. Benefits and drawbacks of household survey data

Household surveys provide a unique source to investigate the determinants of earnings inequality. They allow exploiting information on individual workers, thus involving substantially more variation in the data than aggregate cross-country information. Moreover, they contain specific information on the linkages between earnings and various personal characteristics that cannot be inferred from aggregate data. Compared with administrative data, survey data have the advantage that individuals' answers to survey questions about earnings should pick up all types of labour earnings that are of interest to this study, whereas data from administrative sources often omit some categories such as non-taxable earnings (in the case of fiscal data), or earnings from additional jobs (in the case of firms' compulsory statements on wages and benefits). Moreover, the household surveys used in this study are designed to cover a representative sample of the whole population, while administrative sources may ignore some sub-samples of the population such as non-taxable workers.

However, the use of household survey data also entails a number of drawbacks that need to be kept in mind when interpreting the results. First, although the surveys are designed to ensure that the sample population is representative of the entire population in terms of its major characteristics, this is not fully the case for some population characteristics that are of particular importance for the present study (such as the share of temporary workers, for example). Second, the number of non-responses can be substantial, not only for the dependent variable but also for some of the explanatory variables (in particular information on the sector of employment or the type of work contract is missing for a larger number of individuals). The analysis assumes that the decision not to respond to a survey question is independent from both the dependent variable and all explanatory variables. To the extent that this assumption is violated, the regression results could be biased. Third, it cannot be ruled out that individuals provide wrong answers to some of the questions or that some of the questions are interpreted differently by different individuals. This problem is likely to be negligible in the present study since the quantile regression technique is fairly robust to outliers, as far as these measurement errors are quite rare. Fourth, in contrast to some administrative data sources (such as tax data), household surveys do not allow the observation of the most extreme parts of the distribution, such as top income earners.

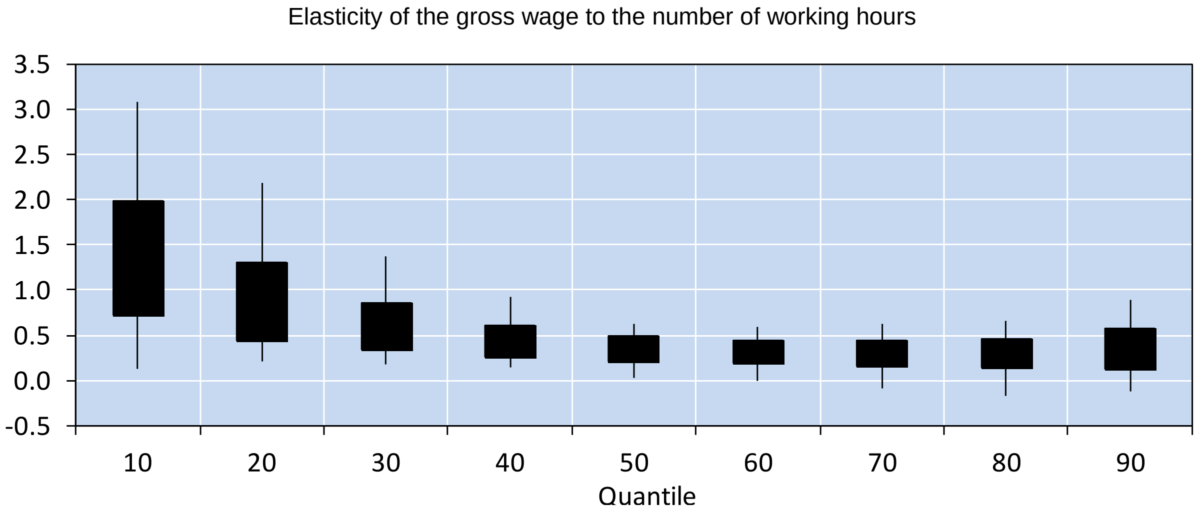
Another issue is the comparability of household survey data across countries. The depth of information varies across surveys, as does the classification of variables and the way in which questions are phrased and thus interpreted by respondents. This article deals with these problems by starting with the European Union Survey of Income and Labour Dynamics (EU-SILC), which provides a unified framework for 23 OECD countries. For the other nine countries for which household survey data could be collected (Australia, Canada, Chile[17], Israel[18], Japan, Korea, Switzerland, the United States and Brazil), all the variables are then chosen and, if necessary, recoded so as to ensure maximum comparability with the EU-SILC dataset. Details on variable manipulation can be found in the Annex.

2.2. The determinants of labour earnings—results from quantile regressions

2.2.1. Hours worked

An important determinant of earnings inequality among the working population is the number of hours worked (generally captured by the number of hours worked per week in all jobs).[19] Unconditional quantile regression results indicate that the marginal returns to increasing the working time by one percent vary substantially across countries, especially at lower quantiles, which may reflect different labour market policy settings and practices, in particular as regards the role of overtime pay (Figure 3 and Table A1 in the Annex). However, one common observation in almost all countries is that the reward for working more is highest for workers at the lower end of the earnings distribution. This could be due to differences in the extent to which time spent at work is recorded, *i.e.* lower-income workers may be more likely to benefit from overtime pay whereas extra hours by middle and high-income workers may be compensated as part of the basic remuneration package.[20] The results suggest that a general decrease in the number of hours worked, triggered for example by an economic recession, would thus particularly hurt lower-income workers through a fall in overtime pay.

Figure 3. **Estimated effect across countries of increasing the working time by one percent (UQR estimates)**



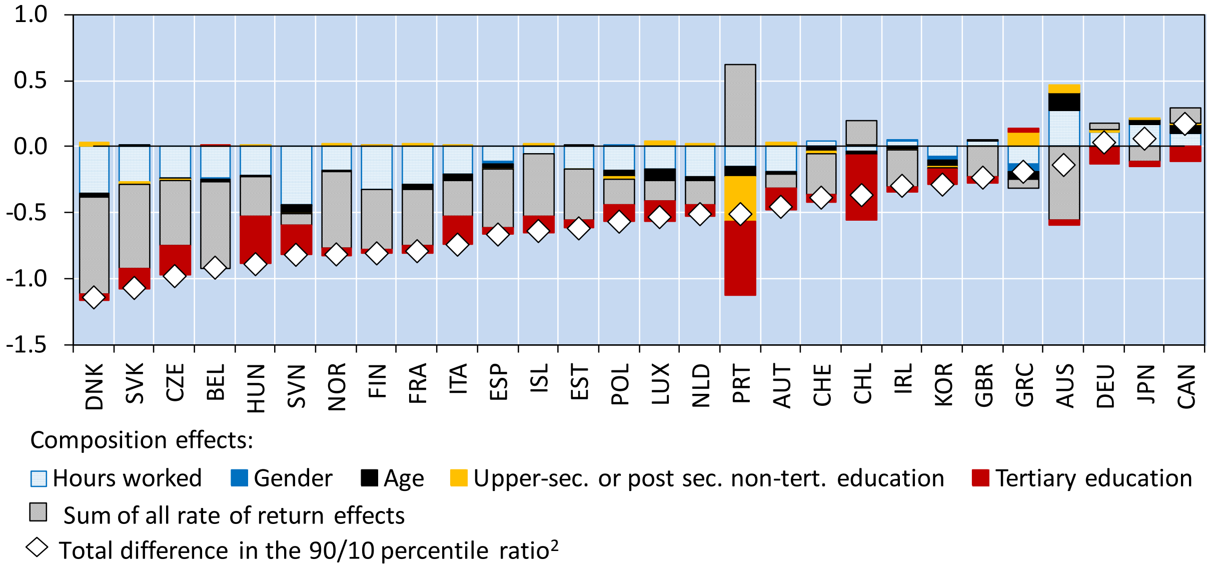
Note: The thick bars depict the cross-country mean of the estimated effect +/- 1 standard deviation across countries, while the thin bars depict the cross-country maximum and minimum of the estimated effect. The standard deviation, the minimum and the maximum thus provide an indication of the variation of the estimated effect across countries.

Source: UQR estimates for employed individuals using data from the Household Income and Labour Dynamics in Australia Survey (HILDA) for Australia, the Survey of Labour and Income Dynamics (SLID) for Canada, the National Socioeconomic Characterization Survey (CASEN) for Chile, the Korean Labour and Income Panel Study (KLIPS) for Korea, the Luxembourg Income Study (LIS) for Brazil and Israel, the Japan Household Panel Survey (JHPS) for Japan, the Swiss Household Panel (SHP) for Switzerland, the Panel Study of Income Dynamics (PSID) for the United States, and the European Union Statistics on Income and Living Conditions (EU-SILC) for 21 EU member countries as well as for Iceland and Norway.

The key role played by the numbers of hours worked in shaping the distribution of earnings is confirmed by two other findings. First, the hypothesis of a unit elasticity, and hence a model in which the dependent variable would be the hourly earnings, is rejected for all countries. Second, the contribution of cross-country differences in the average number of hours to cross-country differences in earnings inequality is substantial (Figure 4 and Table A1 in the Annex). Hours worked are very unevenly distributed across the working population in the United States, Australia and Japan, thus contributing to higher earnings inequality in these countries, while the opposite appears to the case for most European countries.

Figure 4. **Decomposition of cross-country differences in the logarithm of the 90/10 percentile ratio**

The United States is used as reference country, 2007[1]



1. 2008 for Canada; 2009 for Chile and Japan.
2. 90/10 percentile ratio of the country shown on the horizontal axis minus 90/10 percentile ratio of the United States.

Note: A negative (positive) contribution of a factor means a lower (higher) dispersion of that factor in the country considered relative to the United States, so that the factor drives inequality down (up) relative to the United States. The decomposition is based on the UQR results. To better capture the contribution of hours worked, a set of dummies is created, with each dummy capturing a bracket of five hours (Sweden is an exception since the dataset of that country only distinguishes between full-time and part-time workers). The results of the decomposition analysis need to be interpreted with care due to cross-country differences in survey designs and very small samples for several countries, most notably Iceland, Ireland, Luxembourg and Portugal.

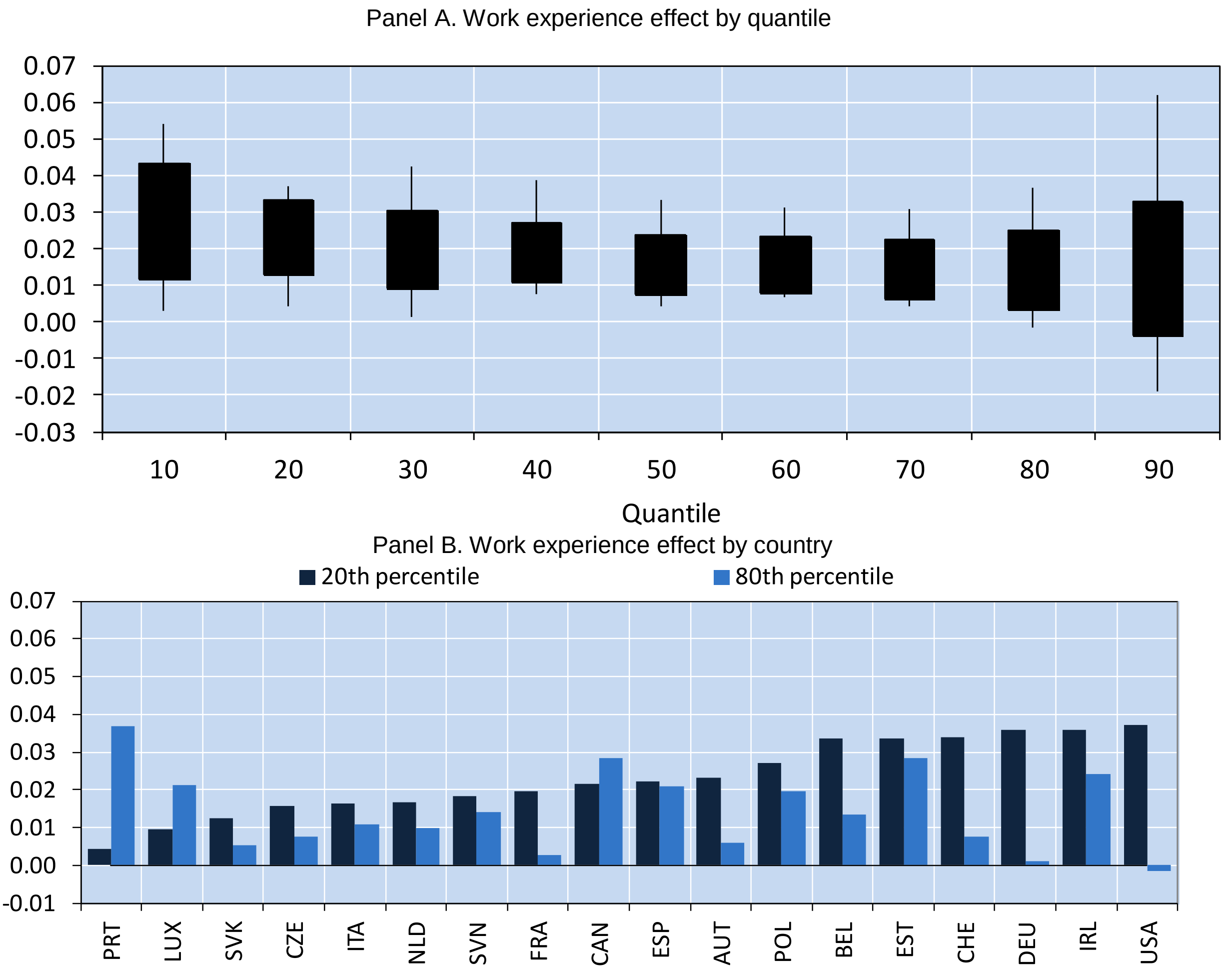
Source: Panel Study of Income Dynamics (PSID) for the United States; Household Income and Labour Dynamics in Australia Survey (HILDA) for Australia; Survey of Labour and Income Dynamics (SLID) for Canada, National Socioeconomic Characterization Survey (CASEN) for Chile, Korean Labour and Income Panel Study (KLIPS) for Korea; Japan Household Panel Survey (JHPS) for Japan; Swiss Household Panel (SHP) for Switzerland; and European Union Statistics on Income and Living Conditions (EU-SILC) for the other countries.

2.2.2. Work experience

The coefficient estimates for the linear and quadratic age terms included in the baseline UQR specification indicate that countries differ widely with respect to the returns to age. In about one-third of the countries returns to age are higher at lower quantiles, whereas the opposite can be observed in another third of the countries. In the remaining countries the difference is either very small or depends on age. Since the age terms may capture work experience, the baseline specification is augmented with a variable directly measuring individuals' work experience for all countries for which this information is available (both the variable itself and its square are included in the regressions).[21] The results from this augmented specification reveal that in many countries returns to experience are larger at the lower end of the earnings distribution (Figure 5 and Table A1 in the Annex). Potential explanations are that work experience plays a larger role in lower-paid jobs or that seniority pay is more prevalent in these types of jobs. The coefficients on the age terms become smaller after controlling for work experience, as could be expected, but remain significant in half countries. There thus seems to be an age-specific reward that goes beyond the pure work experience effect.

Figure 5. **The effect on earnings of having one additional year of work experience (UQR estimates)**

Effect on log earnings of raising the work experience by one year.



Note: In Panel A, the thick bars depict the cross-country mean of the estimated effect +/- 1 standard deviation across countries, while the thin bars depict the cross-country maximum and minimum of the estimated effect. The standard deviation, the minimum and the maximum thus provide an indication of the variation of the estimated effect across countries. The specification includes the number of years of work experience and its square. The chart shows the effect for a worker with 20 years of work experience. In Panel B, each bar depicts the UQR estimate for a given country and quantile.

Source: UQR estimates for employed individuals using data from the Survey of Labour and Income Dynamics (SLID) for Canada, the Swiss Household Panel (SHP) for Switzerland, the Panel Study of Income Dynamics (PSID) for the United States, and the European Union Statistics on Income and Living Conditions (EU-SILC) for 15 EU member countries.

2.2.3. Education

Theory suggests that the link between education and labour earnings inequality is far from straightforward. The impact of a change in the educational composition of the workforce can be thought of as the sum of two separate effects (Knight and Sabot, 1983): *i*) a composition effect, whereby a rise in the share of highly-educated (high-wage) workers raises earnings inequality up to a certain point, but will then lower it as fewer less-educated (low-wage) workers remain; and *ii*) a rate-of-return effect, whereby a rise in the share of highly-educated workers alters the returns to education. The direction of the change in (relative) returns depends on many factors such as the substitutability or complementarity between low-educated workers, highly-educated workers and capital, the interplay between innate ability and schooling (Dur and Teulings, 2004), and the signalling role of education (*e.g.* Hendel *et al.*, 2005).

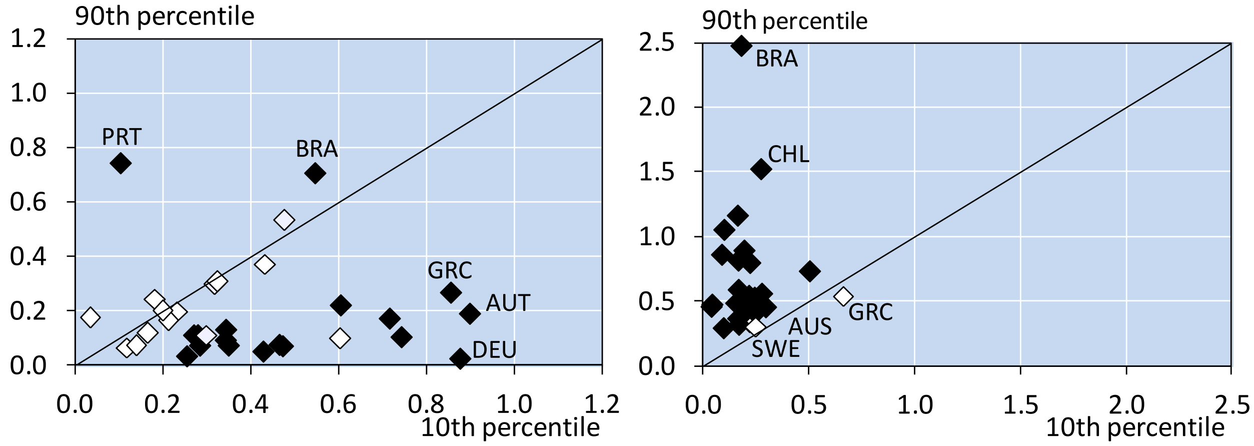
The composition effect of a change in the educational level of the workforce depends on: *i*) the variance of wages among highly-educated workers relative to the variance of wages among low-educated workers; *ii*) the average wage gap between highly- and low-educated workers; and *iii)* the initial share of highly- and low-educated individuals in the total workforce. Specifically, if earnings are more dispersed among highly-educated individuals, then an increase in the share of highly-educated individuals raises earnings inequality, *ceteris paribus*. A second inverted-U-shaped effect is then superimposed on this monotonic first effect, whereby (starting from zero) a rise in the share of highly-educated individuals initially raises earnings inequality as the earnings of some workers now differ from that associated with a low education level, but eventually inequality declines as more and more individuals have higher education and heterogeneity in education attainment is reduced.

The unconditional quantile regressions provide an estimate of the returns to education for nine different earnings quantiles. The results suggest that, on average across countries, an upper-secondary or post-secondary non-tertiary degree is associated with an earnings premium of 700 USD per month (relative to a lower-secondary degree) and a tertiary degree is associated with a further premium of more than 1100 USD per month. The variation in the rates of return across quantiles can be interpreted as the composition effect of a change in the educational composition of the workforce.[22,23] For upper-secondary or post-secondary non-tertiary education, the UQR estimates show that the returns fall along the earnings distribution for most countries (in Panel A of Figure 6 almost all countries with a significant difference between the impact on the 10^{th} and the 90^{th} percentile are located below the 45-degree line), meaning that the dispersion of earnings would fall as more individuals get upper-secondary or post-secondary non-tertiary degrees—a result that is to be expected as the majority of individuals in the countries considered already have upper-secondary education.[24,25] By contrast, a rise in the number of tertiary graduates changes the composition of the workforce in such a way that earnings become more dispersed (in Panel B of Figure 6, Panel B all countries but Greece are located above the 45-degree line): the rate of returns to a tertiary degree rises along the earnings distribution. For the four countries, for which more detailed information on education are available (Australia, Korea, Switzerland and the United States), splitting up the tertiary education dummy into a dummy for bachelor and master degrees and a dummy for PhD degrees shows that a rise in the share of workers with a PhD is associated with a rise in earnings inequality and that this effect is concentrated on the top part of the earnings distribution.[26]

Figure 6. **The impact of education on the distribution of earnings (UQR estimates)**

Panel A. Effect on log earnings of raising the number of upper-secondary or post-secondary non-tertiary graduates

Panel B. Effect on log earnings of raising the number of tertiary graduates



Note: The horizontal axis shows the impact of a 1 percentage point increase in the proportion of workers with respectively upper-secondary or post-secondary non-tertiary (Panel A) and tertiary (Panel B) education on the log earnings of the 10th quantile. The vertical axis shows the impact of the same change on the log earnings of the 90th quantile. A data point below (above) the 45 degree line indicates that the change in the educational composition of the workforce is associated with a fall (rise) in earnings inequality. The equality test is performed at the 5% level.

Source: UQR estimates for employed individuals using data from the Household Income and Labour Dynamics in Australia Survey (HILDA) for Australia, the Survey of Labour and Income Dynamics (SLID) for Canada, the National Socioeconomic Characterization Survey (CASEN) for Chile, the Korean Labour and Income Panel Study (KLIPS) for Korea, the Luxembourg Income Study (LIS) for Brazil and Israel, the Japan Household Panel Survey (JHPS) for Japan, the Swiss Household Panel (SHP) for Switzerland, the Panel Study of Income Dynamics (PSID) for the United States, and the European Union Statistics on Income and Living Conditions (EU-SILC) for 21 EU member countries as well as for Iceland and Norway.

Using the UQR estimates to decompose cross-country differences in the 90/10 percentile ratio suggests that differences in the educational composition of the workforce play an important role (Figure 6 and Table A1 in the Annex). *Ceteris paribus* (*i.e.* assuming in particular that the relative rates of return to education remain unchanged), the high shares of workers with tertiary education in countries such as Ireland and the United States imply a high 90/10 percentile ratio relative to other countries, while low tertiary education attainment in Portugal, Chile and Hungary implies the opposite. The share of workers with an upper-secondary or post-secondary non-tertiary degree does, in general, not play a major role in explaining cross-country differences in earnings inequality, reflecting first that most countries do not differ much in the share of workers holding such a degree and second the smaller impact of this factor in shaping the distribution of earnings in most countries.[27]

The impact of changing the educational composition of the workforce on earnings inequality, as inferred from the UQRs, reflects only a composition effect that assumes unchanged returns to education. However, as discussed above, a change in the educational composition of the workforce may alter the relative returns to education. The resulting repercussions on earnings inequality may strengthen or weaken the composition effect as estimated by the UQRs. A simple cross-country time series regression of the average returns to a certain education degree (obtained from an OLS estimation of the baseline specification) on the share of individuals holding such a degree and country fixed-effects tentatively indicates that a rise in the number of tertiary graduates significantly lowers the relative returns to tertiary degrees,[28] while the returns to upper-secondary and post-secondary non-tertiary degrees are not influenced by the share of workers with such degrees. This means that the impact of a rise in the share of tertiary educated workers on earnings inequality is likely to be smaller than estimated with UQRs (and may even be negative),[29] while for upper-secondary and post-secondary non-tertiary education, the UQR results can be regarded as the total effect.

An individual's earnings may not only be influenced by his own education but, through spillover effects, also by the education level of individuals with whom he interacts. To investigate this issue, the baseline UQR specification for the United States is augmented with three additional variables which measure the proportion of workers in an individual's state of residence who hold an upper-secondary or post-secondary non-tertiary, a tertiary or a PhD degree. For the majority of quantiles, the three additional variables are not significant, suggesting that the spillover effects are at best small. This is in line with the findings of Acemoglu and Angrist (1999) who conclude that spillovers are significant but small.

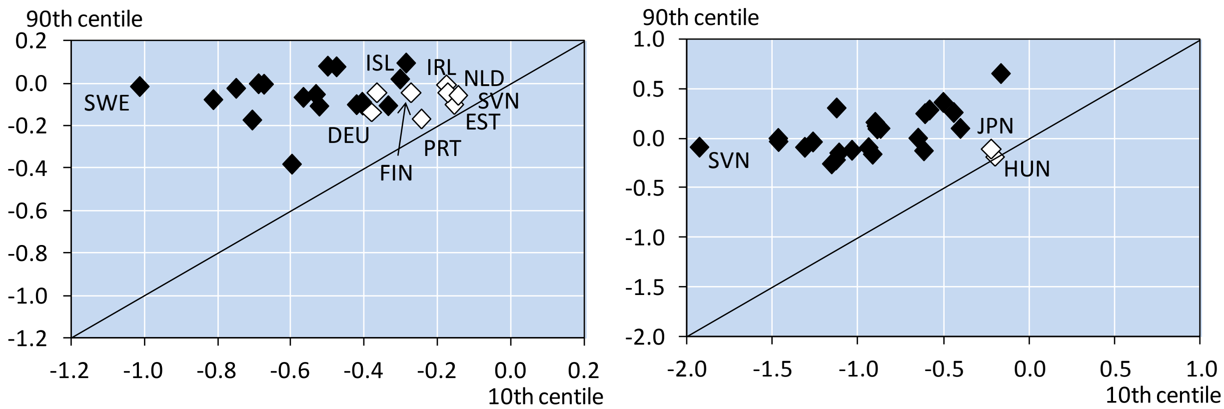
2.2.4. Type of employment

The impact of the type of employment on labour earnings inequality is assessed by augmenting the baseline UQR specification with a dummy variable for being self-employed and a dummy variable for holding a temporary work contract (therefore employees with a permanent work contract serve as the reference group). UQR results provide robust evidence that employees on temporary contracts earn less than those on permanent contracts (Panel A of Figure 7)—a loss that comes on top of the intrinsic lack of job stability. At the median, the earnings penalty amounts to more than 500 USD per month, on average across countries. The difference in earnings is particularly large for workers at the bottom of the earnings distribution. Only the earnings of high-income employees are less dependent on the type of work contract: in almost all countries the coefficient on the contract dummy is smaller in absolute magnitude at the 90th quantile than at the 10th quantile and in about two-thirds of them it is not significantly different from zero.[30]

Figure 7. **The impact of the type of employment on the distribution of earnings (UQR estimates)**

Panel A. Effect on log earnings of raising the share of employees with a temporary work contract

Panel B. Effect on log earnings of raising the share of self-employed



Note: The horizontal axis shows the impact of a 1 percentage point increase in the proportion of workers who are respectively dependent-employed with a temporary work contract (Panel A) or self-employed (Panel B) on the log earnings of the 10th quantile. The vertical axis shows the impact of the same change on the log earnings of the 90th quantile. A data point below (above) the 45 degree line indicates that the change in the composition of the workforce as regards the type of employment is associated with a fall (rise) in earnings inequality. The equality test is performed at the 5% level.

Source: UQR estimates for employed individuals using data from the Household Income and Labour Dynamics in Australia Survey (HILDA) for Australia, the Survey of Labour and Income Dynamics (SLID) for Canada, the National Socioeconomic Characterization Survey (CASEN) for Chile, the Korean Labour and Income Panel Study (KLIPS) for Korea, the Japan Household Panel Survey (JHPS) for Japan, the Swiss Household Panel (SHP) for Switzerland, and the European Union Statistics on Income and Living Conditions (EU-SILC) for 19 EU member countries as well as for Iceland and Norway.

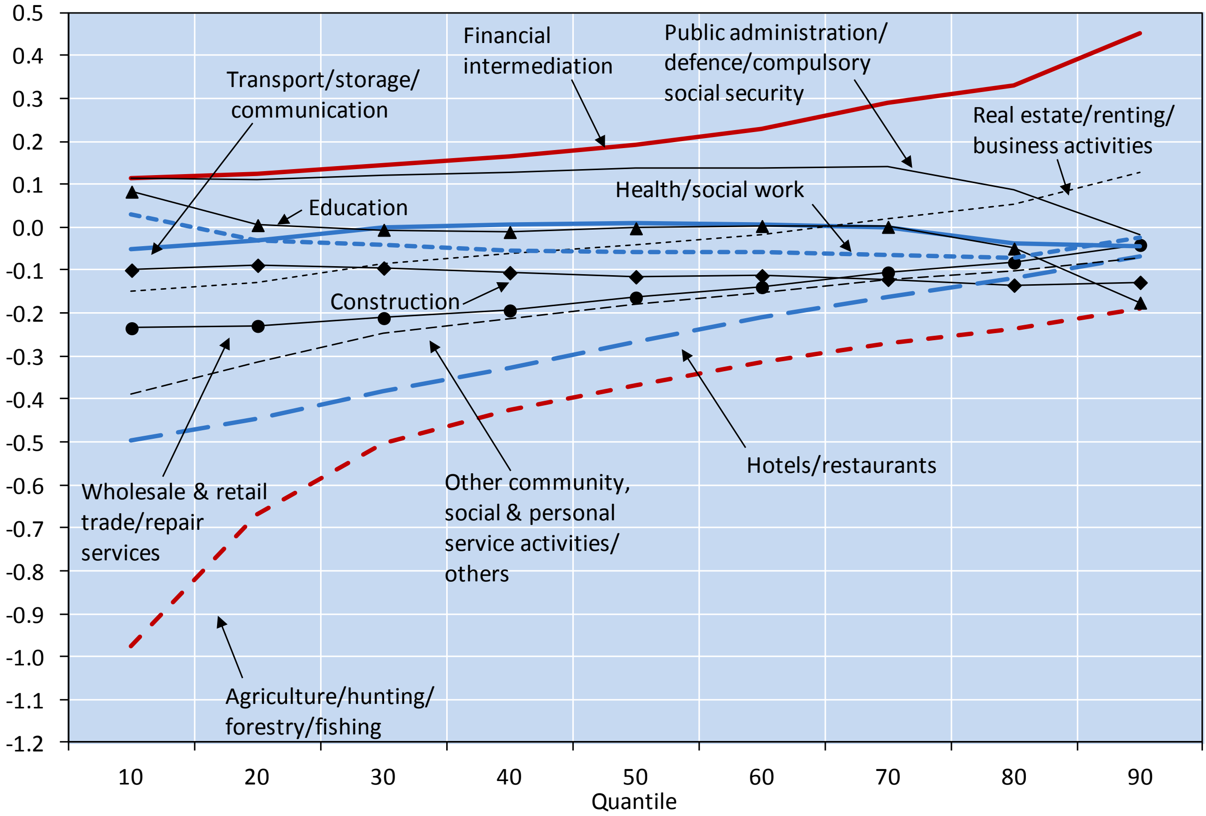
Being self-employed also generally entails an earnings penalty (relative to being employed with a permanent work contract) at lower quantiles according to unconditional quantile regression estimates (Panel A of Figure 7). The effect is particularly sizeable in Slovenia and, to a lesser extent, Poland, Finland, Greece and Sweden, whereas it is relatively small (though still statistically significant) in Hungary and Japan. Also at the median, there is still an earnings penalty for being self-employed. On average across countries, this penalty amounts to around 650 USD per month. For higher quantiles, the regressions yield more diverse results. In about one-half of the countries earnings at the 90^{th} quantile do not depend on whether the worker is self-employed or employees with a permanent contract. In a quarter of the countries, self-employed workers earn significantly more than their counterparts on permanent work contracts (potentially driven by self-employed in the professional services sectors) and in the remaining quarter of the countries they earn less. According to the CQR results the magnitude of this earnings gap at the 90^{th} quantile is rather small (relative to the gap at the 10^{th} quantile) in all countries considered, implying that the earnings among self-employed individuals are more dispersed than those of employees who have a permanent work contract.

2.2.5. Sector of employment

To explore whether the sector composition of the economy has an influence on earnings inequality, the baseline specification is augmented with eleven dummy variables, one for each of the following sectors: "Agriculture/hunting/forestry/fishing"; "construction"; "wholesale and retail trade/repair services"; "hotels/restaurants"; "transport/storage/communication"; "financial intermediation"; "real estate/ renting/business activities"; "public administration/defense/compulsory social security"; "education"; "health/social work"; "other community, social and personal service activities/others".[31] The omitted sector "mining/quarrying/manufacturing/electricity, gas and water supply" serves as the reference sector. The UQR results suggest that a shift in the sector composition would not in general have a large impact on the distribution of earnings. As shown in Figure 8, for most sectors the earnings effect is roughly constant along the earnings distribution. Four sectors, that show some variation along the earnings distribution, are "agriculture/hunting/forestry/fishing", "hotel/restaurants", "other community, social and personal service activities/others" and "financial intermediation". A rise in the share of the first three sectors is associated with a decrease of earnings at the lower end of the earnings distribution. A rise of the share of financial intermediation implies higher inequality for a different reason: the earnings gain is concentrated at the higher end of the earnings distribution. In line with the rather small role played by the sector of employment in driving the distribution of earnings, the contribution of cross-country differences in the sector composition to cross-country differences in earnings inequality is in general fairly limited (Figure 4).

Figure 8. **The impact of the sector composition on the distribution of earnings (UQR estimates)**

Effect on log earnings of increasing the share of a certain sector by 1 percentage point (relative to "mining & quarrying/manufacturing/electricity gas & water supply"), unweighted cross-country average



Note: While standard errors are not reported in the figure for the simplicity of the exposure, the UQR results show that the effect of working in the financial sector (in the agriculture/hunting/forestry/fishing sector) differs significantly between the 10th and 90th quantile in about half (two-thirds) of the countries

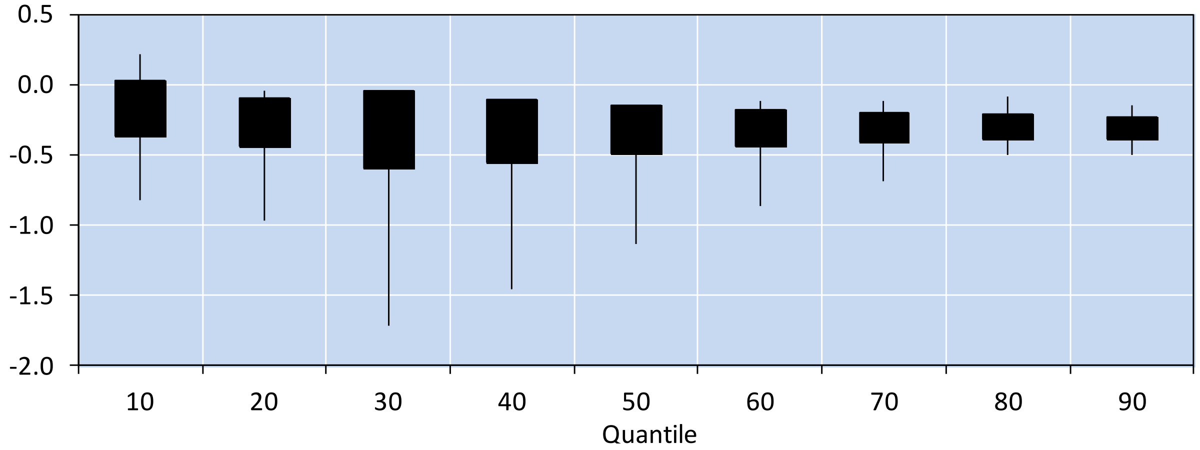
Source: UQR estimates for employed individuals using data from the Household Income and Labour Dynamics in Australia Survey (HILDA), the Korean Labour and Income Panel Study (KLIPS), the Luxembourg Income Study (LIS) for Brazil and Israel, the Japan Household Panel Survey (JHPS), the Swiss Household Panel (SHP), the Panel Study of Income Dynamics (PSID) for the United States, and the European Union Statistics on Income and Living Conditions (EU-SILC) for 21 EU member countries as well as for Iceland and Norway.

2.2.6. Gender inequality

Despite some decline over the past decades, gender differences in labour market performance are still striking in most OECD countries. Women are less likely to be employed than men and those who work typically earn less than their male counterparts (OECD, 2010). For all countries considered, the unconditional quantile regression estimates confirm that women earn less than men—the coefficient on the gender dummy in the baseline specification is significantly negative for almost all quantiles (Figure 9)—even after controlling for factors such as education and the number of working hours. On average across countries, the earnings difference amounts to 750 USD per month at the median. While this might be due to factors that are not controlled for in the estimation, it may also reflect discrimination.[32] While the present analysis does not point to significant differences in the size of the gap along the earnings distribution (linked in part to the rather large standard errors) other studies show that the gap is more pronounced at the upper tail of the distribution (*e.g.* Christofides *et al.*, 2010).

Figure 9. **The gender earnings gap (UQR estimates)**

Effect of being female relative to being male on the log earnings



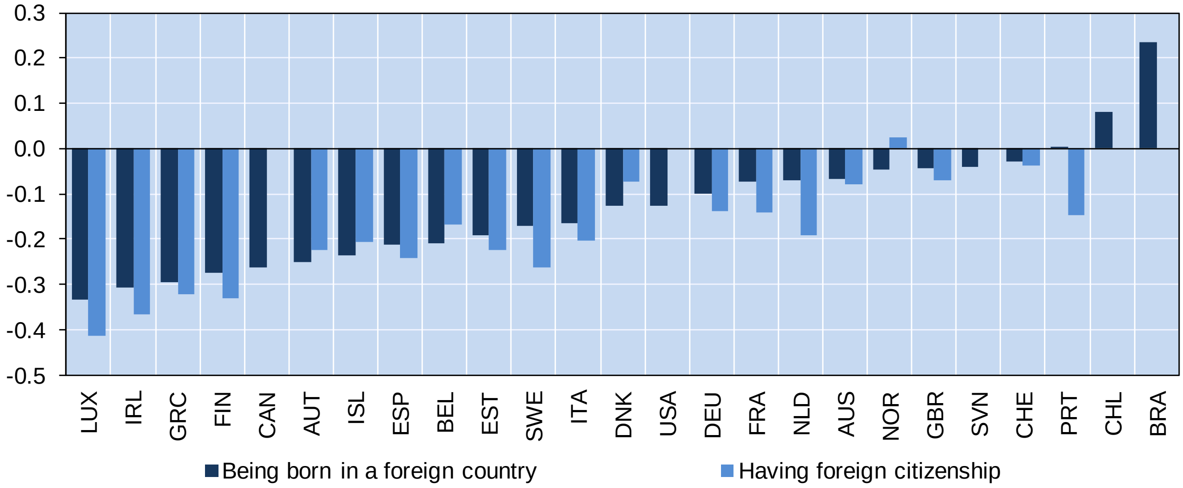
Note: The thick bars depict the cross-country mean of the estimated effect +/- 1 standard deviation across countries, while the thin bars depict the cross-country maximum and minimum of the estimated effect. The standard deviation, the minimum and the maximum thus provide an indication of the variation of the estimated effect across countries.

Source: UQR estimates for employed individuals using data from the Household Income and Labour Dynamics in Australia Survey (HILDA) for Australia, the Survey of Labour and Income Dynamics (SLID) for Canada, the National Socioeconomic Characterization Survey (CASEN) for Chile, the Korean Labour and Income Panel Study (KLIPS) for Korea, the Japan Household Panel Survey (JHPS) for Japan, the Swiss Household Panel (SHP) for Switzerland, the Panel Study of Income Dynamics (PSID) for the United States, and the European Union Statistics on Income and Living Conditions (EU-SILC) for 19 EU member countries as well as for Iceland and Norway.

2.2.7. Migration

Migration may influence labour earnings inequality both because immigrants alter the labour market outcomes of natives and because immigrants may fare differently in the labour market (Borjas, 1999).[33] The latter issue is investigated here by augmenting the baseline specification with two alternative dummy variables, capturing whether a person has foreign citizenship and whether he/she was born in a foreign country, respectively.[34,35] The unconditional quantile regression results point to a substantial cross-country variation in the earnings gap between foreigners and natives (Figure 10).[36] Focusing on the country-of-birth dummy, there is no significant earnings gap between natives and foreigners for most parts of the earnings distribution in eight out of the 21 countries considered (Chile, Hungary, Netherland, Norway, Portugal, Slovenia, Switzerland and the United Kingdom).[37,38] In the remaining countries foreigners typically earn less than natives, with the exception of Brazil where they tend to earn more—even controlling for other factors such as education. Whether the size of this earnings gap differs across quantiles depends again widely on the country considered. The large cross-country differences in the earnings gap between natives and foreigners may reflect, in part, differences in the structure of the immigrant population (in terms of country of origin, timing of immigration or motivation) and differences in countries' policy settings such as restrictions in migrants' rights or targeted measures (Jean *et al.*, 2010).[39]

Figure 10. **The earnings gap between natives and immigrants (UQR estimates)**



Source: UQR estimates for employed individuals using data from the Household Income and Labour Dynamics in Australia Survey (HILDA) for Australia, the Survey of Labour and Income Dynamics (SLID) for Canada, the Luxembourg Income Study (LIS) for Brazil, the Swiss Household Panel (SHP) for Switzerland, the Panel Study of Income Dynamics (PSID) for the United States, and the European Union Statistics on Income and Living Conditions (EU-SILC) for 21 EU member countries as well as for Iceland and Norway.

3. Conclusion

This paper has analyzed the drivers of labour earnings inequality for a sample of 32 countries using quantile regressions. The empirical work has highlighted a number of features that are common among a majority of the countries considered, which allows drawing some quite general conclusions from the analysis. Specifically, the following main findings have emerged from the work:

- The number of hours worked is an important determinant not only of an individual's earnings but also of earnings inequality among the working population. In almost all countries the estimated reward for working one additional hour is highest for workers at the lower end of the earnings distribution, possibly reflecting the role of overtime pay. The number of hours worked appears to play a key role in shaping both the within-country distribution of earnings and cross-country differences in earnings inequality.

- In most countries, the returns to age are higher at lower quantiles. To the extent that the age terms capture an individual's work experience, this suggest that work experience plays a larger role in lower-paid jobs and/or that seniority pay is more prevalent in these types of jobs.

- The link between education and earnings inequality is ambiguous from a theoretical point of view. First, *via* a composition effect a rise in the share of highly-educated (high-wage) workers raises earnings inequality up to a certain point, but will then lower it as fewer low-education (low-wage) workers remain. Second, a rise in the share of highly-educated workers alters the returns to education, with the direction of the change depending on many factors such as the substitutability between low- and high-education workers. The empirical evidence indicates that policies to increase upper-secondary graduation rates (*e.g.* by providing support to pupils at risk in order to reduce drop-outs) should reduce earnings inequality. Whether similar benefits can be expected from reforms that encourage more students to pursue tertiary studies is unclear and depends on the relative magnitudes of the different offsetting effects.

- For those at the bottom of the earnings distribution, being on a temporary rather than on a permanent contract implies lower labour earnings, even controlling for other individual characteristics. Being self-employed also generally entails an earnings penalty (relative to being employed with a permanent work contract) at lower quantiles. For higher quantiles, the type of contract and work status typically matter less.

- Labour earnings vary across different sectors of the economy, but, in general, a shift in the sector composition does not have a large impact on the overall distribution of earnings. Consequently, the contribution of cross-country differences in the sector composition to cross-country differences in earnings inequality also tends to be fairly small. The only exceptions are “agriculture/hunting/forestry/fishing”, “hotel/restaurants”, “other community, social and personal service activities/others” and “financial intermediation”, with a rise in the shares of these four sectors being associated with somewhat higher earnings inequality.

NOTES

1. The discussion of the results often makes reference to the average effect across countries. It should be noted that these cross-country averages shall not be seen as the effect among the entire population in the group of countries considered in this study, but rather as the effect in a representative country. Analysing inequality effects at a more aggregate level is beyond the scope of this paper. The interested reader is referred to the paper by Bourguignon and Morrisson (2002) which investigates inequality at the world level.

2. Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, the Slovak Republic, Slovenia, Spain, Sweden, and the United Kingdom (European Union Statistics on Income and Living Conditions); Australia (Household Income and Labour Dynamics in Australia Survey); Canada (Survey of Labour and Income Dynamics); Chile (National Socioeconomic Characterization Survey) ; Korea (Korean Labour and Income Panel); Japan (Japan Household Panel Survey); Switzerland (Swiss Household Panel) the United States (Panel Study of Income Dynamics); Brazil and Israel (Luxembourg Income Study). Unless explicitly stated otherwise, all results reported refer to the latest available survey year. This is 2008 for all countries with the exception of Israel (2005), Brazil (2006), France, Korea and the United States (2007) as well as Australia, Chile and Japan (2009). Note that the reference year for data on earnings as well as most other variables capturing an individual’s job characteristics is the preceding year.

3. Due to the different designs of the surveys used, the precise definition of this variable differs somewhat across countries, which may limit the comparability of results (see the Annex for details).

4 . Descriptive statistics such as decile ratios hinge crucially on the sample population. The descriptive statistics obtained in our study may therefore differ from those obtained by studies that focus on different samples such as the total population or full-time workers.

5. For all countries covered by the EU SILC survey, this classification matches with the classification used in the survey. For all other countries the data on education had to be recoded (see the Annex for details).

6. Other recent applications of quantile regressions that use a similar dummy variable structure to capture an individual's education level include Budria and Pereira (2005), Budria and Moro-Egido (2008) and Prieto-Rodriguez *et al.* (2008).

7. The results are robust to the addition of a dummy variable for having a post-secondary non-tertiary degree and a dummy variable for having a PhD degree (for those countries for which this information is available).

8. Adding these variables to the baseline specification hardly alters the results obtained for the baseline variables.

9. Unconditional quantile regressions provide an estimate of the partial equilibrium effect of the variable of interest, assuming that the unobserved heterogeneity is independent from the observed characteristics and that there is no reverse causality. The marginal change in X is assumed to have no impact on the joint distribution of X and Y, meaning that rates of return do not vary in the case of small variations in any of the observed characteristics X. While these assumptions may not hold in practice – for instance, a worker's decision to work extra hours may depend on earnings – a comparison between estimates for low and high quantiles is still valid in that case as long as the potential bias is the same across the sample population.

10. Firpo *et al.* (2009) extend the interpretation to dummy variables. For example, the coefficient on a dummy variable that takes value zero if the person works is self-employed and value one otherwise can be interpreted as the impact on earnings of raising the probability of being self-employed by 1 percentage point.

11. Since the quantile regression estimates vary quite smoothly for small changes in the chosen quantile, the results of the analysis would be fairly similar if other quantiles were chosen. Indeed, estimating quantile regressions for 19 quantiles in the range 0.05 to 0.95 did not change the conclusions.

12. Sampling weights typically compensate for unequal probabilities of selection and non-response and adjust the sample distribution for key variables of interest (for example, age and gender) to make it conform to a known population distribution. Still, the samples might not be fully representative with respect to all characteristics that are of interest to this study and thus the results need to be interpreted with care.

13. Only when testing for the homogeneity of effects across quantiles are bootstrapped standard errors also used for CQRs since the analytical standard errors cannot be used for such tests. The bootstrapped standard errors of the CQR procedure are based on unweighted data. While the use of weights is important to obtain correct estimates of key parameters such as the quantiles, they are not crucial for the implementation of the homogeneity test.

14. The main difference with respect to the methodology proposed by Firpo *et al.* (2007b) is that their method makes use of a regression that is run on the country of interest and assumes that all explanatory variables follow the same distribution in that country as they do in the United States. This regression is omitted in the approach adopted in this paper and the information is instead taken from a regression on the country of interest without changing the distribution of the explanatory variables.

This simplified approach assumes that the probability of being above a certain quantile in the distribution is linear in the set of explanatory variables. While this assumption facilitates the derivation of the rate of return effects from the estimation results of the unconditional quantile regressions, it may not hold for countries that deviate considerably from the United States in terms of their population characteristics.

15. Although the precise estimation results depend on the choice of reference country, the general conclusions are fairly robust to this choice. Results for other reference countries are available from the authors upon request.

16. While the rates of return are assumed to be homogenous within each sub group, they are allowed to differ between the two sub groups. However, in case they differ, the results depend on the reference group, reflecting the path dependence of this decomposition.

17. The dataset for Chile is adjusted so as to match national accounts data. This may potentially alter the inequality measures used in this paper (see Bravo and Valderrama Torres, 2011).

18. The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

19. Any cross-country comparison of the regression results for the hours-worked variable needs to be made with great caution as the survey questions used to calculate the number of working hours differ across surveys. Furthermore, special caution is needed in interpreting the price magnitudes of the estimated coefficients because the potential simultaneity bias is not addressed in this analysis which focuses on differences across quantiles.

20. While the basic wage rate may also vary with the number of working hours, this is unlikely to adequately explain the observed heterogeneity in the return to hours worked as several studies show that wage offers to part-timers are actually lower than those to full-time workers (*e.g.* Moffitt, 1984; Simpson, 1986; Ermisch and Wright, 1993).

21. In general, work experience refers to the number of years spent in paid work. The only exception is the United States, where it only includes the experience with the current employer.

22. In the short-run this change will only affect the younger generation, but it will affect the entire population in the long-run once the newly educated generation has grown older. Because younger workers typically earn less than older ones, the short-term effect of a rise of education attainment is thus likely to be more concentrated on the lower-end of the earnings distribution.

23. The unconditional quantile regression technique does not take into account selection effects associated with a potential change in labour force participation (*e.g.* when a rise in the level of education boosts participation rates of women).

24. Two notable exceptions are Portugal and Brazil, where upper secondary and post-secondary non-tertiary education is found to be more profitable for those at the top of the earnings distribution. This could be due to the lower average education level compared with the other countries in the sample. The results for Portugal are in line with existing empirical evidence (*e.g.* Machado and Mata, 2001; Hartog *et al.*, 2001).

25. The results depend somewhat on the choice of the estimator in the second step of the UQRs. When using the logistic estimator instead of the OLS estimator, the finding still holds for 12 countries, while for roughly one-third of the countries the effect at the 90th quantile is then above that at the 10th quantile. For seven countries, the hypothesis of equal coefficients across the entire range of quantiles

cannot be rejected when using the logistic estimator, meaning that, a rise in the share of workers with upper-secondary or post-secondary non-tertiary degrees does not alter the distribution of earnings.

26. The regressions that make use of the logistic estimator in the second step of the UQRs can, however, not confirm this finding, potentially related to the small share of individuals with a PhD in the working population.

27. The only exception is Portugal where this factor contributes to reduce the inequality gap *vis-à-vis* the United States. This reflects the very low share of upper-secondary or post-secondary non-tertiary educated workers in Portugal combined with a strong positive link between the share of such workers and the level of earnings inequality.

28. The estimated coefficient is -0.23 with a standard error of 0.11.

29. The cross-country time-series analysis by Koske *et al*. (2012) tentatively indicates that the total effect is indeed negative, *i.e*. a rise in the share of workers with a tertiary degree is associated with a decline in labour earnings inequality.

30. The interpretation of these results requires considerable care since an individual's earnings and his type of work contract might be influenced by common causes. In that case, the negative relationship may reflect these causes, rather than a causal effect.

31. This classification is used in the surveys of all countries with the exception of Australia, Canada, Chile, Japan, Korea, Switzerland and the United States. For these countries the original sector classification had to be changed so as to approximate the classification of the other countries. As this did not lead to a satisfactory classification in the case of Canada, the variable is not calculated for this country.

32. The same result is obtained using conditional quantile regressions, suggesting that the conclusion is robust to the choice of the estimation technique.

33. At the same time, the level of earnings inequality in the destination country (relative to that in the source country) may influence migration flows (see Liebig and Sousa-Poza, 2004, for a brief overview of the theoretical underpinnings as well as empirical evidence).

34. For a discussion of the former issue see Kierzenkowski and Koske (2012) and the literature cited therein.

35. Data on the two dummy variables are only available for a subset of countries. For all countries for which the analysis is based on the SILC dataset, foreign citizenship means non-EU citizenship and being born in a foreign country means being born outside of the EU. The differences (in terms of the education system, culture, *etc*.) are assumed to be bigger between those born outside the EU and those born inside the EU, as compared to the differences between different EU countries. For Canada, the birth country dummy takes value one if the individual is an immigrant and for the United States, the birth country dummy refers to respondents that are in the immigration sample. For all other countries, the birth country (citizenship) dummy refers to those who are born outside the country (have foreign citizenship).

36. Conditional quantile regressions yield the same conclusion.

37. The finding of significant differences for around two-thirds of the countries is rather encouraging in light of the small number of immigrants in the samples which enlarges the standard errors around the estimated coefficients.

38. In the case of the United States, being black has a negative impact on earnings that is more pronounced for higher quantiles. No evidence of an earning gap is found for other ethnic groups. In the case of Brazil, a similar pattern penalises black workers. In addition, indigenous individuals and individuals of mixed origin also suffer from lower earnings, with the impact stronger for higher quantiles.

39. The contribution of differences in personal characteristics such as education, the sector of employment and the occupation to the earnings gap between natives and foreigners is discussed in Koske *et al*. (2012).

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ANNEX. FURTHER DETAILS ON THE EMPIRICAL ANALYSIS

A1. Further details on the data set

Sample population

Unless explicitly stated otherwise, all results reported refer to the latest available survey year. This is 2008 for all countries with the exception of Israel (2005), Brazil (2006), France, Korea and the United States (2007) as well as Australia, Chile and Japan (2009). The reference year for data on earnings is the preceding year. Although this generally also applies to other variables that capture an individual's job characteristics, there are exceptions. Most notably, in the case of the SILC survey, the number of hours worked refers to the year the survey was conducted, which leads to time inconsistencies with respect to the earnings data. For simplicity, the number of hours worked in the survey year is used as a proxy for the number of hours worked in the preceding year – an assumption that appears reasonable given the strong link between the number of hours worked and the earnings variable as given by the quantile regressions.

All samples are designed to cover the employed population. Individuals of working age (defined as individuals aged between 15 and 64) are included in the analysis if their self-defined economic status is 'working' and if their earnings are positive (although rare in the datasets, negative earnings may occur if self-employed individuals make a loss on their business). For instance, this includes part-time workers but excludes students that regard a job as a secondary activity. The sample covers both dependent and self-employed individuals (restricting the analysis instead to employees hardly affects the results). While some individuals cannot be included in the analysis due to lack of information for one or several of the explanatory variables or the weights, this is rare for all countries except for Israel and the United States. The data set is directly built from individual files for all countries but the United States and Japan, where family files are used, observations being split into two files (head and spouse) if applicable. In cases where descriptive statistics consider full-time workers only, the selection of individuals is generally based on their self-declared employment status. The only exceptions are Brazil, Chile, Israel and the United States, for which no variable is available stating whether a salaried worker works part-time or full-time. For this reason, individuals are considered to work part-time if they work strictly less than 35 hours a week and zero otherwise.

Labour earnings

In all regressions, the dependent variable is gross monthly labour earnings. Due to the different designs of the surveys used, the precise definition of this variable differs somewhat across countries. For all EU-SILC countries, Australia and Korea, gross labour earnings include employees' social security contributions and overtime pay, but exclude employers' social contributions and fringe benefits. Whether stock options are included is not certain. In the case of multiple jobs, the total earnings from all jobs are considered. For Japan, data on labour earnings exclude bonuses, while bonuses are included in the case of Brazil, Israel, Switzerland and the United States. In the case of Chile, the variable used is labour income, with no further details provided on the precise definition of this variable. Finally, it is not clear whether labour earnings data for the United States include fringe benefits. For those who work only for part of a given year, self-declared labour earnings reflect the monthly earnings while working. For Canada, Japan, the United States and all countries covered by the SILC dataset annual labour earnings are divided by the number of months worked during the year. This technical fix was not possible for Chile, Korea and Switzerland.

For all countries, earnings from both dependent employment and self-employment are included. In the case of self-employed individuals all income from self-employment is taken into account irrespective of whether it accrues in the form of labour or capital income (the data do not allow making this distinction). For earnings from self-employment in Canada, only net earnings are available, altering the comparability between earnings from self-employment and earnings from dependent employment. The coefficient on the self-employment dummy obtained for Canada is thus not fully comparable to those obtained for other countries.

Hours worked

As far as possible, hours worked are defined so as to fit with the earnings variable. For the EU-SILC survey this refers to the number of hours usually worked per week in the main job plus the number of hours usually worked per week in other jobs, including overtime work as far as this overtime work is frequent. In the cases of Australia and Canada similar concepts are considered. However, if the number of hours worked in all jobs is unknown as in the Switzerland survey, the number of hours worked in the main job is considered instead. In the case of Chile the number of hours worked is used, with no details provided on which jobs are included in this definition. The survey that is used for the United States builds the number of hours worked on several very detailed questions, and the high number of hours worked may be due to this particular set up that is not comparable to other surveys. In the case of Korea and Japan, there is no information on whether the reported working hours refer to the main job only or all jobs held by the individual. In the case of Brazil, the usual weekly hours worked in all jobs are considered which also include unpaid work. In the case of Israel, the number of hours worked refers to time spent working as an employee (excluding work as a self employed).

Education

To provide a homogenous measure across all countries, the highest education level is captured by two dummies, one for having at least upper-secondary education and another one for having tertiary education. Education in the SILC survey is coded according to the ISCED level, namely pre-primary education; primary education; lower secondary education; upper-secondary education; post-secondary non-tertiary education and tertiary education. No distinction is made between the first three levels (*e.g.* lower secondary education or less) because there are very few workers who have not reached at least lower-secondary education, and hence all workers without at least a lower-secondary degree constitute the reference group. Since for some countries the proportion of workers with a post-secondary non-tertiary degree found in the survey differs substantially from that found in other sources, these workers are gathered together with those who have an upper-secondary education level. In the other surveys, the highest education level is not reported according to the ISCED classification and hence has to be recoded. The recoding procedure exactly follows Fournier and Koske (2012).

Birth country and citizenship

For all countries for which the EU-SILC data set is used the birth country dummy takes value one if the respondent is born outside the European Union.[1] Similarly, the citizenship dummy takes value one if the respondent is a citizen of a non-EU country. For Canada, the birth country dummy takes value one if the individual is an immigrant. In the case of the United States, the birth country dummy refers to respondents that are in the immigration sample (this implies a wrong coding for the particular case of individuals who are born in the United States and married to an immigrant). For all other

1. Poland and the Slovak Republic are excluded from the analysis of the birth country effect because less than 30 individuals reported to be born in a foreign country.

countries, the birth country (citizenship) dummy refers to those who are born outside the country (have foreign citizenship).

Work experience

In the SILC survey, work experience refers to the number of years spent in paid work. For Canada, the concept is the same, but full-year, full-time equivalents are computed. For the United States, work experience only includes the experience with the current employer.

Sector of employment

The sector of employment is coded according to the NACE (REV 1.1) classification because this is the classification used for most countries (all countries covered by the EU-SILC survey plus Brazil and Israel). For Australia, Chile, Japan, Korea, Switzerland and the United States, the original sector classification was changed so as to approximate the classification of the other countries. As this does not lead to a satisfactory classification in the case of Canada, the variable is not calculated for this country.

Self-employment versus dependent employment and type of work contract

The analysis of the temporary contract dummy is combined with the analysis of the self-employment dummy. Whether a worker has a temporary or a permanent contract is meaningful for dependent workers only. The dummy for temporary contracts takes value one if the individual is a dependent worker with a fixed-term contract, and takes value zero otherwise (*i.e.* for self-employed individuals and for employees with a permanent contract). The self-employment dummy takes the value one if the individual declares in the survey that he/she is self-employed.

Weights

The analysis makes use of weighted data so as to obtain a representative picture of the entire employed population. In general, the cross-sectional weights provided in the surveys are used to weigh the data. In the case of Japan, no weights are available in the survey and, hence, unweighted data are used. In the case of Chile, the so-called regional expansion factor is used as a weight, which corrects for the share of the population that participates in the survey. In the case of the United States, the longitudinal weights that are available in the individual file are used, since no cross-sectional weights are available at individual level.

A2. Further details on the estimation results

Table A1. **Baseline unconditional quantile regression estimates**

Variable	Quantile	AUS	AUT	BEL	BRA	CAN	CHE	CHL	CZE
Age	0.1	0.283 (0.034)	0.154 (0.021)	0.124 (0.020)	0.061 (0.004)	0.175 (0.013)	0.085 (0.035)	0.041 (0.005)	0.012 (0.006)
	0.5	0.054 (0.005)	0.054 (0.005)	0.053 (0.005)	0.090 (0.002)	0.087 (0.004)	0.065 (0.008)	0.061 (0.003)	0.040 (0.004)
	0.9	0.027 (0.006)	0.000 (0.007)	0.016 (0.008)	0.069 (0.003)	0.020 (0.004)	0.030 (0.009)	0.032 (0.007)	0.048 (0.007)
Age squared	0.1	-0.00322 (0.00042)	-0.00177 (0.00025)	-0.00140 (0.00024)	-0.00072 (0.00004)	-0.00196 (0.00015)	-0.00096 (0.00040)	-0.00044 (0.00006)	-0.00017 (0.00007)
	0.5	-0.00058 (0.00006)	-0.00057 (0.00007)	-0.00052 (0.00006)	-0.00096 (0.00002)	-0.00092 (0.00005)	-0.00067 (0.00009)	-0.00059 (0.00004)	-0.00045 (0.00005)
	0.9	-0.00025 (0.00008)	0.00017 (0.00010)	-0.00002 (0.00011)	-0.00054 (0.00004)	-0.00012 (0.00005)	-0.00022 (0.00011)	-0.00017 (0.00009)	-0.00053 (0.00008)
Sex	0.1	0.172 (0.082)	-0.146 (0.055)	-0.186 (0.049)	-0.189 (0.012)	-0.140 (0.037)	-0.440 (0.118)	-0.403 (0.032)	-0.213 (0.018)
	0.5	-0.266 (0.024)	-0.312 (0.024)	-0.234 (0.017)	-0.454 (0.007)	-0.333 (0.016)	-0.385 (0.032)	-0.322 (0.013)	-0.276 (0.013)
	0.9	-0.380 (0.028)	-0.217 (0.029)	-0.225 (0.026)	-0.501 (0.015)	-0.330 (0.019)	-0.268 (0.030)	-0.430 (0.032)	-0.285 (0.024)
Hours worked	0.1	2.455 (0.213)	1.393 (0.139)	1.167 (0.112)	1.038 (0.060)	1.494 (0.079)	2.277 (0.404)	0.893 (0.073)	0.681 (0.066)
	0.5	0.481 (0.022)	0.391 (0.030)	0.281 (0.022)	0.425 (0.007)	0.367 (0.016)	0.280 (0.029)	0.189 (0.014)	0.387 (0.029)
	0.9	0.190 (0.019)	0.293 (0.042)	0.326 (0.042)	0.296 (0.012)	0.097 (0.013)	0.146 (0.027)	0.094 (0.027)	0.801 (0.082)
Upper-secondary education or more	0.1	0.463 (0.126)	0.897 (0.114)	0.268 (0.069)	0.545 (0.028)	0.741 (0.069)	0.602 (0.344)	0.431 (0.035)	0.282 (0.047)
	0.5	0.083 (0.027)	0.391 (0.031)	0.106 (0.021)	0.708 (0.007)	0.219 (0.022)	0.261 (0.051)	0.474 (0.016)	0.283 (0.020)
	0.9	0.074 (0.025)	0.189 (0.028)	0.109 (0.026)	0.705 (0.019)	0.102 (0.019)	0.097 (0.032)	0.371 (0.025)	0.071 (0.032)
Tertiary education	0.1	0.219 (0.079)	0.041 (0.049)	0.163 (0.050)	0.178 (0.011)	0.162 (0.034)	0.195 (0.086)	0.272 (0.024)	0.164 (0.018)
	0.5	0.379 (0.026)	0.254 (0.026)	0.247 (0.017)	0.657 (0.007)	0.412 (0.020)	0.221 (0.025)	0.676 (0.020)	0.362 (0.017)
	0.9	0.335 (0.039)	0.472 (0.050)	0.364 (0.034)	2.474 (0.052)	0.492 (0.027)	0.413 (0.043)	1.521 (0.090)	0.813 (0.057)
Constant	0.1	-7.915 (1.200)	-2.198 (0.826)	0.040 (0.646)	2.774 (0.305)	-2.795 (0.422)	-2.440 (1.877)	7.485 (0.359)	2.958 (0.272)
	0.5	5.396 (0.115)	4.803 (0.161)	5.451 (0.141)	5.539 (0.041)	4.773 (0.097)	6.097 (0.216)	10.102 (0.087)	4.014 (0.137)
	0.9	7.733 (0.101)	6.850 (0.210)	6.383 (0.212)	7.404 (0.069)	7.943 (0.066)	7.837 (0.214)	11.945 (0.138)	2.997 (0.349)

Note: Standard errors in parentheses. Estimates for the latest available year.

Table A1. **Baseline unconditional quantile regression estimates,** *continued*

Variable	Quantile	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC
Age	0.1	0.140 (0.032)	0.250 (0.030)	0.068 (0.014)	-0.007 (0.010)	0.090 (0.017)	0.080 (0.016)	0.065 (0.015)	0.202 (0.045)
	0.5	0.094 (0.005)	0.043 (0.004)	0.042 (0.004)	0.020 (0.008)	0.030 (0.004)	0.047 (0.004)	0.055 (0.005)	0.113 (0.008)
	0.9	0.025 (0.005)	0.029 (0.007)	0.010 (0.006)	0.046 (0.013)	0.014 (0.005)	0.009 (0.009)	0.033 (0.008)	0.032 (0.010)
Age squared	0.1	-0.00134 (0.00034)	-0.00267 (0.00033)	-0.00080 (0.00016)	-0.00002 (0.00012)	-0.00096 (0.00019)	-0.00094 (0.00019)	-0.00079 (0.00019)	-0.00248 (0.00055)
	0.5	-0.00094 (0.00006)	-0.00043 (0.00005)	-0.00037 (0.00005)	-0.00034 (0.00009)	-0.00029 (0.00004)	-0.00043 (0.00005)	-0.00060 (0.00006)	-0.00112 (0.00009)
	0.9	-0.00020 (0.00006)	-0.00028 (0.00008)	0.00010 (0.00008)	-0.00061 (0.00015)	-0.00008 (0.00006)	0.00013 (0.00011)	-0.00033 (0.00010)	-0.00013 (0.00012)
Sex	0.1	0.211 (0.058)	-0.117 (0.054)	-0.311 (0.039)	-0.207 (0.032)	-0.105 (0.037)	-0.225 (0.040)	0.068 (0.054)	-0.822 (0.178)
	0.5	-0.322 (0.021)	-0.219 (0.015)	-0.246 (0.015)	-0.462 (0.029)	-0.267 (0.014)	-0.191 (0.015)	-0.335 (0.024)	-0.348 (0.027)
	0.9	-0.254 (0.022)	-0.260 (0.026)	-0.197 (0.023)	-0.426 (0.055)	-0.305 (0.021)	-0.290 (0.028)	-0.327 (0.036)	-0.249 (0.035)
Hours worked	0.1	3.087 (0.378)	0.812 (0.203)	1.807 (0.125)	0.976 (0.129)	1.578 (0.143)	1.413 (0.127)	2.212 (0.142)	1.212 (0.216)
	0.5	0.621 (0.028)	0.300 (0.035)	0.212 (0.020)	0.428 (0.055)	0.233 (0.017)	0.300 (0.023)	0.537 (0.027)	0.179 (0.034)
	0.9	0.246 (0.020)	0.452 (0.069)	0.192 (0.030)	0.402 (0.082)	0.226 (0.025)	0.458 (0.053)	0.311 (0.035)	0.442 (0.060)
Upper-secondary education or more	0.1	0.875 (0.145)	0.426 (0.091)	0.231 (0.047)	0.118 (0.058)	0.252 (0.068)	0.277 (0.057)	0.199 (0.093)	0.854 (0.184)
	0.5	0.164 (0.032)	0.142 (0.017)	0.171 (0.018)	0.223 (0.039)	0.070 (0.018)	0.145 (0.016)	0.282 (0.034)	0.341 (0.029)
	0.9	0.023 (0.023)	0.049 (0.029)	0.196 (0.023)	0.064 (0.074)	0.032 (0.021)	0.110 (0.029)	0.201 (0.038)	0.266 (0.037)
Tertiary education	0.1	-0.045 (0.050)	0.095 (0.050)	0.250 (0.047)	0.262 (0.031)	0.294 (0.040)	0.215 (0.038)	0.241 (0.043)	0.662 (0.132)
	0.5	0.286 (0.019)	0.189 (0.014)	0.259 (0.019)	0.380 (0.030)	0.303 (0.015)	0.303 (0.016)	0.460 (0.025)	0.463 (0.031)
	0.9	0.515 (0.027)	0.290 (0.034)	0.419 (0.033)	0.437 (0.057)	0.453 (0.028)	0.541 (0.040)	0.526 (0.042)	0.540 (0.061)
Constant	0.1	-9.072 (2.020)	-1.301 (1.114)	-1.592 (0.588)	2.284 (0.501)	-0.982 (0.705)	-0.080 (0.622)	-2.840 (0.625)	-2.750 (1.334)
	0.5	3.217 (0.178)	5.987 (0.158)	5.350 (0.126)	4.501 (0.230)	6.162 (0.094)	5.153 (0.124)	4.354 (0.158)	3.628 (0.223)
	0.9	6.777 (0.124)	6.290 (0.290)	6.509 (0.171)	4.934 (0.375)	7.040 (0.117)	5.850 (0.260)	6.463 (0.209)	5.017 (0.309)

Note: Standard errors in parentheses. Estimates for the latest available year.

Table A1. **Baseline unconditional quantile regression estimates,** *continued*

Variable	Quantile	HUN	IRL	ISL	ISR	ITA	JPN	KOR	LUX
Age	0.1	0.022 (0.005)	0.054 (0.020)	0.088 (0.017)	0.164 (0.024)	0.087 (0.011)	0.034 (0.016)	0.112 (0.026)	0.069 (0.032)
	0.5	0.038 (0.006)	0.093 (0.010)	0.053 (0.006)	0.099 (0.007)	0.047 (0.003)	0.162 (0.012)	0.115 (0.011)	0.074 (0.015)
	0.9	0.038 (0.009)	0.022 (0.013)	0.037 (0.007)	0.059 (0.010)	0.016 (0.009)	0.045 (0.009)	0.065 (0.011)	-0.054 (0.022)
Age squared	0.1	-0.00025 (0.00007)	-0.00063 (0.00024)	-0.00094 (0.00020)	-0.00182 (0.00028)	-0.00089 (0.00013)	-0.00032 (0.00017)	-0.00132 (0.00030)	-0.00074 (0.00037)
	0.5	-0.00040 (0.00007)	-0.00098 (0.00011)	-0.00054 (0.00007)	-0.00103 (0.00009)	-0.00040 (0.00004)	-0.00169 (0.00014)	-0.00131 (0.00013)	-0.00065 (0.00017)
	0.9	-0.00038 (0.00011)	-0.00004 (0.00017)	-0.00036 (0.00009)	-0.00052 (0.00013)	0.00007 (0.00011)	-0.00033 (0.00010)	-0.00042 (0.00014)	0.00107 (0.00029)
Sex	0.1	-0.002 (0.013)	0.115 (0.077)	-0.160 (0.056)	0.139 (0.064)	-0.282 (0.029)	-0.356 (0.057)	-0.311 (0.062)	-0.219 (0.056)
	0.5	-0.147 (0.017)	-0.221 (0.040)	-0.325 (0.026)	-0.284 (0.022)	-0.190 (0.011)	-1.137 (0.062)	-0.511 (0.034)	-0.319 (0.049)
	0.9	-0.291 (0.031)	-0.275 (0.058)	-0.339 (0.035)	-0.400 (0.041)	-0.265 (0.028)	-0.419 (0.032)	-0.253 (0.033)	-0.326 (0.056)
Hours worked	0.1	0.589 (0.074)	1.603 (0.168)	0.937 (0.124)	2.377 (0.177)	1.139 (0.086)	0.816 (0.071)	0.918 (0.141)	1.647 (0.360)
	0.5	0.433 (0.047)	0.486 (0.043)	0.298 (0.036)	0.561 (0.028)	0.336 (0.019)	0.324 (0.032)	0.032 (0.046)	0.563 (0.061)
	0.9	0.396 (0.066)	0.279 (0.044)	0.225 (0.041)	0.511 (0.037)	0.824 (0.072)	0.070 (0.018)	-0.130 (0.043)	0.457 (0.070)
Upper-secondary education or more	0.1	0.164 (0.027)	0.316 (0.099)	0.138 (0.060)	0.180 (0.107)	0.324 (0.032)	0.033 (0.084)	0.476 (0.092)	0.341 (0.092)
	0.5	0.291 (0.028)	0.150 (0.041)	0.144 (0.027)	0.304 (0.034)	0.247 (0.011)	0.222 (0.073)	0.450 (0.045)	0.432 (0.057)
	0.9	0.116 (0.021)	0.296 (0.060)	0.070 (0.028)	0.243 (0.034)	0.308 (0.027)	0.174 (0.044)	0.531 (0.042)	0.091 (0.049)
Tertiary education	0.1	0.098 (0.017)	0.218 (0.066)	0.228 (0.059)	0.276 (0.068)	0.220 (0.029)	-0.073 (0.045)	0.166 (0.051)	0.087 (0.057)
	0.5	0.582 (0.023)	0.476 (0.050)	0.321 (0.029)	0.310 (0.024)	0.220 (0.013)	0.311 (0.036)	0.471 (0.036)	0.525 (0.051)
	0.9	1.051 (0.061)	0.485 (0.064)	0.472 (0.051)	0.557 (0.042)	0.795 (0.068)	0.279 (0.033)	0.587 (0.052)	0.858 (0.095)
Constant	0.1	2.820 (0.303)	-0.363 (0.755)	1.774 (0.625)	-4.967 (1.026)	0.508 (0.425)	-1.610 (0.446)	0.636 (0.895)	-0.392 (1.819)
	0.5	3.402 (0.221)	3.909 (0.255)	5.777 (0.177)	4.387 (0.197)	4.972 (0.104)	-1.304 (0.307)	4.727 (0.278)	3.836 (0.411)
	0.9	4.359 (0.286)	6.588 (0.254)	7.083 (0.202)	6.404 (0.260)	4.222 (0.337)	2.515 (0.176)	6.496 (0.249)	7.422 (0.487)

Note: Standard errors in parentheses. Estimates for the latest available year.

Table A1. **Baseline unconditional quantile regression estimates,** *continued*

Variable	Quantile	NLD	NOR	POL	PRT	SVK	SVN	SWE	USA
Age	0.1	0.072 (0.021)	0.173 (0.021)	0.089 (0.014)	0.026 (0.011)	0.019 (0.009)	0.010 (0.007)	0.265 (0.027)	0.202 (0.030)
	0.5	0.080 (0.005)	0.037 (0.004)	0.080 (0.005)	0.066 (0.008)	0.032 (0.004)	0.052 (0.005)	0.046 (0.003)	0.077 (0.009)
	0.9	0.036 (0.007)	0.040 (0.007)	0.051 (0.008)	0.077 (0.016)	0.033 (0.007)	-0.002 (0.008)	0.038 (0.005)	0.083 (0.019)
Age squared	0.1	-0.00073 (0.00022)	-0.00180 (0.00023)	-0.00111 (0.00017)	-0.00033 (0.00013)	-0.00023 (0.00011)	-0.00015 (0.00008)	-0.00263 (0.00029)	-0.00220 (0.00035)
	0.5	-0.00079 (0.00006)	-0.00036 (0.00005)	-0.00085 (0.00006)	-0.00066 (0.00009)	-0.00036 (0.00005)	-0.00053 (0.00006)	-0.00045 (0.00004)	-0.00078 (0.00011)
	0.9	-0.00022 (0.00008)	-0.00038 (0.00008)	-0.00047 (0.00010)	-0.00054 (0.00020)	-0.00037 (0.00009)	0.00019 (0.00010)	-0.00035 (0.00006)	-0.00084 (0.00024)
Sex	0.1	-0.085 (0.076)	-0.233 (0.051)	-0.167 (0.036)	-0.089 (0.027)	-0.185 (0.025)	-0.032 (0.019)	-0.296 (0.069)	-0.257 (0.067)
	0.5	-0.338 (0.022)	-0.278 (0.015)	-0.252 (0.016)	-0.340 (0.029)	-0.245 (0.013)	-0.150 (0.013)	-0.227 (0.012)	-0.294 (0.029)
	0.9	-0.317 (0.026)	-0.361 (0.030)	-0.240 (0.027)	-0.372 (0.071)	-0.242 (0.024)	-0.153 (0.020)	-0.275 (0.021)	-0.414 (0.059)
Hours worked	0.1	1.597 (0.154)	1.617 (0.170)	0.995 (0.118)	0.697 (0.090)	1.287 (0.112)	0.128 (0.091)	0.816 (0.131)	1.612 (0.164)
	0.5	0.456 (0.027)	0.383 (0.025)	0.261 (0.029)	0.222 (0.047)	0.352 (0.029)	0.167 (0.032)	0.295 (0.018)	0.590 (0.038)
	0.9	0.261 (0.035)	0.386 (0.045)	0.542 (0.052)	0.487 (0.133)	0.665 (0.093)	0.362 (0.045)	0.122 (0.022)	0.897 (0.099)
Upper-secondary education or more	0.1	0.341 (0.061)	0.471 (0.082)	0.714 (0.100)	0.101 (0.036)	0.347 (0.106)	0.210 (0.035)	0.297 (0.106)	0.603 (0.136)
	0.5	0.096 (0.019)	0.147 (0.018)	0.322 (0.028)	0.319 (0.037)	0.247 (0.027)	0.366 (0.018)	0.111 (0.019)	0.319 (0.048)
	0.9	0.129 (0.021)	0.069 (0.024)	0.171 (0.025)	0.742 (0.117)	0.071 (0.031)	0.164 (0.011)	0.109 (0.026)	0.219 (0.063)
Tertiary education	0.1	0.154 (0.081)	0.167 (0.042)	0.502 (0.048)	0.161 (0.037)	0.239 (0.027)	0.192 (0.016)	0.250 (0.065)	0.037 (0.074)
	0.5	0.305 (0.021)	0.194 (0.015)	0.542 (0.021)	0.459 (0.046)	0.331 (0.016)	0.506 (0.017)	0.177 (0.012)	0.361 (0.037)
	0.9	0.483 (0.033)	0.317 (0.032)	0.731 (0.045)	1.161 (0.170)	0.418 (0.041)	0.891 (0.046)	0.301 (0.025)	0.456 (0.068)
Constant	0.1	-0.536 (0.868)	-2.746 (0.884)	-0.654 (0.578)	3.069 (0.385)	0.138 (0.461)	5.621 (0.357)	-2.420 (0.861)	-3.988 (1.110)
	0.5	4.408 (0.186)	5.866 (0.124)	3.257 (0.151)	4.396 (0.241)	4.045 (0.139)	4.890 (0.152)	5.612 (0.098)	3.748 (0.274)
	0.9	6.433 (0.208)	6.410 (0.206)	3.577 (0.251)	3.533 (0.626)	3.530 (0.370)	5.867 (0.219)	6.887 (0.122)	3.571 (0.638)

Note: Standard errors in parentheses. Estimates for the latest available year. For Sweden, the results for hours worked may be affected by the coding of the variable which only distinguishes between full-time workers and part-time workers.