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Less Income Inequality and More Growth – Are they Compatible? Part 7. The Drivers of Labour Earnings Inequality – An Analysis Based on Conditional and Unconditional Quantile Regressions

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LESS INCOME INEQUALITY AND MORE GROWTH - ARE THEY COMPATIBLE? PART 7. THE DRIVERS OF LABOUR EARNINGS INEQUALITY - ANALYSIS BASED ON CONDITIONAL AND UNCONDITIONAL QUANTILE REGRESSIONS

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ABSTRACT/RESUMÉ

Less income inequality and more growth – Are they compatible? Part 7. The drivers of labour earnings inequality – An analysis based on conditional and unconditional quantile regressions

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, a rise in trade union membership, a rise in the share of public employment 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; J51; J41; J45
Keywords: Income inequality; labour income; quantile regressions; education; union membership; temporary work contract; public employment

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Moins d'inégalités de revenu et plus de croissance – Ces deux objectifs sont-ils compatibles? Partie 7. Les facteurs des inégalités de revenu – analyse fondée sur des régressions quantiles conditionnelles et inconditionnelles

On utilise les régressions quantiles conditionnelles et inconditionnelles pour étudier les déterminants des revenus du travail le long de la distribution et, par voie de conséquence, les déterminants des inégalités de revenus du travail. Cette analyse regroupe plusieurs enquêtes menées auprès des ménages afin de produire des estimations comparables pour 32 pays. Les travaux économétriques suggèrent qu'en général, l'augmentation de la part des travailleurs titulaires d'un diplôme du deuxième cycle de l'enseignement secondaire ou post-secondaire, non universitaire, la montée de l'adhésion syndicale, le gonflement de la part de l'emploi public et la hausse de la part des travailleurs sous contrat à durée indéterminée ont pour corollaire un resserrement de la répartition des revenus. En revanche, selon les conclusions de l'étude, l'évolution de la composition sectorielle de l'économie n'a pas d'impact important sur les inégalités globales de revenu. Pour ce qui est de l'enseignement supérieur, l'impact n'est pas net car plusieurs effets jouent dans des directions opposées.

Classification JEL : D31 ; C21 ; I24 ; J51 ; J41 ; J45
Mots clés : Inégalités de revenu ; revenu du travail ; régressions de quantiles ; éducation ; adhésion syndicale ; contrat de travail à durée déterminée ; emploi public

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LESS INCOME INEQUALITY AND MORE GROWTH – ARE THEY COMPATIBLE?

PART 7. THE DRIVERS OF LABOUR EARNINGS INEQUALITY – AN ANALYSIS BASED ON CONDITIONAL AND UNCONDITIONAL QUANTILE REGRESSIONS

by Jean-Marc Fournier and Isabell Koske[1]

1. Introduction and main findings

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. To shed further light on the role of institutions and structural policies in shaping the distribution of earnings, this paper explores the determinants of labour earnings inequality for 32 countries based on 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 makes mainly 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).

1. The authors are members of the Economics Department of the OECD. This is one of the background papers for the OECD's project on Income Distribution and Growth-enhancing Policies. The authors would like to thank Alexandra Vo for her excellent research assistance, Romain Duval, Peter Hoeller and Florian Pelgrin for their useful comments and suggestions and Susan Gascard for her excellent editorial support.

The following main findings emerge from the empirical 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 an additional year of work experience are higher at lower quantiles, suggesting 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 income 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 off-setting 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.
- For the majority of countries for which data on union membership are available the results indicate that unions tend to compress the wage distribution.
- Labour earnings vary across different sectors of the economy, but a shift in the sector composition does in general 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.
- A higher share of the public sector in total employment is found to be associated with lower earnings inequality in a large majority of OECD countries. However, cross-country differences in the size of the public sector or in public/private sector wage structures do not seem to play an important role in explaining cross-country differences in inequality.

This paper is structured as follows. Section 2 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 3 briefly discusses the benefits and drawbacks of the data set that is employed in the empirical analysis before presenting the estimation results. An Annex provides country-specific quantile regression results and discusses in detail the household survey data that underlie the empirical analysis.

2. The empirical methodology

2.1. The earnings equation

The empirical analysis makes use of household survey data for 32 countries.[2] It relates individual 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] A description of the data set is provided in the Annex.

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. 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, this paper starts by estimating a baseline model which relates the logarithm of an individual's gross labour earnings to the logarithm of working hours, gender, age and age squared (to proxy work experience which is not available for all countries), 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.[4] While this measure is rather simple, it is the only measure that is available for all countries covered in the study.[5] 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.

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.[6] 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 being member of a union, for working in the public sector, for having foreign citizenship, for being born in a foreign country, and for having a PhD. These variables are

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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).

3. Individuals with zero or negative earnings are excluded from the analysis since the earnings variable is expressed in logarithmic terms (see below). Although rare in the data sets, negative earnings may occur if self-employed individuals make a loss on their business. In total, this concerns less than one per cent of all observations.

4. 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).

5. 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).

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

added on top of the baseline in a number of alternative specifications, the details of which are set out in Section 3.

2.2. 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 paper 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.* (2007*a*, 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.* (2007*a*, 2009) over alternative techniques such as the nonparametric 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 would 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?[7] Since the unconditional

7. 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 in the private sector and value one otherwise can be interpreted as the impact on earnings of raising the probability to work in the public sector by one percentage point.

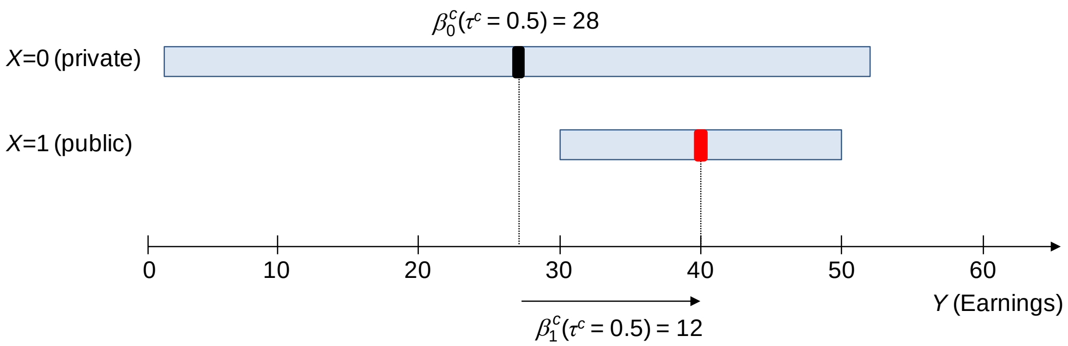
quantile of an individual is simply the share of individuals in the sample population whose earnings are lower than the earnings of the individual of interest, the results of UQRs are easier to interpret than those of CQRs. Since UQRs allow assessing the impact of a particular variable on *overall* earnings inequality, they are also more suitable than CQRs in the context of this paper 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 income within different groups, which helps to understand the mechanisms at work. Box 1 illustrates the interpretation of CQR and UQR results with the help of a simple example.

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 working in the public sector and zero otherwise. Assume further that earnings are higher on average and less dispersed in the public than in the private sector. 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 public sector dummy obtained from a *conditional quantile regression* gives the change in earnings associated with moving from a private to a public sector job, 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 private sector workers before the job change ($\tau^c = 0.5$), he will have the median earnings among all public sector workers 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 private sector workers, which here is 28 for the median.

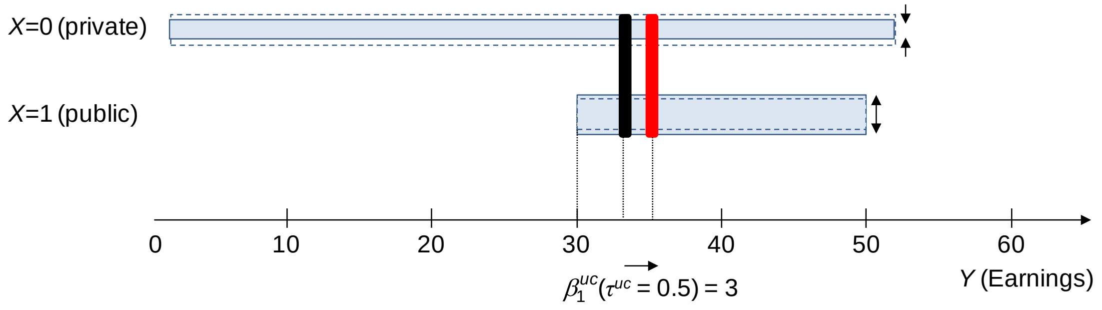
Figure 1. **Interpreting conditional quantile regressions**



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 decreases along the earnings distribution. This reflects that earnings are less dispersed among public sector employees than among private-sector ones.[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.

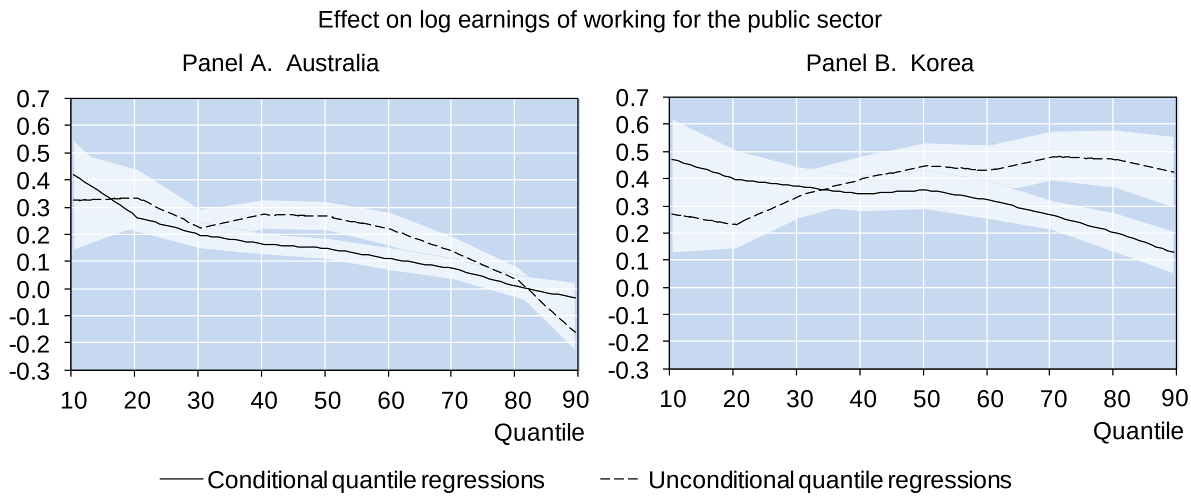
The coefficient $\beta_1^{uc}(\tau^{uc})$ on the public sector dummy obtained from an *unconditional quantile regression* gives the change in a certain earnings quantile of the observed distribution – say, the median – associated with an increase in the share of public sector employment by 1 percentage point. As shown in Figure 2, the size of the two sectors is affected by such a change with the public sector increasing and the private sector shrinking in size.[2] As there are now more individuals in the economy that earn the higher public sector earnings, the median earnings of the entire population increase. In the example shown in Figure 2, median earnings rise by 3, from 33 to 36. 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**



Turning to the analysis carried out in this paper, Figure 3 shows the output of the two types of quantile regressions for two countries, Australia and Korea. In addition to the public sector dummy, the specifications include age, age squared, gender, education and hours worked as explanatory variables. When interpreting the results of the CQRs, workers to the left of the figure (*i.e.* workers with a lower conditional quantile) are those, whose earnings are reduced by unobserved characteristics that are not controlled for in the estimation such as ability or work experience. For both countries, these types of workers benefit more from transferring to a public sector job than workers in a high conditional quantile, as indicated by the downward sloping solid lines in the figure.

Figure 3. **Conditional and unconditional quantile regression estimates of the impact on earnings from working in the public sector**



Note: The shaded areas indicate the 95% confidence interval around the estimates.

The interpretation of the UQRs is very different. Workers to the left (right) of the figure are those with low (high) earnings. The downward sloping dashed line for Australia means that a 1 percentage point increase in the share of the public sector in total employment raises earnings more at the bottom than at the top, whereas the opposite holds in Korea where the dashed line is upward sloping for most quantiles. In other words, a rise in the share of public sector employment reduces earnings inequality in Australia but raises it in Korea.[3] Note that these are partial equilibrium effects however.

While the CQR results are thus very similar for the two countries, the UQR results are exactly the opposite. To better understand the UQR results, it is useful to disentangle the effect of a rise in the public sector employment share into a within inequality and a between inequality component:

- Assuming for simplicity that earnings in the two sectors are characterised by the same means (*i.e.* without *between* inequality) but differing variances (with earnings being less dispersed in the public sector), starting from an economy where all workers are employed by the private sector, an increase in public sector employment lowers overall earnings inequality in a monotonous way.
- Assuming instead for simplicity that earnings in the two sectors are characterised by zero variances (*i.e.* without *within* inequality) but differing means, starting from an economy where all workers are employed by the private sector, an increase in public sector employment first raises overall earnings inequality (as

suddenly not all persons have the same earnings anymore so that the variance of earnings in the total economy becomes strictly positive), but eventually reduces it as fewer private sector employees remain. Once all workers are employed by the public sector, the variance of earnings goes back to zero. The relationship between the public sector employment share and earnings inequality is thus inverted U-shaped.

The effect of a rise in the public sector employment share on earnings inequality thus depends on the initial size of the public sector and the means and variances of earnings in the two sectors. Measuring earnings inequality simply by the log variance of earnings in the total population *Var*, the level of earnings inequality can be expressed as follows (Robinson, 1976):

$$Var = W_0 * Var_0 + W_1 * Var_1 + W_0\,(Y_0 - \mathrm{Y})^2 + W_1\,(Y_1 - \mathrm{Y})^2$$

where W_0 and W_1 denote the employment shares of the two sectors, Y_0 , Y_1 and Y denote the log mean earnings in the two sectors and the entire economy, and Var_0 and Var_1 denote the log variances of earnings in the two sectors. The variance of earnings in the total economy *Var* peaks when the share of public sector employment W_1 is equal to:

$$\hat{W}_1 = \frac{Var_1 - Var_0}{2(Y_1 - Y_0)^2} + \frac{1}{2}$$

In the case of Korea, the variances of earnings in the two sectors are very similar, while the earnings of public sector employees are much higher than those of private sector employees. Data from the Korean Labor and Income Panel Study suggest that inequality would peak when the share of public employment reaches around 40% of the total. Since the actual share is much lower (around 10%), an increase in the proportion of public sector employees is associated with a rise in earnings inequality as indicated by the upward-sloping dashed line in Panel B of Figure 3. In the case of Australia the dispersion of earnings among public sector employees is much smaller than among private sector employees, so that the formula implies a marginal negative link between inequality and the share of public sector employees, whatever the level of this share. This is consistent with the downward-sloping dashed line in Panel A of Figure 3.

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 public sector and education dummies, but also on an unobserved determinant such as performance related pay. If the coefficient on the public sector dummy decreases along the earnings distribution, this solely reflects that the dispersion that is due to performance related pay is smaller among public sector employees 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 jobs.
3. A line that peaks in the middle of the distribution would refer to a change that favours the middle class, with an ambiguous effect on overall inequality.

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 9 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 9 different coefficients, one for each conditional or unconditional quantile in the range 0.1 to 0.9.[8] In the estimation each observation is weighted by the sampling weight of the individual to correct for imperfections in the representativeness of the sample.[9] 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

8. 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.

9. 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. For Japan, unweighted data are used as no sampling weights are provided in the data set.

used.[10] 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. Further technical details of the estimation procedures are provided in Box 2.

Box 2. **The estimation of conditional and unconditional quantile regressions**

Conditional quantile regressions

For the purpose of estimating a CQR, the τ^{th} conditional quantile of a random variable Y (*e.g.* earnings) is assumed to be a linear function of randomly distributed exogenous factors X (*e.g.* age, gender, hours worked):

$$q_{Y|X}(\tau)[Y] = X\beta(\tau)$$

where τ takes values between 0 and 1, $0 < \tau < 1$. The equation implies that the earnings y_i of an individual i with $\tau = \tau_i$ are exactly equal to $x_i\beta(\tau_i)$, where x_i are the characteristics of individual i.[1] Any differences in earnings that cannot be explained by differences in personal characteristics are reflected in differences in the constant across quantiles. Similar to standard OLS, the parameter $\beta(\tau)$ is estimated by minimizing the following criteria:

$$\underset{\beta(\tau)}{\arg\min} \sum_i \rho_\tau\left(y_i - x_i\beta(\tau)\right)$$

where $\rho_\tau(y_i - x_i\beta(\tau)) = (y_i - x_i\beta(\tau))(\tau - 1)$ if $y_i \le x_i\beta(\tau)$ and $\rho_\tau(y_i - x_i\beta(\tau)) = (y_i - x_i\beta(\tau))\tau$ if $y_i > x_i\beta(\tau)$.

Three special cases of a CQR can help to understand this tool:

- When estimating the impact of X on the median of Y (*i.e.*, $\tau = 0.5$) the quantile regression estimator becomes equal to the least absolute deviations estimator, which minimizes the sum of absolute deviations, *i.e.* $\arg\min_\beta \Sigma_i|y_i - x_i\beta|$. This estimator is more robust to extreme values than the standard OLS estimator which minimises the sum of squared deviations (similar to the higher robustness of the median relative to the mean).
- If the constant is the only explanatory variable, then the estimate of $\beta(\tau)$ is equal to the τ^{th} quantile of Y. This can be checked by looking at the first order condition, which can be computed by looking separately at the two cases $y_i < \beta(\tau)$ and $y_i > \beta(\tau)$:

  $$\frac{\partial}{\partial\beta}\sum_i \rho_\tau\left(y_i - \beta(\tau)\right) = \sum_{i|y_i<\beta(\tau)}(1-\tau) + \sum_{i|y_i>\beta(\tau)}(-\tau) = 0.$$

  This derivative is equal to zero if the share of individuals below $\beta(\tau)$ is equal to τ. In this particular example, the conditional quantile coincides with the unconditional quantile.
- If the only explanatory variables are a constant and a 0/1 dummy variable X, then the conditional quantile of an individual with a zero value (value of one) for that dummy variable is the quantile among all individuals with a zero value (value of one) for that dummy variable (the red and black markers in Figure 1 in Box 1). This can be generalised to multiple explanatory variables as the conditional quantile of an individual i is the position of that individual in a virtual population in which all individuals have the same observed characteristics as individual i.

10. 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.

Unconditional quantile regressions

The object of interest of a UQR is the marginal effect on the unconditional quantile of a small increase in the characteristic X:

$$\gamma(t) = \lim_{t \to 0} \frac{q_Y(\tau)[h(X+t,\varepsilon)] - q_Y(\tau)[h(X,\varepsilon)]}{t}$$

where earnings Y are a function h of observed characteristics X and unobserved characteristics $\boldsymbol{\varepsilon}$ and $q_Y(\tau)[Y]$ is the τ^{th} quantile of the unconditional distribution of Y. The method is rather general as it does not only allow investigating the impact on a particular quantile, but also on other measures of the earnings distribution such as the mean (the usual OLS framework is thus a particular case of the UQR technique) or the Gini index.

The unconditional marginal effect is estimated using the two-step procedure proposed by Firpo *et al.* (2009). The first stage involves the estimation of a so-called recentered influence function (RIF) for each individual:[2]

$$RIF = q_Y(\tau) + \frac{\tau - 1}{f_Y(q_Y(\tau))} \text{ if } Y \leq q_Y(\tau) \text{ and } RIF = q_Y(\tau) + \frac{\tau}{f_Y(q_Y(\tau))} \text{ if } Y > q_Y(\tau)$$

where the density of earnings f_Y is estimated using a Gaussian kernel estimator.[3] In the second stage, the RIF is regressed on the explanatory variables X using OLS, and hence the probability for a worker to have earnings above a certain quantile is assumed to be linear in the observed characteristics. Since the RIF takes on only two different values, a logistic estimator is a natural choice for the second-stage estimation. This estimator is used as an alternative to the OLS estimator to check the robustness of the results. Apart from a few exceptions, the results are not affected by this modification, confirming the conclusion of Firpo *et al.* (2009) who also experiment with alternative methods. The linearisation thus seems to be a reasonable simplification.

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 would still be valid in that case as long as the potential bias is the same across the sample population.

The quantile regression techniques are fairly robust to outliers, which is a highly desirable property given the use of household survey data that are prone to measurement error. This is particularly the case for CQRs, where even large measurement errors would have only a small impact on the parameter estimates (provided the number of observations with a large measurement error is reasonably small), whereas estimates from standard OLS techniques would be severely biased in such a case.[4] While the UQR estimator is highly robust to outliers in the dependent variable (Hampel *et al.*, 2005), it is somewhat more sensitive to outliers in the explanatory variables because of the use of OLS in the second stage. In the particular case of tail quantiles, such as the 5th or 95th quantiles, both CQR and UQR estimators hinge crucially on extreme observations and, hence, are more fragile (which is why such quantile estimates are not reported here). In addition, standard errors are generally larger for these extreme quantiles.

1. The conditional quantile itself is generally not identifiable for a given individual i because the equation $x_i\beta(\tau)= y_i$ may have no or several solutions for the unknown parameter τ.
2. The RIF allows estimating how each explanatory variable affects the probability to have earnings above a given quantile. This is why the dependent variable divides the population into two groups: those below and those above the given quantile. The rescaling factor (inverse of the density of earnings) allows converting the probability of earnings to switch above the given quantile into an earnings gain at that quantile.
3. The results of such a kernel estimator depend on the choice of the bandwidth. This paper employs a bandwidth that minimises the mean integrated squared error under the assumption that the data are Gaussian for all countries with the exception of Brazil and Chile where a larger bandwidth is chosen due to the existence of mass points in the data (Firpo *et al.*, 2009 also use a larger bandwidth when applying their methodology to the Current Population Survey of the United States).
4. The coefficients obtained from CQRs are indeed locally estimated. They are barely affected by observations that are not around the percentile of interest. In the neighbourhood of a zero value for the first order condition, the objective function changes only for pivotal individuals for which the conditional quantile is very close to τ, that is when $x_i\ \beta(\tau)$ is very close to y_i. All other individuals have no sizeable weight in this estimation.

2.3. 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 paper adopts a methodology that is close to the one proposed by Firpo *et al.* (2007*b*) and builds on the UQRs discussed above.[11] The United States are used as the reference country so that each country's level of earnings inequality is compared to the level of inequality in the United States.[12]

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 paper. 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 to that of the 10th percentile, *i.e.* $(E(X_{k,i}) - E(X_{k,USA}))\beta_{k,i}^{10}$:

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

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 to the United States) and $E(X_{k,i})$ is the expectation of

11. The main difference with respect to the methodology proposed by Firpo *et al.* (2007*b*) 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 (see Box 2). 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.

12. Although the precise estimation results depend somewhat on the choice of reference country, the general conclusions are fairly robust to this choice.

the variable X_k conditioned on the fact that the worker belongs to country *i* (proxied here by the empirical mean within the country).[13]

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:

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

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.

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

3.1. 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 income 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

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

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 paper 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, Israel[14], 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 data set (see the Annex for details on variable selection and coding).

3.2. The determinants of labour earnings – results from quantile regressions

This section summarizes the overall conclusions that can be drawn from the quantile regression exercise regarding the linkages between the distribution of labour earnings and hours worked, work experience, education, the type of employment, union membership, the sector of employment, gender, and migration status. Detailed country results are shown in the Annex.

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).[15] Unconditional quantile regression results indicate that the marginal returns to working one additional hour 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 4). However, one common observation in almost all countries is that the reward for working one additional hour 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.[16] 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.

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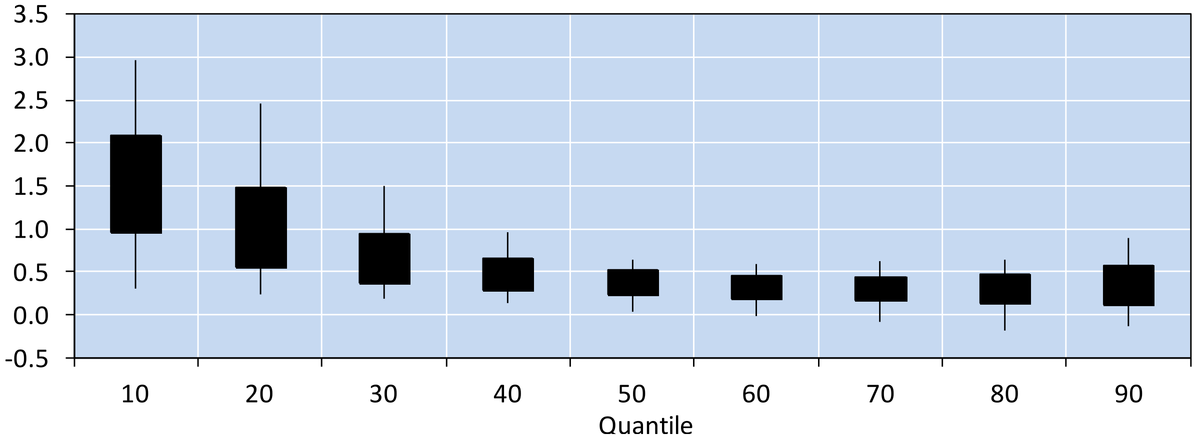
14. The statistical data for Israel are supplied by and under the responsibility of the relevant Israeli authorities. The use of such data by the OECD is without prejudice to the status of the Golan Heights, East Jerusalem and Israeli settlements in the West Bank under the terms of international law.

15. 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.

16. 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.* Simpson, 1986; Ermisch and Wright, 1993).

Figure 4. **Estimated effect across countries of working an additional hour (UQR estimates)**

Elasticity of the gross wage to the number of working hours



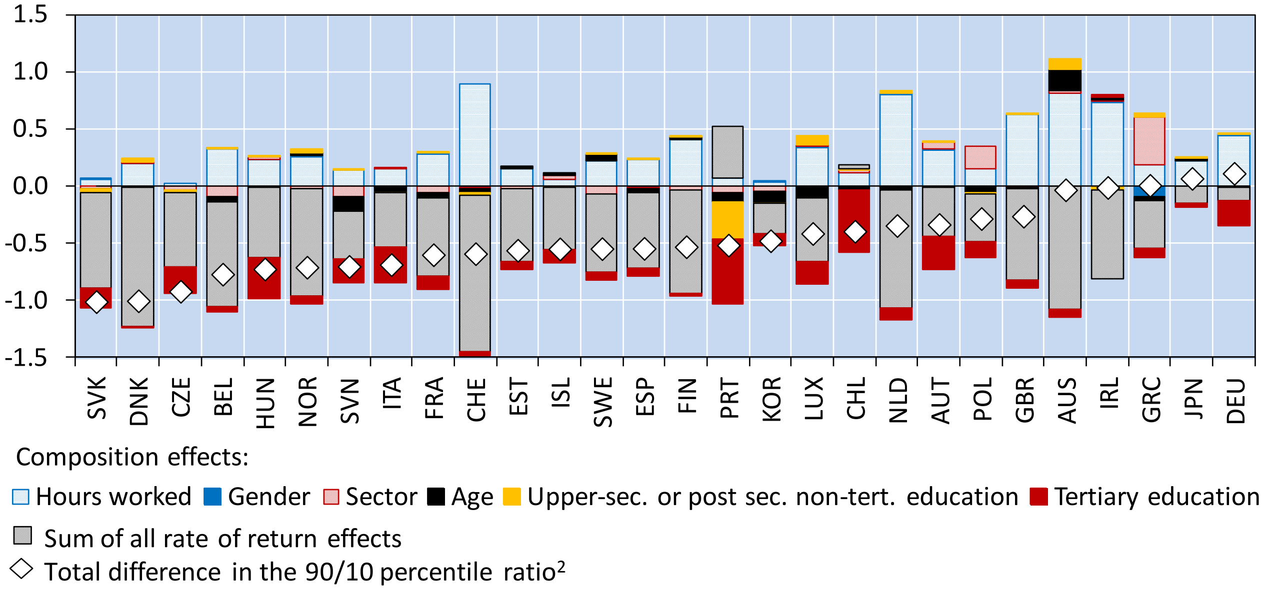
Note: The thick bars depict the cross-country mean of the estimated effect +/- 1 standard deviation across countries, while the thin bars depict the cross-country maximum and minimum of the estimated effect.

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 5). Since hours worked are highest in the United States, the decomposition of countries' inequality gap *vis-à-vis* the United States shows that this factor contributes positively to the gap for all countries. The contribution is highest for countries such as Switzerland, the Netherlands or Canada, where weekly working hours are shorter.

Figure 5. **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: The decomposition is based on the UQR results. Composition effects can be altered because questionnaires differ across surveys, and hence should be interpreted with care.

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.

Work experience

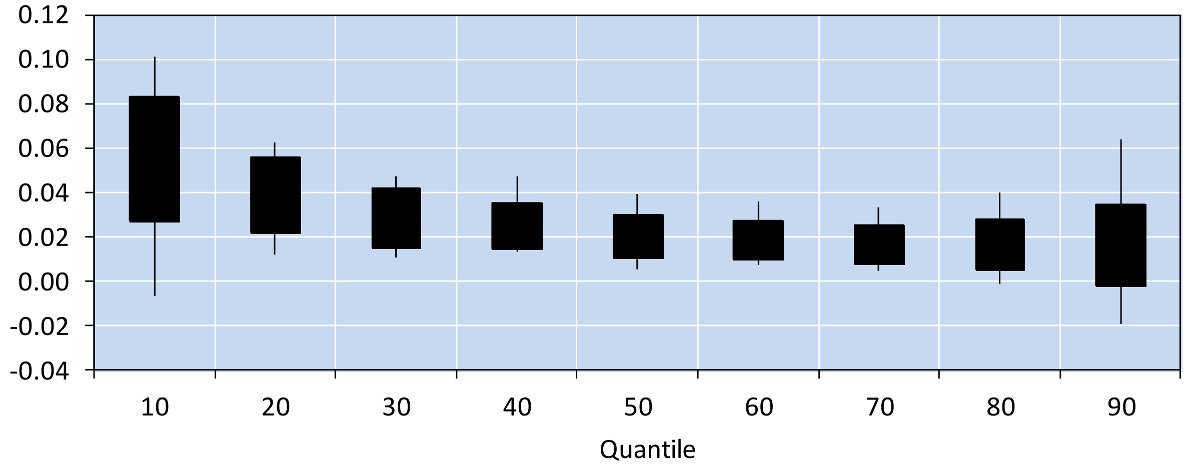
The linear and quadratic age terms included in the baseline UQR specification are likely to capture roughly the impact of work experience on earnings inequality. The coefficient estimates indicate that the average returns to age are higher for lower quantiles, suggesting that work experience plays a larger role in lower-paid jobs or that seniority pay is more prevalent in these types of jobs (the main exceptions are Brazil, Israel, Japan, Korea and Portugal, where the returns to age are larger at higher quantiles). The results also reveal a sizeable variation across countries, possibly reflecting cross-country heterogeneity in the prevalence of seniority pay. The returns to age are particularly high in Belgium, Germany and Poland.

To explore the issue further, the baseline specification is augmented with a variable directly measuring individuals' work experience (typically the number of years worked since the first job) for all countries for which this information is available (both the variable itself and its square are included in the regressions). The results from this augmented specification confirm the two conclusions drawn from the baseline specification, *i.e.* the returns to experience are larger at the lower end of the earnings distribution and they vary considerably across countries (Figure 6). The coefficients on the age terms become smaller once controlling for work experience, as could be expected, but remain significant, particularly for the lower quantiles. There thus seems to be an age-specific reward that goes beyond the pure work experience effect.

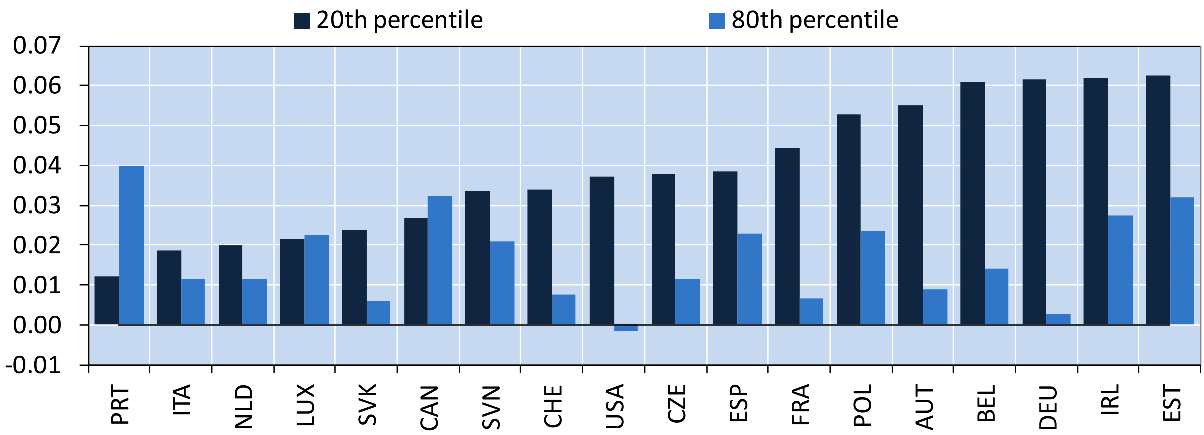
Figure 6. **The effect on earnings of having one additional year of work experience (UQR estimates)**

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

Panel A. Work experience effect by quantile



Panel B. Work experience effect by country



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 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.

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.

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 combination 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- and highly-educated workers.

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 9 different earnings quantiles. 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.[17] For upper-secondary or post-secondary non-tertiary education, the UQR estimates show that the returns fall along the earnings distribution for most countries, 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 (Figure 7, Panel A).[18,19] 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 (Figure 7, Panel B): the rate of returns to a tertiary degree rises along the earnings distribution. For the three countries, for which more detailed information on education are available (Australia, 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.[20]

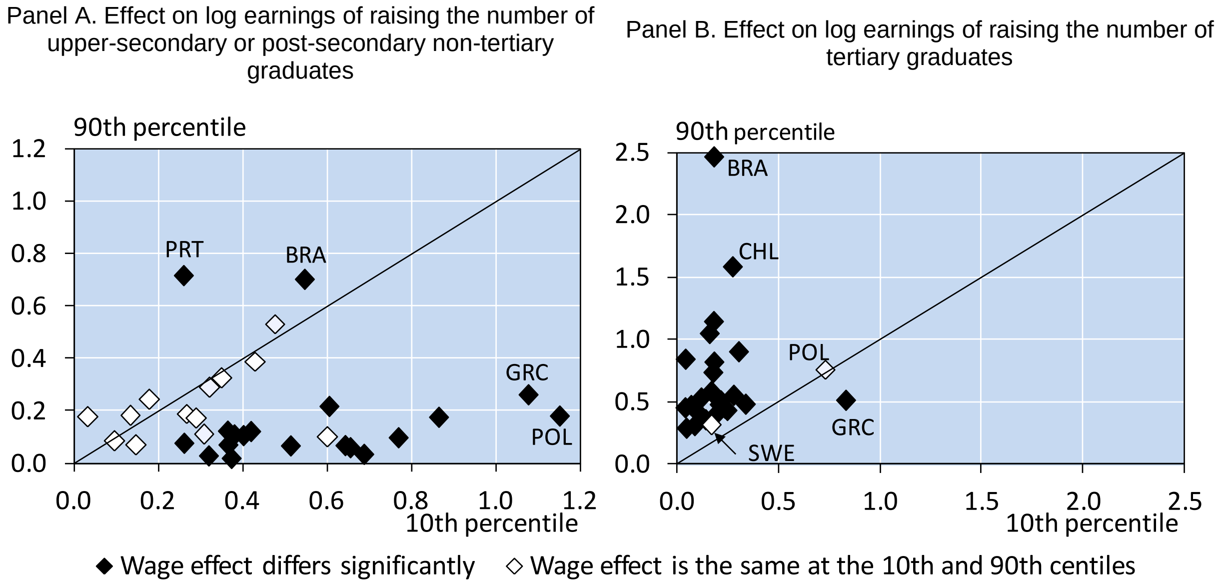
17. In the short-run this change will only affect the younger generation, but it will affect the entire population in the long-run once the newly educated generation has grown older. Because younger workers typically earn less than older ones, the short-term effect of a rise of education attainment is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

18. 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).

19. 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.

20. 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.

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



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 10^{th} quantile. The vertical axis shows the impact of the same change on the log earnings of the 90^{th} 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 5). *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 counties, while low tertiary education attainment in Portugal 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.[21]

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

21. 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.

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,[22] 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),[23] 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.

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 dependent employed individuals with a permanent work contract serve as the reference group). UQR results provide robust evidence that employees on temporary contracts who are at the bottom of the earnings distribution earn less than those on permanent contracts (Figure 8, Panel A) – a loss that comes on top of the intrinsic lack of job stability. The earnings penalty at the 10^{th} quantile is particularly large in Austria, Belgium, Finland, Luxembourg and Sweden. 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 90^{th} quantile than at the 10^{th} quantile and in about half them it is not significantly different from zero.[24]

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 8). The effect is particularly sizeable in Slovenia and, to a lesser extent, Poland, Finland, the Netherlands and Sweden, whereas it is relatively small (though still statistically significant) in Hungary and Japan. For higher quantiles, the regressions yield more diverse results. In about one-third of the countries earnings at the 90^{th} quantile do not depend on whether the worker is self-employed or dependent employed with a permanent contract. In another third 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 third 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 in all countries considered, implying that the earnings among self-employed individuals are more dispersed than those of dependent employed individuals who have a permanent work contract.

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

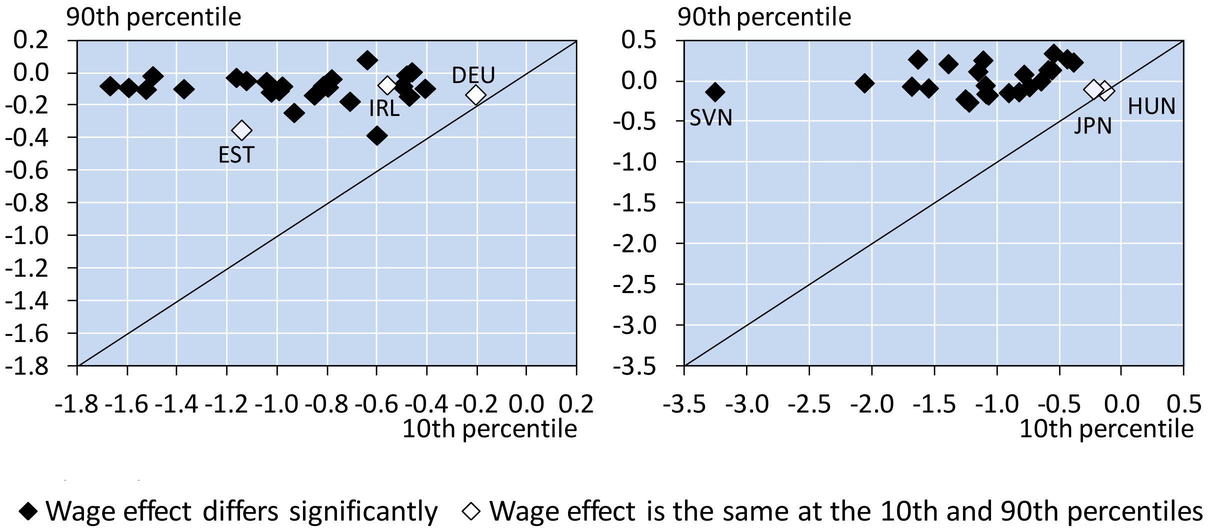
23. The cross-country time-series analysis by Koske *et al*. (2012) tentatively indicates that the total effect is indeed negative, *i.e*. a rise in the share of workers with a tertiary degree is associated with a decline in labour earnings inequality.

24. According to preliminary results, a significantly negative average earnings effect of having a temporary work contract can hold even when controlling for person-specific fixed effects.

Figure 8. **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.

Unionisation

For reasons already discussed above, the relationship between the number of workers covered by collective agreements and overall earnings inequality is inverted U-shaped, with the shape of the curve depending on the relative means and variances of earnings in the two groups of workers (see the discussion on public sector employment in Box 1). The influence of unions on wage inequality thus depends on both the number of workers who are covered by collective agreements – be it through union membership or through administrative extensions of collective agreements – and the influence of unions on bargained earnings (in terms of the wage gap between union and non-union members and the dispersion of wages of union members relative to those of non-union members).

For the six countries for which data on union membership are available (Australia, Canada, Japan, Korea, Switzerland and the United States) simple descriptive statistics indicate that the earnings of union-members are less dispersed than those of non-union members (Table 1). Moreover, with the exception of the United States, average wages are higher among union members than among non-union members. To explore this issue further and properly control for the influence of other personal characteristics, the baseline specification is augmented with a dummy variable that takes value one if a worker is a member of a union and this augmented specification is then estimated with the CQR technique.[25] The coefficient on the union membership dummy is positive for most quantiles and smaller for higher than for lower quantiles, implying that the earnings of union members are higher and less dispersed than those of other workers, even if one controls for the influence of other factors such as age, education and gender. These findings are in line with earlier evidence (*e.g.* Gosling and Machin, 1995; Machin, 1997). The lower dispersion of earnings among union members may reflect that unions push for greater wage equality among their members or that individuals with higher earnings potential have lower incentives to join a union.

Table 1. **A comparison of wages among union and non-union members**

USD, latest available year[1]

	Union members		Non-union members	
	Average earnings	Standard deviation	Average earnings	Standard deviation
Australia	3 794	2 153	3 190	3 059
Canada	3 734	2 304	3 033	3 854
Chile	921	740	759	1 057
Japan	4 680	2 150	3 276	2 880
Korea	3 078	1 457	1 979	1 495
Switzerland	6 821	5 225	5 906	6 861
United States	4 502	2 591	5 078	7 077

1. 2009 for Australia, Chile and Japan; 2008 for Canada; 2007 for Korea and the United States.

Source: 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; Japan Household Panel Survey (JHPS) for Japan; Korean Labour and Income Panel Study (KLIPS) for Korea; Panel Study on Income Dynamics (PSID) for the United States.

Based on the unconditional quantile regression results, it appears that higher union density would help to reduce earnings inequality among workers in Australia, Canada, Switzerland and the United States (Figure 9). In all four countries a broad-based (marginal) increase in union membership (spread evenly across the population) has a strong positive effect on the lower quantiles of the earnings distribution, while having no (or even a negative) effect on higher quantiles. For the United States, this finding confirms the results obtained by Firpo *et al.* (2009) using data from the Current Population Survey (CPS).[26] However, insofar as the same changes turned out to have adverse employment effects (see the discussion in Koske *et al.*, 2012), the inequality-reducing impact associated with the more compressed wage distribution would be reduced. While in the case of Chile[27] and Japan the effect is also significantly positive for low quantiles and insignificant for the 90th quantile, the overall impact on inequality is ambiguous: union membership is most beneficial for medium-income earners. Finally, in Korea, union membership benefits all workers to a more or less similar extent, so that a rise in unionisation does not alter the distribution of earnings or may even marginally increase inequality.

25. For simplicity, this paper follows Firpo *et al*. (2009) and assumes that an individual's union status is exogenous. This assumption is supported by Lemieux (1998) who shows that the exogeneity assumption only introduces a small bias in the estimation.

26. Card *et al.* (2004), who, in their analysis of Canada, the United Kingdom and the United States, explicitly distinguish between men and women, show that unions reduce wage inequality among men, but not among women.

27. In the case of Chile, according to the survey, only 1.8% of workers report to belong to a union.

Figure 9. **The impact of union membership on the distribution of earnings (UQR estimates)**

Effect on log earnings of raising the share of workers affiliated to a union by 1 percentage point

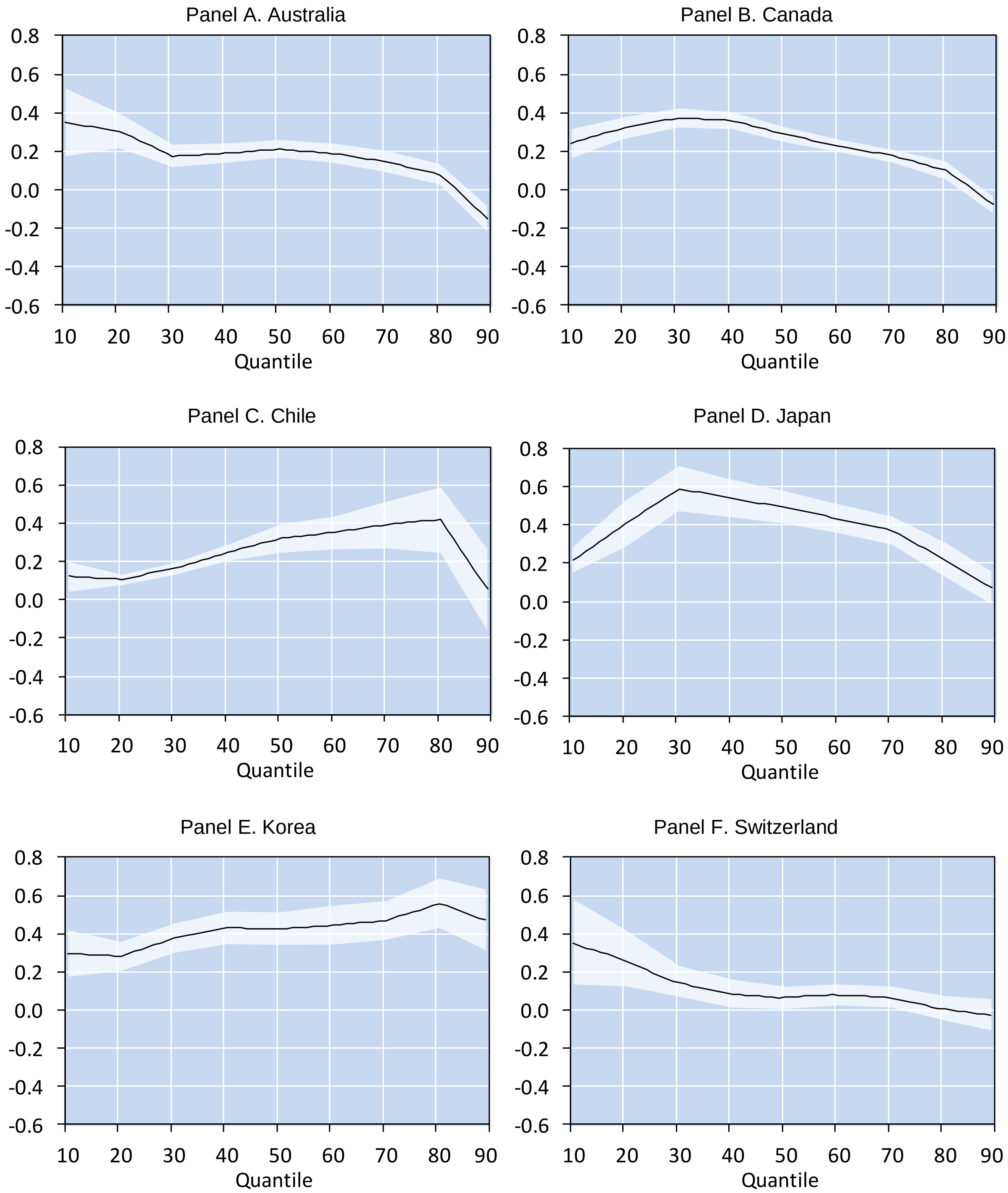
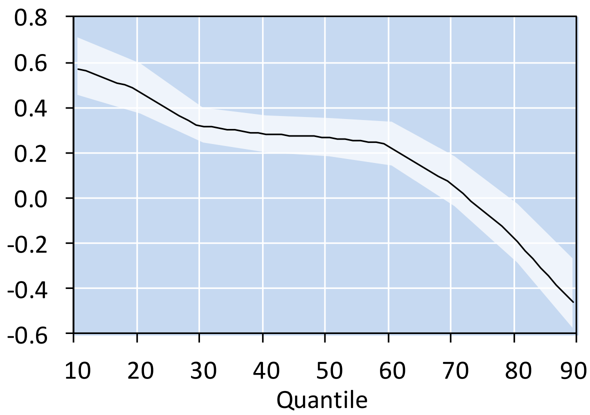


Figure 9. **The impact of union membership on the distribution of earnings (UQR estimates)**, *continued*

Panel G. United States



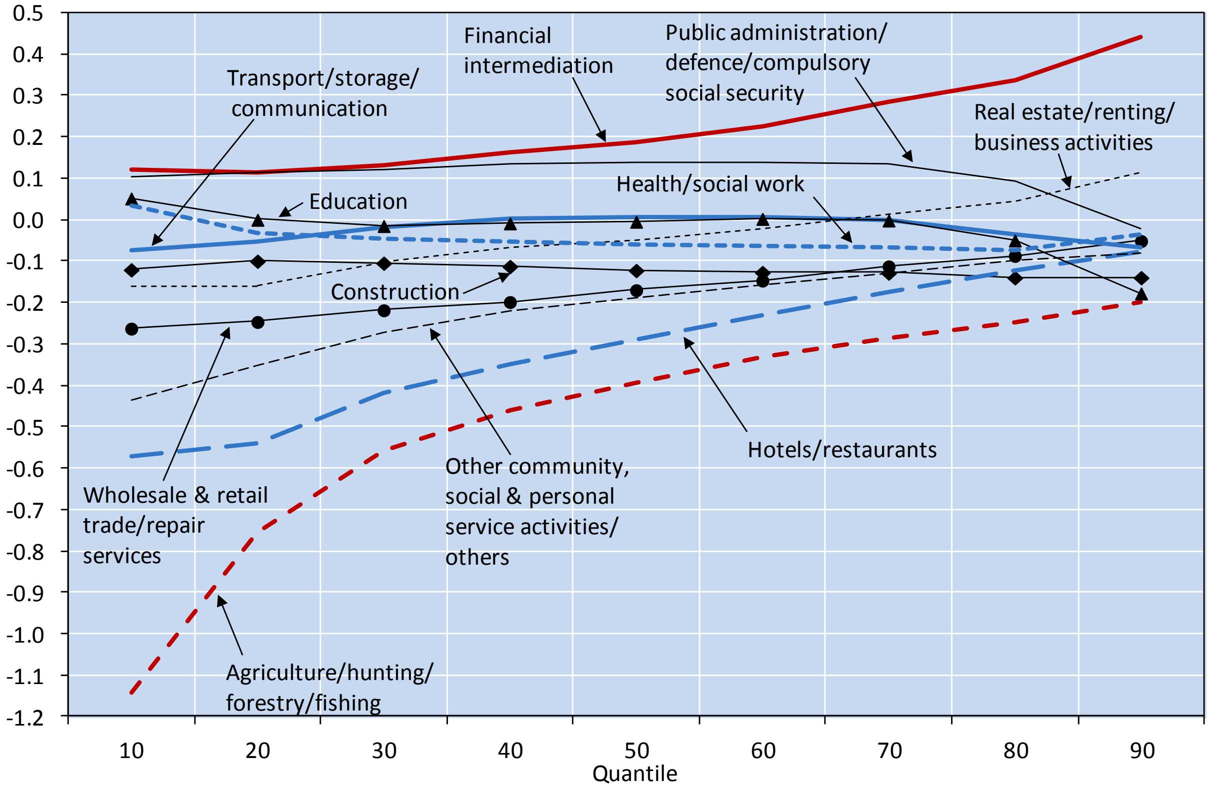
Source: UQR estimates for employed individuals using data from the Household Income and Labour Dynamics in Australia Survey (HILDA), the Survey of Labour and Income Dynamics (SLID) for Canada, the National Socioeconomic Characterization Survey (CASEN) for Chile, the Japan Household Panel Survey (JHPS), the Korean Labour and Income Panel Study (KLIPS), the Swiss Household Panel (SHP), and the Panel Study on Income Dynamics (PSID) for the United States.

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". 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 10, 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 5).

Figure 10. **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



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.

A related question is the role played by the public sector. For the seven countries for which data on the type of employer are available (Australia, Brazil, Chile, Japan, Korea, Switzerland and the United States), descriptive evidence indicates that in most countries average wages are higher and less dispersed in the public than in the private sector (Table 2). This is consistent with existing empirical evidence (*e.g.* García *et al.*, 2001). To go beyond simple descriptive statistics and control for other observable characteristics when comparing the dispersion of earnings of public versus private sector workers (for example, the higher dispersion of private sector wages could be because private sector workers are more diverse in terms of their education level), conditional quantile regressions are run on a specification that includes all baseline variables plus a dummy variable capturing whether a person is employed by the government or a government-related entity. For countries where no data on the type of employer are available, this dummy variable is created using information on an individual’s sector of employment and information on the share of public employment by sector (see the Annex for details). The CQRs reveal that the lower dispersion of public sector earnings cannot be explained by other observed characteristics. It could be due to greater prevalence of centralised wage bargaining in that sector

(Grimshaw, 2000), less reliance on performance-related pay (especially in Europe), or the purposeful use of public sector employment to achieve redistribution (Alesina *et al.*, 2000).[28]

Table 2. **A comparison of earnings among public and private sector workers**

USD, latest available year[1]

	Public sector		Private sector	
	Average earnings	Standard deviation	Average earnings	Standard deviation
Australia	3 835	2 267	3 180	3 043
Brazil	730	926	361	506
Chile	1 015	1 137	729	1 036
Japan	4 877	2 560	3 416	3 054
Korea	3 028	1 539	1 912	1 448
Switzerland	5 896	3 237	6 137	3 790
United States	4 470	4 045	4 991	6 796

1. 2009 for Australia and Japan; 2008 for Switzerland; 2007 for Korea and the United States; 2006 for Brazil.
Source: Household Income and Labour Dynamics in Australia Survey (HILDA); Luxembourg Income Study (LIS) for Brazil; National Socioeconomic Characterization Survey (CASEN) for Chile; the Korean Labour and Income Panel Study (KLIPS); Japan Household Panel Survey (JHPS); Swiss Household Panel (SHP); Panel Study of Income Dynamics (PSID) for the United States.

The implications of the higher average level and the lower dispersion of public sector earnings for overall earnings inequality are explored using unconditional quantile regressions. They are a priori ambiguous, as already discussed in Box 1. In practice, the results indicate that in the majority of OECD countries a (marginal) rise in the public-sector employment share would tend to lower earnings inequality by raising earnings at the lower end of the earnings distribution while leaving those at the upper tail broadly unchanged or even reducing them (Figure 11). As with the results above regarding union membership or education, this finding should be interpreted with care as it ignores possible changes in the relative earnings of public and private sector workers that would result from such a shift. However, cross-country differences in the size of the public sector or in the public/private sector wage structures do not seem to play an important role in explaining cross-country differences in inequality (results not shown).

Gender inequality

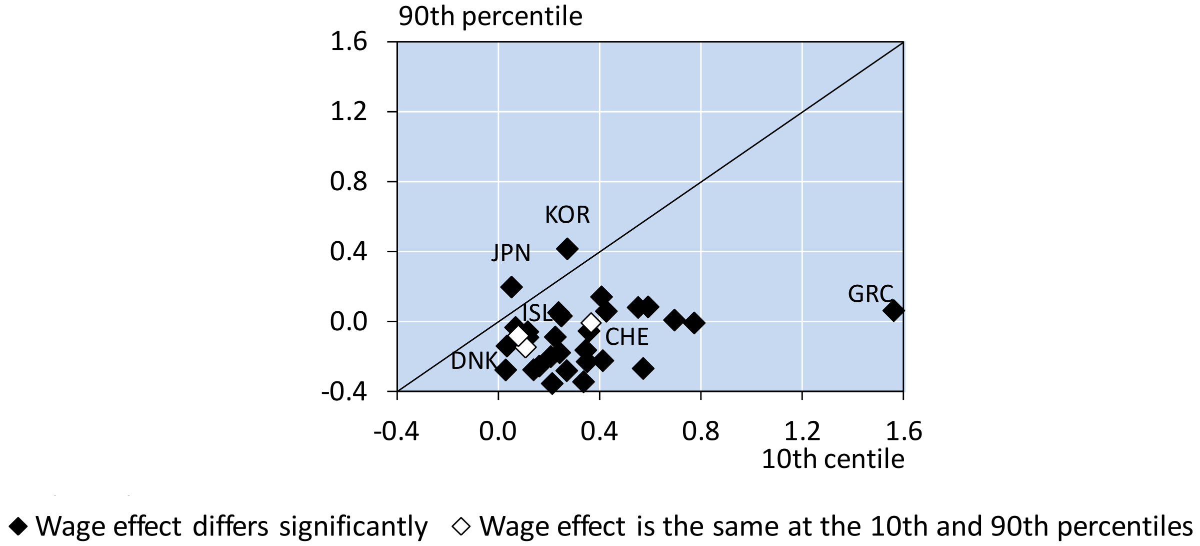
Despite some decline over the past decades, gender differences in labour market performance are still striking in most OECD countries. Women are less likely to be employed than men and those who work typically earn less than their male counterparts (OECD, 2010). For all countries considered, the unconditional 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 12) – even after controlling for factors such as education and the number of working hours. While this might be due to factors that are not controlled for in the estimation, it may also reflect discrimination.[29] Whether this earnings gap is bigger at the lower or upper tail of the earnings distribution varies by country, with no clear overall pattern.

28. Alesina *et al.* (2000) propose a model of public sector employment, in which the latter is not chosen solely based on efficiency considerations, but based on its redistributive impact.

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

Figure 11. **The impact of public sector employment (UQR estimates)**

Effect on log earnings of a 1 percentage point increase in the share of public sector employment

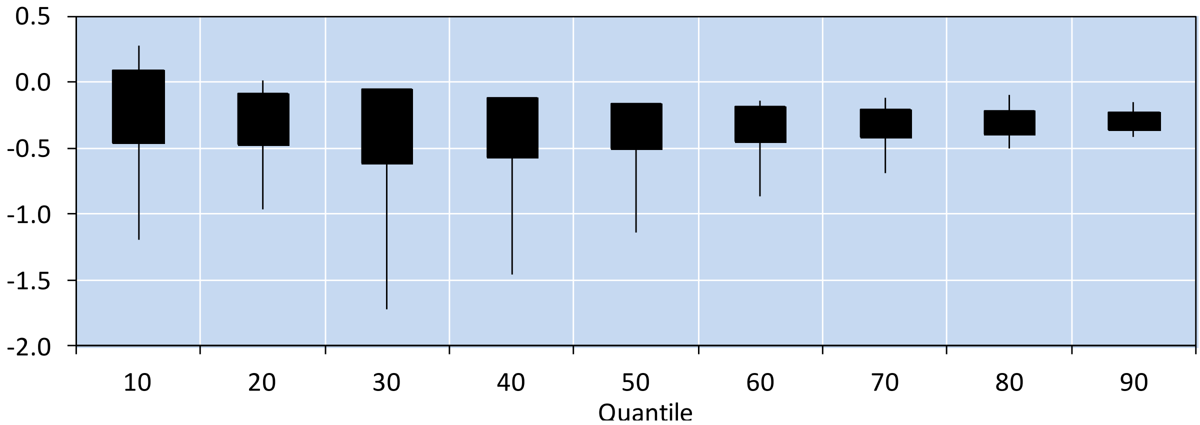


Note: A data point below (above) the 45 degree line indicates that a rise in the public sector employment share is associated with a fall (rise) in the 90/10 percentile ratio.

Source: UQR estimates 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.

Figure 12. **The gender earnings gap (UQR estimates)**

Effect on log earnings of being female relative to being male



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.

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.

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.[30] 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.[31,32] The unconditional quantile regression results point to a substantial cross-country variation in the earnings gap between foreigners and natives (Figure 13).[33] 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 6 out of the 21 countries considered (Australia, Germany, Norway, Portugal, Slovenia and Switzerland). 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 (Jean *et al.*, 2010).[34]

30. 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).

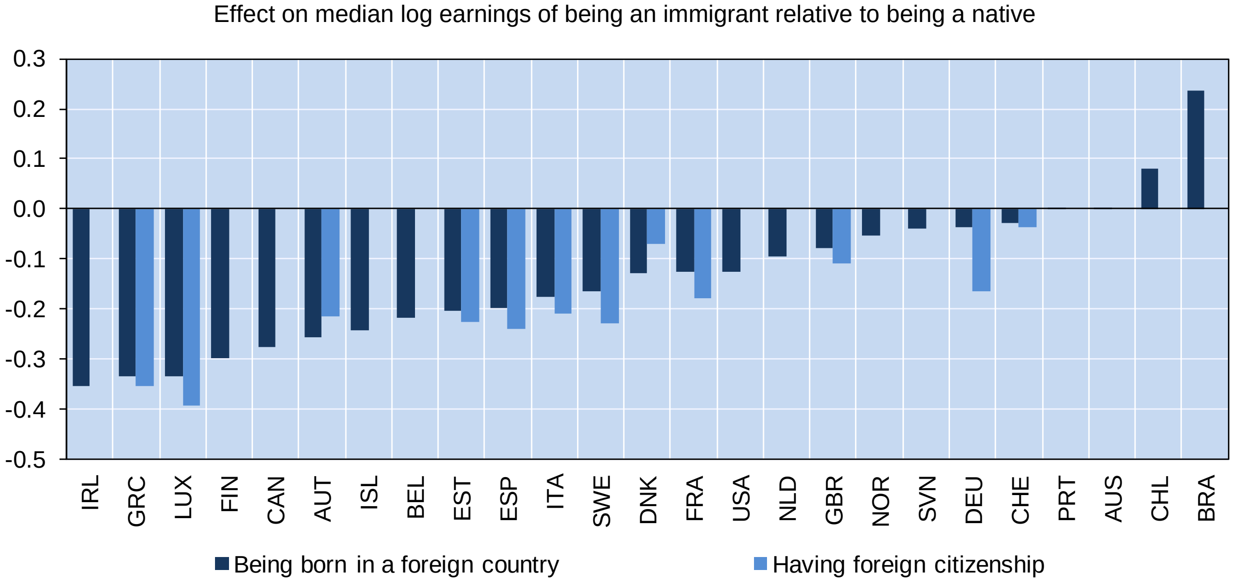
31. For a discussion of the former issue see Koske *et al*. (2012) and the literature cited therein.

32. 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 data set, 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.

33. Conditional quantile regressions yield the same conclusion.

34. 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 colours. In the case of Brazil, a similar pattern penalizes black workers. In addition, indigenous individuals and individuals of mixed origin also suffer from lower earnings, with the impact stronger for higher quantiles.

Figure 13. **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.

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Annex

Further details on the data set and estimation results

A1. Further details on the data set

This section reviews the data set that underlies the empirical analysis, focusing in particular on the construction of the variables. Since different household surveys are used, the original data from the surveys have to be manipulated in order to obtain data that are, as far as possible, comparable across all countries. The section also presents descriptive statistics to provide an overview of the data used.

A1.1. Household surveys

Eight different household surveys are used. The European Union Statistics on Income and Living Conditions (EU-SILC) for 21 EU member countries as well as for Iceland and Norway provides homogeneous data and is used as a reference for the construction of the final data set. Results for the other countries are built on the following additional surveys: 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 and the Panel Study of Income Dynamics (PSID) for the United States. The Luxembourg Income Study itself is built on national surveys: the National Household Sampling Survey (PNAD, or Pesquisa Nacional por Amostra de Domicilios) for Brazil and the Israel Household Expenditure Survey and Income Survey for Israel. All surveys are designed to be representative of the entire population.[35]

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.

A1.2. Sample population

Samples used in quantile regressions 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. For instance, this includes part-time workers but excludes students that regard a job as a secondary activity. The sample covers both

35. Although the informal sector is covered in the case of Brazil, results should be interpreted with caution because informal activity is unlikely to be fully declared.

dependent and self-employed individuals. 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.[36] 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. This codification is consistent with the Cross National Equivalent file (Burkhauser *et al*, 2000).

A1.3. Construction of the variables

Labour earnings

In all regressions, the dependent variable is gross 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 this reason, when earnings are observed on an annual basis (*e.g.* for Japan and the United States), the annual labour earnings are divided by the number of months worked during the year.

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

36. In the case of the United States, data on weights are missing for a large part of the sample population, while for Israel no information on the working hours of self-employed individuals is available, implying that the sample includes employees only.

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 accordeing 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. In the case of Australia, "certificates I or II", "certificate not defined" and "year 11 and below" are regarded as lower-secondary education or less, "year 12 level" and "certificates III or IV" are regarded as upper-secondary education, and "Bachelor or honours" as well as "higher tertiary diplomas" are coded as tertiary education. In the case of Canada, "11-13 years of elementary", "secondary school (but did not graduate)" and levels below these two are coded as lower-secondary education or less. "Graduated high school", "some non-university postsecondary education with or without certificate" and "some university without certificates" are all coded as upper-secondary education. Those who gained a university certificate, including those below a Bachelor's degree, are coded as tertiary education. In the case of Chile, the tertiary education dummy takes value one if an individual has gained a "technical degree" or a "university degree". In the case of Korea, "two years of college, vocational, technical or associate degree" is coded as upper-secondary education. In the case of Japan, those that have not graduated from high school are coded as lower-secondary education, those who graduated from high school as well as those who dropped out from junior college or a specialised school are coded as upper-secondary education, and those who at least graduated from junior college or a specialized school are coded as having obtained a tertiary degree. In the case of Switzerland, compulsory school and elementary vocational training are coded as lower-secondary education. Individuals who have graduated from a general training school, a full-time vocational school or a high school or who have completed an apprenticeship are coded as having an upper-secondary degree, and individuals with an education level higher than these are coded as having a tertiary degree. In the case of the United States, upper-secondary education corresponds to high school graduates. If the individual attended college, then the codification is tertiary education. For Brazil, upper-secondary education includes the levels "complete upper secondary" and "complete secondary", while "complete tertiary" and "complete master's or doctorate" are coded as tertiary education. For Israel, the second digit of the LIS codification provides an ISCED codification. In addition "last attended pre-elementary education, 6 to 12 years of schooling" is recoded as lower-secondary education and "last attended non-academic tertiary, less than 16 years of schooling" and higher levels are recoded as tertiary education.

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.[37] 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 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.

Working for the public sector

Whether an individual works for the public sector is self-reported only for Australia, Brazil, Chile, Japan, Korea, Switzerland and the United States. This public sector dummy captures employment at both the local and central government level as well as employment in public companies. For all other countries, the variable is constructed using information on the sector of employment. Specifically, the public employment dummy is replaced by the proportion of individuals who work for a public employer within the individual's sector of employment. Information on this proportion is taken from the ILO Labour Statistics Database. For countries for which no information is available on these proportions in the ILO Labour Statistics Database (Austria, Belgium, France, Germany, Hungary, Ireland, Iceland, Portugal, Slovakia, Sweden and the United Kingdom), the average proportions across all OECD countries for which information is available are used instead. This assumption seems reasonable for most sectors as the shares of public employment vary little across countries.

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.

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37. 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.

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.

A1.4. Selected descriptive statistics

Tables A1 and A2 present some descriptive statistics to provide an overview of the underlying data set. In general, the statistics are in line with those that can be obtained from alternative sources. Two notable exceptions are the rather high average number of hours worked for the United States (Table A2), which might be due to the way the questions are formulated, and the rather high ratio of the median earnings to the earnings at the 10^{th} centile for Canada. In the case of Japan, caution is warranted when interpreting the results of the regressions that include the work contract variable, since the share of temporary contracts is much smaller than commonly acknowledged. As regards the distribution of earnings, a very detailed description cannot be obtained for a few countries because significant mass points (due to rounding) are observed in the data. This problem seems to be particularly prevalent in the case of the Slovak Republic, where the estimation of the density function of earnings is less accurate than in the other countries as revealed by larger standard errors in the unconditional quantile regressions.

Table A1. **Overview of the sample used in the empirical analysis**

Country	Survey	Year coverage	Average sample size	Missing obs. for the baseline (%)	50/10 percentile ratio (last year)	90/50 percentile ratio (last year)
Australia	HILDA	2001-09	8 033	5	4.93	2.16
Austria	EU-SILC	2004-08	5 866	4	3.19	2.12
Belgium	EU-SILC	2004-08	5 494	7	2.56	1.74
Brazil	PNAD (LIS)	2006	179 491	20	2.56	4.00
Canada	SLID	2008	33 524	4	5.74	2.58
Chile	CASEN	2009	79 938	2	2.01	3.08
Czech Republic	EU-SILC	2005-08	8 138	1	2.00	1.85
Denmark	EU-SILC	2004-08	7 389	3	2.21	1.66
Estonia	EU-SILC	2004-08	5 549	4	2.28	2.20
Finland	EU-SILC	2004-08	12 689	5	2.84	1.86
France	EU-SILC	2004-07	9 885	5	2.55	2.02
Germany	EU-SILC	2005-08	9 885	4	5.30	1.97
Greece	EU-SILC	2007-08	5 907	3	4.10	2.31
Hungary	EU-SILC	2005-08	7 569	5	1.95	2.20
Iceland	EU-SILC	2004-08	4 317	3	2.73	1.94
Ireland	EU-SILC	2004-08	5 032	4	3.57	2.35
Israel	HES (LIS)	2001-05	7 149	11	2.74	2.82
Italy	EU-SILC	2007-08	19 460	3	2.31	2.01
Japan	JHPS	2009	3 665	11	4.21	2.44
Korea	KLIPS	2003-07	5 168	16	2.44	2.37
Luxembourg	EU-SILC	2004-08	4 217	3	2.68	2.37
Netherlands	EU-SILC	2005-08	11 191	5	3.55	1.99
Norway	EU-SILC	2004-08	7 069	4	2.71	1.77
Poland	EU-SILC	2005-08	14 851	9	3.01	2.28
Portugal	EU-SILC	2007-08	4 765	17	2.03	2.75
Slovak Republic	EU-SILC	2005-08	3 935	5	1.97	1.71
Slovenia	EU-SILC	2005-08	12 417	2	2.10	2.00
Spain	EU-SILC	2006-08	13 851	9	2.57	2.06
Sweden	EU-SILC	2004-08	7 756	7	3.21	1.68
Switzerland	SHP	2002-08	5 126	35.5	2.93	1.82
United Kingdom	EU-SILC	2005-08	8 995	4	3.23	2.37
United States	PSID	1994-07	8 251	42	2.85	2.59

Note: The column labelled "Missing observations for the baseline" reports the share of working individuals who cannot be included in the baseline estimation due to the lack of information on explanatory variables or on weights. Descriptive statistics are calculated for the subsample used in the baseline estimation. Due to the small sample sizes of some of the surveys, the 90/50 and 50/10 percentile ratios should only be seen as a description of the data used. Alternative country-specific sources may provide more accurate values for these ratios.

Source: 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; the European Union Statistics on Income and Living Conditions (EU-SILC) for 21 EU member countries as well as for Iceland and Norway.

Table A2. **Descriptive statistics of key explanatory variables**

Weighted statistics

Country	Avg. hours worked	Upper-secondary education or more (%)	Tertiary education (%)	Born in foreign country (%)	Foreign citizen-ship (%)	Self employed (%)	Temporary contract (%)	Working for public employer (%)	Union member (%)
AUS	37.1	77.6	36.8	21.8	0.4	13.9	25.5	22	21.3
AUT	40.4	85.7	20.4	11.2	6.5	12.1	5	21.3	n.a.
BEL	38.7	82.1	44	4.1	1.2	10.7	8.2	32.3	n.a.
BRA	43.2	41	10.9	3.4	n.a.	n.a.	n.a.	15.3	n.a.
CAN	33.1	86.9	24.5	n.a.	30.1	11.9	13.7	20	30.5
CHE	34.5	92.3	37.2	23.7	23.7	12.1	4.6	32.2	20.4
CHL	43.4	63.6	19.7	1.6	n.a.	18.4	24.8	11.6	1.8
CZE	43.5	94.6	15.9	0.8	0.5	15.5	10.5	22.3	n.a.
DEU	38.3	89.7	17.7	5.2	2.2	5.8	8	24.4	n.a.
DNK	38.3	79.1	32.1	3.3	1.5	7.8	n.a.	35.9	n.a.
ESP	40.2	62.5	37.4	6.3	4.5	12.1	22.1	18.4	n.a.
EST	40.6	90.9	34.9	13.6	15.3	5.7	0.7	24.5	n.a.
FIN	38.8	84.7	37.4	1.1	0.5	12.4	12.6	26.9	n.a.
FRA	38.5	78.5	31.8	6.8	2.4	7.8	14.8	28.8	n.a.
GBR	37.7	89.8	34.9	6.7	4.9	9.9	n.a.	27.9	n.a.
GRC	43.1	69.6	28.3	8	6.3	28.7	16.1	23.1	n.a.
HUN	41.2	87.5	22.5	0.5	0.2	11.9	8.6	21.8	n.a.
IRL	36.4	74.9	37.6	3.1	2.1	12.8	7.8	26.6	n.a.
ISL	45.5	71.2	29.9	3.2	1.4	14.2	5.5	24	n.a.
ISR	41.3	94.9	42.3	n.a.	n.a.	n.a.	n.a.	28.8	n.a.
ITA	39.8	62.6	17.4	6.8	5.5	21.5	11	17.6	n.a.
JPN	40.2	93.1	47.7	n.a.	n.a.	11.2	3.5	10.1	24.0
KOR	46.7	84.9	33.8	n.a.	n.a.	0	19	17	11.2
LUX	39.8	70.2	30.5	6.7	3.4	5.7	7.2	19.5	n.a.
NLD	34.2	79.6	35.4	3.9	0.3	10.9	12.4	37.6	n.a.
NOR	39.5	81.5	35.1	3	0.5	7.7	6.9	34.9	n.a.
POL	42.8	92.9	24.5	0.2	0.1	14.6	22	28.5	n.a.
PRT	41	33.2	16.2	6.4	3	11.4	17.3	21.8	n.a.
SVK	41.7	97.3	20.3	0.1	0	9.5	10	12	n.a.
SVN	41.4	84.4	23.7	9.3	n.a.	7.6	9.9	29.8	n.a.
SWE	33.6	89.4	33.2	6.4	1.2	8.7	9.4	27	n.a.
USA	52.2	88.8	58.7	8.9	n.a.	12.8	n.a.	19.2	12.8

Note: Weighted mean or weighted proportions for the latest available year. Descriptive statistics are calculated within the subsample used in the estimation.

Source: 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; the European Union Statistics on Income and Living Conditions (EU-SILC) for 21 EU member countries as well as for Iceland and Norway.

A2. Further details on estimation results

This section provides the country-specific estimation results obtained from the unconditional quantile regressions, allowing the reader to compare the effects across countries and also across different earnings quantiles (*e.g.* to see whether, for a certain country, the effects differ along the earnings distribution). Table A3 (respectively A4) summarises the unconditional (respectively conditional) quantile regression results for the baseline specification. In addition, the estimated effects are presented in graphs in two different ways, depending on the determinant of interest. For Figures A1 and A6, the determinant (age and work experience respectively) is reported on the horizontal axis, and two lines allow comparing the effects on the 20th quantile and on the 80th quantile. For all other figures, earnings quantiles are reported on the horizontal axis, and hence the left side of the figure shows the effect on the lower part of the earnings distribution, while the right side shows the effect on the upper part of the distribution. The unconditional quantile regressions are estimated with the RIF-OLS method, and standard errors are computed using a 200-replication bootstrap procedure.

Table A3. **Baseline unconditional quantile regression estimates**

Variable	Quantile	AUS	AUT	BEL	BRA	CAN	CHE	CHL	CZE
Age	0.1	0.306 (0.042)	0.224 (0.028)	0.289 (0.034)	0.061 (0.004)	0.162 (0.014)	0.085 (0.035)	0.040 (0.005)	0.084 (0.012)
	0.5	0.056 (0.005)	0.060 (0.006)	0.060 (0.006)	0.090 (0.002)	0.097 (0.005)	0.065 (0.007)	0.060 (0.003)	0.048 (0.004)
	0.9	0.026 (0.006)	0.001 (0.008)	0.015 (0.008)	0.069 (0.003)	0.018 (0.003)	0.030 (0.008)	0.034 (0.007)	0.052 (0.007)
Age squared	0.1	-0.00341 (0.00051)	-0.00250 (0.00033)	-0.00321 (0.00038)	-0.00072 (0.00004)	-0.00180 (0.00016)	-0.00096 (0.00040)	-0.00044 (0.00006)	-0.00093 (0.00014)
	0.5	-0.00060 (0.00006)	-0.00061 (0.00007)	-0.00059 (0.00007)	-0.00096 (0.00002)	-0.00104 (0.00006)	-0.00067 (0.00008)	-0.00059 (0.00003)	-0.00054 (0.00005)
	0.9	-0.00023 (0.00008)	0.00017 (0.00011)	0.00001 (0.00010)	-0.00054 (0.00004)	-0.00010 (0.00005)	-0.00022 (0.00010)	-0.00018 (0.00009)	-0.00058 (0.00009)
Sex	0.1	0.237 (0.093)	-0.217 (0.073)	-0.156 (0.057)	-0.189 (0.012)	-0.071 (0.037)	-0.440 (0.110)	-0.402 (0.027)	-0.285 (0.030)
	0.5	-0.265 (0.023)	-0.319 (0.028)	-0.250 (0.017)	-0.454 (0.007)	-0.337 (0.018)	-0.385 (0.034)	-0.318 (0.013)	-0.283 (0.014)
	0.9	-0.403 (0.029)	-0.195 (0.031)	-0.255 (0.024)	-0.501 (0.015)	-0.335 (0.017)	-0.268 (0.030)	-0.449 (0.034)	-0.287 (0.025)
Hours worked	0.1	2.570 (0.303)	1.778 (0.184)	1.451 (0.184)	1.038 (0.060)	1.653 (0.082)	2.277 (0.431)	0.889 (0.058)	1.064 (0.106)
	0.5	0.512 (0.025)	0.433 (0.031)	0.286 (0.023)	0.425 (0.007)	0.428 (0.016)	0.280 (0.028)	0.187 (0.014)	0.392 (0.032)
	0.9	0.188 (0.018)	0.309 (0.042)	0.302 (0.037)	0.296 (0.012)	0.121 (0.007)	0.146 (0.027)	0.098 (0.030)	0.823 (0.073)
Upper-secondary education or more	0.1	0.570 (0.147)	0.863 (0.134)	0.417 (0.093)	0.545 (0.028)	0.767 (0.077)	0.602 (0.303)	0.429 (0.029)	0.363 (0.072)
	0.5	0.105 (0.027)	0.419 (0.034)	0.113 (0.020)	0.708 (0.007)	0.216 (0.023)	0.261 (0.053)	0.469 (0.014)	0.299 (0.022)
	0.9	0.089 (0.026)	0.178 (0.027)	0.123 (0.024)	0.705 (0.019)	0.100 (0.018)	0.097 (0.030)	0.388 (0.024)	0.072 (0.032)
Tertiary education	0.1	0.120 (0.084)	-0.045 (0.071)	0.138 (0.056)	0.178 (0.011)	0.116 (0.043)	0.195 (0.082)	0.271 (0.022)	0.180 (0.031)
	0.5	0.367 (0.026)	0.240 (0.026)	0.251 (0.019)	0.657 (0.007)	0.425 (0.022)	0.221 (0.026)	0.669 (0.016)	0.361 (0.019)
	0.9	0.323 (0.038)	0.463 (0.048)	0.360 (0.033)	2.474 (0.052)	0.535 (0.030)	0.413 (0.041)	1.590 (0.081)	0.824 (0.058)
Constant	0.1	-6.595 (1.768)	-2.785 (1.048)	-2.300 (1.191)	2.774 (0.305)	-3.239 (0.416)	-2.440 (2.028)	7.501 (0.281)	2.265 (0.537)
	0.5	7.679 (0.122)	6.934 (0.174)	7.757 (0.145)	5.539 (0.041)	4.333 (0.112)	6.097 (0.204)	10.125 (0.076)	6.270 (0.157)
	0.9	10.202 (0.111)	9.234 (0.215)	8.962 (0.213)	7.404 (0.069)	7.882 (0.056)	7.837 (0.199)	11.869 (0.147)	5.316 (0.321)

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

Table A3. **Baseline unconditional quantile regression estimates,** *continued*

Variable	Quantile	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC
Age	0.1	0.157 (0.015)	0.323 (0.069)	0.135 (0.019)	0.073 (0.014)	0.173 (0.021)	0.227 (0.030)	0.083 (0.015)	0.347 (0.057)
	0.5	0.102 (0.005)	0.051 (0.004)	0.048 (0.004)	0.035 (0.008)	0.037 (0.004)	0.060 (0.004)	0.071 (0.005)	0.127 (0.009)
	0.9	0.027 (0.005)	0.037 (0.005)	0.014 (0.006)	0.053 (0.011)	0.014 (0.005)	0.017 (0.008)	0.044 (0.007)	0.032 (0.009)
Age squared	0.1	-0.00163 (0.00017)	-0.00346 (0.00074)	-0.00147 (0.00022)	-0.00085 (0.00017)	-0.00178 (0.00023)	-0.00247 (0.00034)	-0.00093 (0.00018)	-0.00398 (0.00065)
	0.5	-0.00102 (0.00006)	-0.00051 (0.00005)	-0.00043 (0.00005)	-0.00050 (0.00010)	-0.00036 (0.00004)	-0.00055 (0.00005)	-0.00076 (0.00006)	-0.00128 (0.00011)
	0.9	-0.00022 (0.00006)	-0.00036 (0.00007)	0.00006 (0.00008)	-0.00070 (0.00014)	-0.00007 (0.00007)	0.00004 (0.00011)	-0.00043 (0.00008)	-0.00013 (0.00011)
Sex	0.1	0.187 (0.035)	-0.083 (0.073)	-0.363 (0.046)	-0.199 (0.041)	-0.110 (0.051)	-0.245 (0.057)	0.110 (0.050)	-1.198 (0.183)
	0.5	-0.330 (0.022)	-0.230 (0.015)	-0.267 (0.017)	-0.477 (0.033)	-0.282 (0.014)	-0.192 (0.015)	-0.356 (0.023)	-0.379 (0.028)
	0.9	-0.246 (0.018)	-0.280 (0.025)	-0.193 (0.023)	-0.415 (0.052)	-0.337 (0.021)	-0.272 (0.025)	-0.340 (0.036)	-0.238 (0.034)
Hours worked	0.1	1.870 (0.247)	1.061 (0.319)	1.789 (0.149)	1.320 (0.183)	1.849 (0.193)	1.725 (0.170)	2.232 (0.156)	1.395 (0.271)
	0.5	0.638 (0.025)	0.332 (0.035)	0.241 (0.023)	0.452 (0.052)	0.260 (0.019)	0.358 (0.022)	0.553 (0.028)	0.202 (0.035)
	0.9	0.211 (0.015)	0.453 (0.073)	0.196 (0.028)	0.415 (0.084)	0.236 (0.026)	0.519 (0.044)	0.334 (0.028)	0.412 (0.049)
Upper-secondary education or more	0.1	0.685 (0.087)	0.371 (0.115)	0.266 (0.057)	0.095 (0.068)	0.317 (0.091)	0.399 (0.084)	0.132 (0.085)	1.075 (0.155)
	0.5	0.177 (0.026)	0.124 (0.016)	0.185 (0.018)	0.203 (0.041)	0.056 (0.018)	0.155 (0.017)	0.277 (0.034)	0.395 (0.032)
	0.9	0.036 (0.022)	0.021 (0.025)	0.189 (0.022)	0.084 (0.074)	0.030 (0.022)	0.108 (0.029)	0.181 (0.038)	0.264 (0.036)
Tertiary education	0.1	-0.052 (0.023)	0.043 (0.072)	0.244 (0.054)	0.232 (0.038)	0.335 (0.049)	0.194 (0.056)	0.213 (0.049)	0.828 (0.124)
	0.5	0.289 (0.018)	0.181 (0.016)	0.252 (0.020)	0.400 (0.033)	0.316 (0.015)	0.297 (0.018)	0.466 (0.026)	0.498 (0.029)
	0.9	0.522 (0.032)	0.292 (0.032)	0.435 (0.034)	0.452 (0.053)	0.485 (0.027)	0.533 (0.037)	0.512 (0.039)	0.516 (0.060)
Constant	0.1	-2.271 (1.061)	-1.363 (2.476)	-0.743 (0.746)	1.632 (0.781)	-1.757 (0.938)	-2.294 (1.094)	-0.768 (0.683)	-4.544 (1.691)
	0.5	5.475 (0.164)	8.168 (0.158)	7.582 (0.112)	6.573 (0.228)	8.342 (0.099)	7.098 (0.122)	6.553 (0.163)	5.666 (0.243)
	0.9	9.315 (0.101)	8.609 (0.301)	8.861 (0.167)	7.200 (0.385)	9.443 (0.107)	7.905 (0.230)	8.782 (0.173)	7.620 (0.274)

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

Table A3. **Baseline unconditional quantile regression estimates,** *continued*

Variable	Quantile	HUN	IRL	ISL	ISR	ITA	JPN	KOR	LUX
Age	0.1	0.101 (0.023)	0.176 (0.031)	0.154 (0.020)	0.164 (0.024)	0.142 (0.015)	0.034 (0.015)	0.112 (0.025)	0.240 (0.051)
	0.5	0.050 (0.006)	0.108 (0.011)	0.064 (0.006)	0.099 (0.007)	0.053 (0.003)	0.162 (0.013)	0.115 (0.010)	0.095 (0.016)
	0.9	0.045 (0.010)	0.021 (0.014)	0.042 (0.007)	0.059 (0.010)	0.021 (0.008)	0.045 (0.009)	0.065 (0.013)	-0.053 (0.022)
Age squared	0.1	-0.00109 (0.00026)	-0.00198 (0.00036)	-0.00159 (0.00022)	-0.00182 (0.00028)	-0.00146 (0.00017)	-0.00032 (0.00017)	-0.00132 (0.00030)	-0.00264 (0.00058)
	0.5	-0.00053 (0.00008)	-0.00114 (0.00013)	-0.00064 (0.00008)	-0.00103 (0.00009)	-0.00046 (0.00004)	-0.00169 (0.00015)	-0.00131 (0.00012)	-0.00086 (0.00018)
	0.9	-0.00046 (0.00013)	-0.00002 (0.00018)	-0.00042 (0.00009)	-0.00052 (0.00013)	0.00002 (0.00010)	-0.00033 (0.00011)	-0.00042 (0.00017)	0.00107 (0.00030)
Sex	0.1	-0.039 (0.031)	0.153 (0.106)	-0.176 (0.063)	0.139 (0.064)	-0.276 (0.037)	-0.356 (0.058)	-0.311 (0.055)	-0.261 (0.105)
	0.5	-0.164 (0.017)	-0.233 (0.046)	-0.334 (0.025)	-0.284 (0.022)	-0.195 (0.011)	-1.137 (0.066)	-0.511 (0.033)	-0.320 (0.052)
	0.9	-0.304 (0.031)	-0.285 (0.060)	-0.351 (0.031)	-0.400 (0.041)	-0.286 (0.025)	-0.419 (0.033)	-0.253 (0.032)	-0.320 (0.047)
Hours worked	0.1	1.475 (0.264)	1.752 (0.220)	1.082 (0.144)	2.377 (0.177)	1.263 (0.089)	0.816 (0.067)	0.918 (0.142)	2.972 (0.453)
	0.5	0.492 (0.042)	0.488 (0.048)	0.322 (0.033)	0.561 (0.028)	0.354 (0.018)	0.324 (0.028)	0.032 (0.045)	0.609 (0.064)
	0.9	0.454 (0.070)	0.253 (0.049)	0.198 (0.041)	0.511 (0.037)	0.777 (0.062)	0.070 (0.018)	-0.130 (0.042)	0.481 (0.066)
Upper-secondary education or more	0.1	0.362 (0.078)	0.322 (0.133)	0.147 (0.068)	0.180 (0.107)	0.351 (0.032)	0.033 (0.082)	0.476 (0.088)	0.641 (0.148)
	0.5	0.288 (0.028)	0.195 (0.048)	0.138 (0.028)	0.304 (0.034)	0.250 (0.012)	0.222 (0.072)	0.450 (0.041)	0.450 (0.057)
	0.9	0.125 (0.022)	0.290 (0.056)	0.067 (0.025)	0.243 (0.034)	0.324 (0.026)	0.174 (0.041)	0.531 (0.046)	0.070 (0.051)
Tertiary education	0.1	0.157 (0.044)	0.206 (0.087)	0.212 (0.068)	0.276 (0.068)	0.175 (0.036)	-0.073 (0.044)	0.166 (0.050)	0.038 (0.110)
	0.5	0.575 (0.023)	0.451 (0.052)	0.304 (0.028)	0.310 (0.024)	0.207 (0.014)	0.311 (0.038)	0.471 (0.036)	0.526 (0.051)
	0.9	1.054 (0.060)	0.482 (0.062)	0.478 (0.048)	0.557 (0.042)	0.740 (0.060)	0.279 (0.033)	0.587 (0.050)	0.847 (0.091)
Constant	0.1	-0.030 (1.443)	-1.129 (1.124)	2.042 (0.753)	-4.967 (1.026)	1.182 (0.478)	-1.610 (0.418)	0.636 (0.876)	-6.684 (2.395)
	0.5	5.375 (0.202)	6.004 (0.292)	7.939 (0.182)	4.387 (0.197)	7.242 (0.101)	-1.304 (0.303)	4.727 (0.271)	5.671 (0.457)
	0.9	6.482 (0.287)	9.116 (0.229)	9.554 (0.193)	6.404 (0.260)	6.726 (0.301)	2.515 (0.186)	6.496 (0.264)	9.778 (0.472)

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

Table A3. **Baseline unconditional quantile regression estimates,** *continued*

Variable	Quantile	NLD	NOR	POL	PRT	SVK	SVN	SWE	USA
Age	0.1	0.353 (0.043)	0.302 (0.033)	0.244 (0.025)	0.098 (0.026)	0.080 (0.008)	0.172 (0.027)	0.384 (0.041)	0.202 (0.030)
	0.5	0.089 (0.005)	0.049 (0.004)	0.097 (0.005)	0.076 (0.008)	0.046 (0.005)	0.074 (0.005)	0.050 (0.003)	0.077 (0.009)
	0.9	0.032 (0.006)	0.041 (0.006)	0.054 (0.008)	0.073 (0.016)	0.039 (0.006)	0.011 (0.007)	0.040 (0.005)	0.083 (0.019)
Age squared	0.1	-0.00378 (0.00045)	-0.00309 (0.00035)	-0.00288 (0.00031)	-0.00107 (0.00029)	-0.00088 (0.00009)	-0.00198 (0.00032)	-0.00387 (0.00043)	-0.00220 (0.00034)
	0.5	-0.00089 (0.00006)	-0.00048 (0.00005)	-0.00104 (0.00007)	-0.00078 (0.00010)	-0.00051 (0.00006)	-0.00076 (0.00006)	-0.00049 (0.00004)	-0.00078 (0.00011)
	0.9	-0.00020 (0.00007)	-0.00039 (0.00007)	-0.00049 (0.00010)	-0.00049 (0.00019)	-0.00043 (0.00008)	0.00005 (0.00009)	-0.00036 (0.00006)	-0.00084 (0.00024)
Sex	0.1	0.259 (0.126)	-0.331 (0.061)	-0.190 (0.053)	-0.171 (0.061)	-0.139 (0.021)	-0.116 (0.034)	-0.364 (0.082)	-0.257 (0.068)
	0.5	-0.358 (0.023)	-0.301 (0.016)	-0.261 (0.017)	-0.328 (0.031)	-0.263 (0.017)	-0.167 (0.012)	-0.241 (0.013)	-0.294 (0.031)
	0.9	-0.295 (0.023)	-0.370 (0.028)	-0.237 (0.026)	-0.349 (0.076)	-0.250 (0.023)	-0.154 (0.021)	-0.299 (0.022)	-0.414 (0.059)
Hours worked	0.1	2.346 (0.259)	1.557 (0.202)	1.566 (0.162)	1.282 (0.191)	1.000 (0.092)	0.298 (0.182)	0.895 (0.149)	1.612 (0.158)
	0.5	0.563 (0.030)	0.388 (0.025)	0.293 (0.028)	0.232 (0.050)	0.374 (0.037)	0.186 (0.031)	0.309 (0.017)	0.590 (0.039)
	0.9	0.298 (0.027)	0.382 (0.041)	0.545 (0.045)	0.449 (0.113)	0.642 (0.096)	0.354 (0.044)	0.133 (0.020)	0.897 (0.097)
Upper-secondary education or more	0.1	0.378 (0.091)	0.511 (0.097)	1.150 (0.131)	0.257 (0.074)	0.259 (0.082)	0.291 (0.069)	0.307 (0.127)	0.603 (0.127)
	0.5	0.105 (0.019)	0.158 (0.017)	0.369 (0.033)	0.333 (0.040)	0.290 (0.026)	0.384 (0.020)	0.122 (0.018)	0.319 (0.046)
	0.9	0.111 (0.020)	0.068 (0.022)	0.183 (0.026)	0.720 (0.127)	0.079 (0.031)	0.171 (0.011)	0.110 (0.025)	0.219 (0.060)
Tertiary education	0.1	0.066 (0.127)	0.084 (0.052)	0.731 (0.056)	0.178 (0.084)	0.097 (0.021)	0.301 (0.047)	0.170 (0.072)	0.037 (0.074)
	0.5	0.300 (0.023)	0.198 (0.016)	0.572 (0.021)	0.436 (0.047)	0.336 (0.020)	0.508 (0.017)	0.178 (0.013)	0.361 (0.035)
	0.9	0.475 (0.029)	0.313 (0.029)	0.758 (0.045)	1.149 (0.171)	0.421 (0.037)	0.907 (0.046)	0.308 (0.027)	0.456 (0.064)
Constant	0.1	-7.196 (1.784)	-3.141 (1.297)	-4.204 (0.893)	1.664 (1.055)	2.412 (0.414)	3.882 (0.925)	-2.985 (1.259)	-3.988 (1.036)
	0.5	6.306 (0.185)	8.049 (0.133)	5.182 (0.153)	6.593 (0.253)	6.086 (0.181)	6.806 (0.156)	7.919 (0.104)	3.748 (0.265)
	0.9	8.906 (0.153)	8.868 (0.203)	5.975 (0.231)	6.213 (0.596)	5.961 (0.389)	8.076 (0.208)	9.256 (0.119)	3.571 (0.622)

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

Table A4. **Baseline conditional quantile regression estimates**

Variable	Quantile	AUS	AUT	BEL	BRA	CAN	CHE	CHL	CZE
Age	0.1	0.146 (0.017)	0.150 (0.017)	0.190 (0.016)	0.076 (0.002)	0.093 (0.009)	0.095 (0.019)	0.031 (0.003)	0.093 (0.010)
	0.5	0.080 (0.004)	0.069 (0.005)	0.055 (0.004)	0.063 (0.001)	0.092 (0.003)	0.045 (0.007)	0.037 (0.002)	0.047 (0.004)
	0.9	0.086 (0.006)	0.041 (0.006)	0.041 (0.006)	0.082 (0.002)	0.111 (0.004)	0.058 (0.008)	0.055 (0.006)	0.050 (0.005)
Age squared	0.1	-0.00171 (0.00023)	-0.00165 (0.00021)	-0.00214 (0.00019)	-0.00089 (0.00003)	-0.00106 (0.00011)	-0.00105 (0.00022)	-0.00032 (0.00004)	-0.00103 (0.00012)
	0.5	-0.00087 (0.00005)	-0.00069 (0.00006)	-0.00053 (0.00005)	-0.00066 (0.00002)	-0.00096 (0.00004)	-0.00043 (0.00008)	-0.00034 (0.00003)	-0.00053 (0.00004)
	0.9	-0.00089 (0.00008)	-0.00030 (0.00008)	-0.00032 (0.00007)	-0.00076 (0.00003)	-0.00113 (0.00006)	-0.00056 (0.00009)	-0.00047 (0.00007)	-0.00055 (0.00006)
Sex	0.1	-0.066 (0.058)	-0.416 (0.059)	-0.232 (0.047)	-0.282 (0.009)	-0.201 (0.033)	-0.633 (0.053)	-0.280 (0.010)	-0.316 (0.026)
	0.5	-0.151 (0.017)	-0.208 (0.018)	-0.187 (0.013)	-0.325 (0.005)	-0.250 (0.012)	-0.292 (0.025)	-0.271 (0.009)	-0.265 (0.011)
	0.9	-0.313 (0.023)	-0.240 (0.023)	-0.242 (0.020)	-0.477 (0.008)	-0.329 (0.017)	-0.283 (0.037)	-0.378 (0.022)	-0.309 (0.017)
Hours worked	0.1	1.163 (0.061)	0.692 (0.103)	0.682 (0.095)	0.815 (0.010)	0.924 (0.023)	0.947 (0.081)	0.639 (0.011)	0.599 (0.093)
	0.5	0.979 (0.015)	0.847 (0.024)	0.685 (0.017)	0.543 (0.005)	0.827 (0.008)	0.722 (0.028)	0.302 (0.009)	0.662 (0.027)
	0.9	0.642 (0.025)	0.779 (0.031)	0.614 (0.027)	0.340 (0.010)	0.477 (0.015)	0.327 (0.046)	0.141 (0.024)	0.861 (0.055)
Upper-secondary education or more	0.1	0.321 (0.078)	0.463 (0.082)	0.263 (0.060)	0.731 (0.009)	0.349 (0.048)	0.180 (0.116)	0.320 (0.011)	0.284 (0.054)
	0.5	0.152 (0.022)	0.445 (0.027)	0.145 (0.017)	0.522 (0.005)	0.283 (0.017)	0.219 (0.053)	0.352 (0.009)	0.250 (0.022)
	0.9	0.153 (0.029)	0.398 (0.034)	0.111 (0.026)	0.681 (0.009)	0.301 (0.024)	0.265 (0.062)	0.453 (0.022)	0.290 (0.035)
Tertiary education	0.1	0.305 (0.064)	0.101 (0.067)	0.239 (0.048)	0.807 (0.015)	0.294 (0.041)	0.210 (0.057)	0.454 (0.015)	0.332 (0.037)
	0.5	0.279 (0.019)	0.279 (0.021)	0.245 (0.013)	1.060 (0.008)	0.416 (0.015)	0.283 (0.023)	0.786 (0.014)	0.415 (0.014)
	0.9	0.275 (0.025)	0.313 (0.026)	0.324 (0.020)	1.095 (0.014)	0.398 (0.021)	0.313 (0.028)	0.979 (0.034)	0.485 (0.021)
Constant	0.1	2.539 (0.279)	3.330 (0.512)	2.857 (0.439)	3.456 (0.059)	1.630 (0.144)	2.704 (0.488)	8.639 (0.069)	3.942 (0.395)
	0.5	5.358 (0.077)	5.106 (0.132)	6.338 (0.101)	5.557 (0.031)	2.809 (0.051)	4.905 (0.186)	10.279 (0.055)	5.329 (0.122)
	0.9	7.044 (0.100)	6.373 (0.169)	7.241 (0.147)	6.767 (0.056)	4.322 (0.070)	6.412 (0.247)	11.168 (0.135)	4.976 (0.244)

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

Table A4. **Baseline conditional quantile regression estimates,** *continued*

Variable	Quantile	DEU	DNK	ESP	EST	FIN	FRA	GBR	GRC
Age	0.1	0.153 (0.009)	0.193 (0.018)	0.128 (0.012)	0.072 (0.016)	0.111 (0.015)	0.143 (0.015)	0.062 (0.007)	0.237 (0.029)
	0.5	0.116 (0.004)	0.090 (0.004)	0.049 (0.005)	0.042 (0.007)	0.056 (0.003)	0.059 (0.004)	0.061 (0.004)	0.107 (0.008)
	0.9	0.088 (0.004)	0.075 (0.005)	0.047 (0.005)	0.057 (0.007)	0.051 (0.006)	0.050 (0.006)	0.084 (0.008)	0.095 (0.008)
Age squared	0.1	-0.00153 (0.00010)	-0.00203 (0.00021)	-0.00141 (0.00015)	-0.00084 (0.00018)	-0.00116 (0.00017)	-0.00141 (0.00018)	-0.00073 (0.00008)	-0.00268 (0.00034)
	0.5	-0.00115 (0.00005)	-0.00093 (0.00005)	-0.00042 (0.00006)	-0.00057 (0.00008)	-0.00054 (0.00003)	-0.00054 (0.00005)	-0.00065 (0.00005)	-0.00107 (0.00010)
	0.9	-0.00088 (0.00005)	-0.00074 (0.00006)	-0.00037 (0.00006)	-0.00076 (0.00009)	-0.00048 (0.00007)	-0.00037 (0.00007)	-0.00088 (0.00010)	-0.00085 (0.00010)
Sex	0.1	-0.238 (0.032)	-0.164 (0.057)	-0.396 (0.038)	-0.292 (0.046)	-0.212 (0.042)	-0.253 (0.044)	-0.101 (0.022)	-0.853 (0.092)
	0.5	-0.139 (0.015)	-0.194 (0.013)	-0.261 (0.018)	-0.413 (0.021)	-0.251 (0.008)	-0.168 (0.013)	-0.187 (0.015)	-0.301 (0.025)
	0.9	-0.180 (0.016)	-0.264 (0.018)	-0.237 (0.018)	-0.508 (0.024)	-0.328 (0.019)	-0.251 (0.018)	-0.359 (0.032)	-0.256 (0.025)
Hours worked	0.1	1.167 (0.039)	0.590 (0.192)	0.650 (0.087)	1.013 (0.126)	0.916 (0.082)	0.762 (0.084)	1.091 (0.026)	0.298 (0.171)
	0.5	1.158 (0.016)	0.603 (0.029)	0.613 (0.029)	0.778 (0.045)	0.701 (0.013)	0.836 (0.020)	1.076 (0.016)	0.406 (0.037)
	0.9	1.039 (0.018)	0.587 (0.056)	0.518 (0.030)	0.566 (0.061)	0.565 (0.033)	0.790 (0.031)	0.732 (0.041)	0.670 (0.037)
Upper-secondary education or more	0.1	0.492 (0.049)	0.221 (0.072)	0.222 (0.045)	0.216 (0.072)	0.267 (0.059)	0.290 (0.055)	0.124 (0.035)	0.718 (0.095)
	0.5	0.366 (0.024)	0.162 (0.018)	0.185 (0.021)	0.196 (0.037)	0.094 (0.012)	0.164 (0.017)	0.244 (0.024)	0.398 (0.029)
	0.9	0.277 (0.026)	0.109 (0.025)	0.219 (0.022)	0.136 (0.049)	0.079 (0.027)	0.153 (0.024)	0.350 (0.048)	0.258 (0.031)
Tertiary education	0.1	0.267 (0.029)	0.127 (0.061)	0.225 (0.046)	0.309 (0.049)	0.465 (0.046)	0.365 (0.046)	0.254 (0.024)	0.603 (0.101)
	0.5	0.273 (0.014)	0.173 (0.013)	0.311 (0.022)	0.371 (0.023)	0.323 (0.009)	0.326 (0.014)	0.432 (0.016)	0.463 (0.029)
	0.9	0.300 (0.014)	0.241 (0.018)	0.341 (0.021)	0.491 (0.027)	0.390 (0.019)	0.432 (0.020)	0.498 (0.030)	0.520 (0.030)
Constant	0.1	1.093 (0.233)	3.417 (0.763)	3.842 (0.421)	2.826 (0.544)	3.319 (0.346)	2.957 (0.399)	4.387 (0.158)	2.024 (0.863)
	0.5	2.864 (0.101)	6.258 (0.129)	6.151 (0.149)	5.218 (0.196)	6.259 (0.061)	5.359 (0.109)	4.802 (0.098)	5.368 (0.208)
	0.9	4.598 (0.102)	7.086 (0.241)	6.990 (0.146)	6.408 (0.259)	7.327 (0.146)	6.087 (0.163)	6.086 (0.212)	5.212 (0.211)

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

Table A4. **Baseline conditional quantile regression estimates,** *continued*

Variable	Quantile	HUN	IRL	ISL	ISR	ITA	JPN	KOR	LUX
Age	0.1	0.113 (0.011)	0.150 (0.020)	0.101 (0.020)	0.110 (0.009)	0.125 (0.008)	0.107 (0.013)	0.163 (0.021)	0.117 (0.021)
	0.5	0.044 (0.005)	0.083 (0.008)	0.075 (0.006)	0.078 (0.006)	0.056 (0.003)	0.082 (0.008)	0.097 (0.008)	0.047 (0.011)
	0.9	0.045 (0.008)	0.105 (0.009)	0.081 (0.007)	0.085 (0.008)	0.043 (0.005)	0.077 (0.009)	0.086 (0.010)	0.059 (0.011)
Age squared	0.1	-0.00123 (0.00013)	-0.00168 (0.00024)	-0.00098 (0.00024)	-0.00119 (0.00011)	-0.00127 (0.00009)	-0.00111 (0.00014)	-0.00184 (0.00025)	-0.00114 (0.00025)
	0.5	-0.00045 (0.00006)	-0.00082 (0.00010)	-0.00078 (0.00007)	-0.00080 (0.00008)	-0.00049 (0.00004)	-0.00081 (0.00009)	-0.00110 (0.00010)	-0.00029 (0.00014)
	0.9	-0.00045 (0.00009)	-0.00104 (0.00011)	-0.00084 (0.00008)	-0.00080 (0.00010)	-0.00029 (0.00006)	-0.00068 (0.00010)	-0.00080 (0.00012)	-0.00041 (0.00014)
Sex	0.1	-0.033 (0.026)	-0.125 (0.079)	-0.195 (0.073)	-0.184 (0.031)	-0.270 (0.023)	-0.878 (0.040)	-0.402 (0.057)	-0.345 (0.059)
	0.5	-0.153 (0.014)	-0.155 (0.033)	-0.306 (0.021)	-0.183 (0.022)	-0.195 (0.010)	-0.933 (0.027)	-0.427 (0.024)	-0.233 (0.032)
	0.9	-0.209 (0.022)	-0.259 (0.037)	-0.352 (0.027)	-0.292 (0.029)	-0.237 (0.016)	-0.552 (0.034)	-0.311 (0.027)	-0.235 (0.036)
Hours worked	0.1	0.978 (0.070)	0.798 (0.097)	0.729 (0.138)	1.020 (0.037)	0.563 (0.051)	0.673 (0.033)	0.429 (0.117)	1.088 (0.116)
	0.5	0.772 (0.030)	0.924 (0.033)	0.561 (0.029)	0.933 (0.025)	0.653 (0.018)	0.508 (0.020)	0.083 (0.035)	0.938 (0.046)
	0.9	0.546 (0.071)	0.702 (0.048)	0.360 (0.044)	0.860 (0.038)	0.812 (0.032)	0.219 (0.024)	-0.219 (0.025)	0.764 (0.053)
Upper-secondary education or more	0.1	0.218 (0.040)	0.302 (0.091)	0.127 (0.083)	0.036 (0.061)	0.336 (0.023)	0.046 (0.073)	0.306 (0.083)	0.373 (0.066)
	0.5	0.240 (0.021)	0.219 (0.039)	0.112 (0.024)	0.207 (0.048)	0.250 (0.010)	0.138 (0.050)	0.388 (0.036)	0.426 (0.037)
	0.9	0.307 (0.034)	0.253 (0.043)	0.128 (0.030)	0.402 (0.057)	0.291 (0.016)	0.230 (0.058)	0.652 (0.044)	0.260 (0.040)
Tertiary education	0.1	0.426 (0.032)	0.341 (0.084)	0.461 (0.085)	0.220 (0.029)	0.184 (0.029)	0.203 (0.037)	0.357 (0.061)	0.228 (0.069)
	0.5	0.578 (0.016)	0.430 (0.036)	0.306 (0.024)	0.417 (0.022)	0.314 (0.013)	0.257 (0.025)	0.424 (0.026)	0.429 (0.035)
	0.9	0.697 (0.025)	0.448 (0.037)	0.349 (0.028)	0.533 (0.027)	0.467 (0.020)	0.268 (0.030)	0.332 (0.031)	0.438 (0.036)
Constant	0.1	1.647 (0.311)	3.209 (0.486)	4.556 (0.595)	1.946 (0.216)	4.231 (0.242)	-2.158 (0.293)	1.538 (0.618)	2.950 (0.613)
	0.5	4.478 (0.141)	4.834 (0.181)	6.787 (0.144)	3.329 (0.154)	6.070 (0.093)	-0.453 (0.183)	4.939 (0.213)	5.434 (0.290)
	0.9	5.880 (0.306)	5.749 (0.188)	7.968 (0.192)	3.910 (0.219)	6.163 (0.166)	1.040 (0.206)	6.418 (0.211)	6.400 (0.304)

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

Table A4. **Baseline conditional quantile regression estimates,** *continued*

Variable	Quantile	NLD	NOR	POL	PRT	SVK	SVN	SWE	USA
Age	0.1	0.211 (0.017)	0.154 (0.012)	0.196 (0.013)	0.094 (0.017)	0.110 (0.008)	0.181 (0.015)	0.212 (0.015)	0.150 (0.020)
	0.5	0.097 (0.004)	0.079 (0.004)	0.093 (0.005)	0.063 (0.007)	0.045 (0.004)	0.061 (0.005)	0.082 (0.003)	0.084 (0.007)
	0.9	0.085 (0.004)	0.069 (0.006)	0.084 (0.008)	0.076 (0.012)	0.046 (0.007)	0.044 (0.006)	0.076 (0.005)	0.088 (0.015)
Age squared	0.1	-0.00220 (0.00020)	-0.00150 (0.00014)	-0.00231 (0.00016)	-0.00098 (0.00020)	-0.00121 (0.00009)	-0.00207 (0.00018)	-0.00203 (0.00017)	-0.00161 (0.00024)
	0.5	-0.00097 (0.00005)	-0.00079 (0.00004)	-0.00099 (0.00006)	-0.00061 (0.00009)	-0.00049 (0.00005)	-0.00060 (0.00006)	-0.00083 (0.00004)	-0.00086 (0.00009)
	0.9	-0.00080 (0.00005)	-0.00070 (0.00008)	-0.00085 (0.00009)	-0.00066 (0.00014)	-0.00051 (0.00009)	-0.00037 (0.00008)	-0.00077 (0.00005)	-0.00089 (0.00018)
Sex	0.1	-0.237 (0.077)	-0.475 (0.041)	-0.204 (0.038)	-0.188 (0.051)	-0.253 (0.022)	-0.093 (0.037)	-0.321 (0.056)	-0.284 (0.060)
	0.5	-0.157 (0.015)	-0.256 (0.013)	-0.231 (0.014)	-0.275 (0.024)	-0.244 (0.011)	-0.142 (0.012)	-0.221 (0.011)	-0.253 (0.023)
	0.9	-0.237 (0.018)	-0.373 (0.023)	-0.261 (0.022)	-0.424 (0.045)	-0.285 (0.020)	-0.176 (0.017)	-0.270 (0.017)	-0.307 (0.048)
Hours worked	0.1	1.063 (0.112)	0.680 (0.097)	0.657 (0.092)	0.621 (0.119)	0.740 (0.088)	0.160 (0.162)	0.513 (0.096)	0.937 (0.089)
	0.5	1.025 (0.019)	0.768 (0.022)	0.538 (0.029)	0.583 (0.044)	0.727 (0.031)	0.309 (0.032)	0.419 (0.016)	0.976 (0.026)
	0.9	0.819 (0.028)	0.773 (0.041)	0.626 (0.051)	0.556 (0.090)	0.883 (0.073)	0.517 (0.044)	0.370 (0.022)	1.041 (0.060)
Upper-secondary education or more	0.1	0.155 (0.064)	0.496 (0.057)	0.761 (0.068)	0.271 (0.069)	0.223 (0.063)	0.280 (0.053)	0.330 (0.083)	0.534 (0.098)
	0.5	0.187 (0.016)	0.166 (0.018)	0.380 (0.026)	0.357 (0.033)	0.307 (0.033)	0.279 (0.017)	0.100 (0.017)	0.321 (0.038)
	0.9	0.186 (0.021)	0.162 (0.031)	0.334 (0.041)	0.528 (0.059)	0.340 (0.058)	0.335 (0.024)	0.116 (0.026)	0.368 (0.076)
Tertiary education	0.1	0.240 (0.085)	0.216 (0.043)	0.759 (0.045)	0.453 (0.088)	0.308 (0.027)	0.525 (0.044)	0.211 (0.056)	0.161 (0.066)
	0.5	0.318 (0.014)	0.206 (0.013)	0.599 (0.017)	0.714 (0.042)	0.355 (0.013)	0.586 (0.014)	0.207 (0.011)	0.335 (0.026)
	0.9	0.368 (0.016)	0.236 (0.022)	0.638 (0.026)	0.507 (0.070)	0.366 (0.025)	0.603 (0.019)	0.272 (0.017)	0.451 (0.052)
Constant	0.1	0.977 (0.495)	3.502 (0.422)	0.646 (0.431)	4.107 (0.548)	2.828 (0.360)	4.172 (0.651)	2.234 (0.451)	-0.106 (0.551)
	0.5	4.291 (0.103)	5.917 (0.109)	4.301 (0.136)	5.539 (0.215)	4.762 (0.137)	6.681 (0.147)	6.813 (0.079)	2.121 (0.181)
	0.9	5.704 (0.137)	6.636 (0.193)	4.842 (0.225)	5.896 (0.413)	4.626 (0.309)	6.662 (0.199)	7.547 (0.120)	2.470 (0.403)

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

Figure A1. **Effect on log earnings of having a certain age relative to the age of 15**

Unconditional quantile regression estimates (baseline)

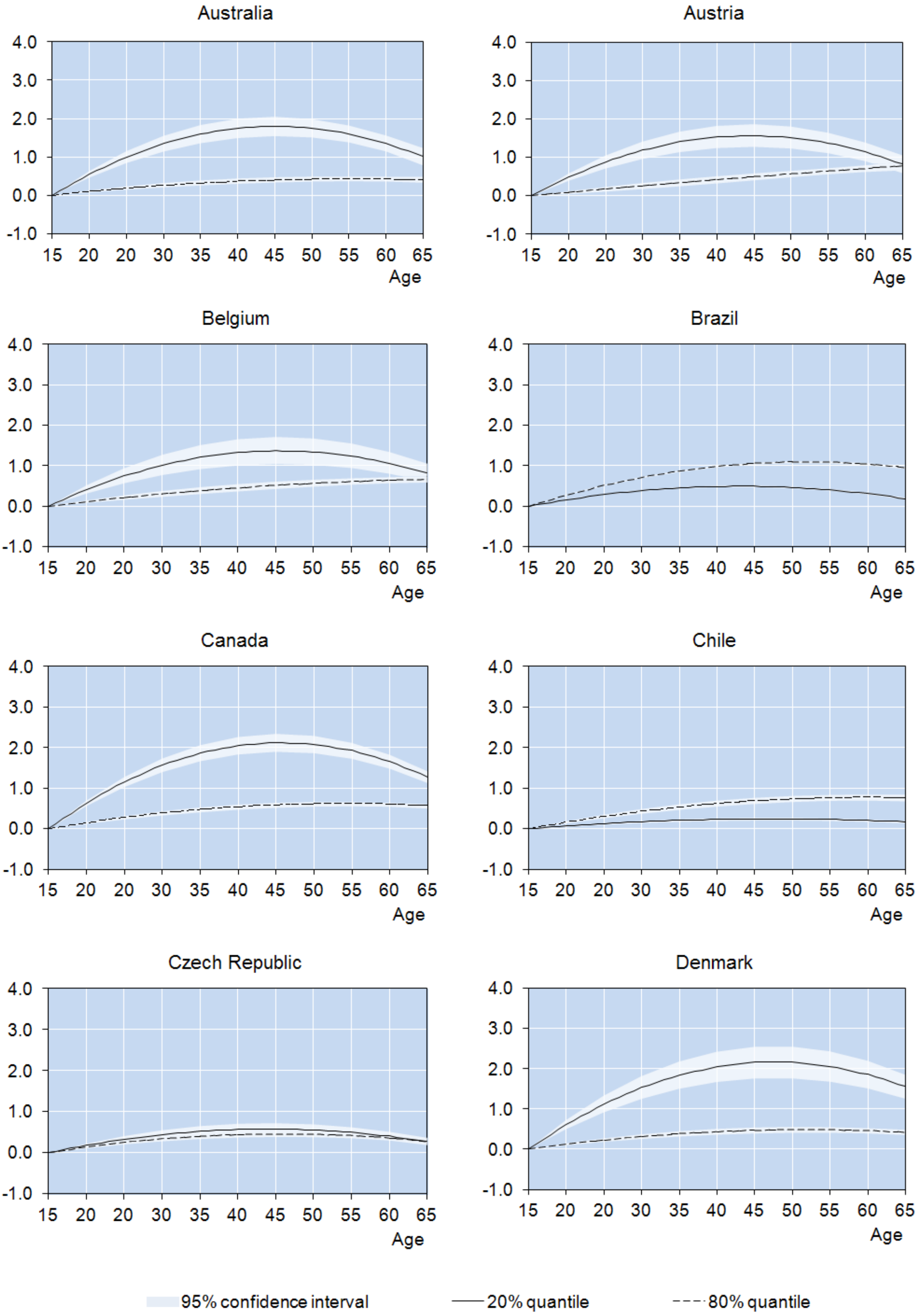


Figure A1. **Effect on log earnings of having a certain age relative to the age of 15**, *continued*

Unconditional quantile regression estimates (baseline)

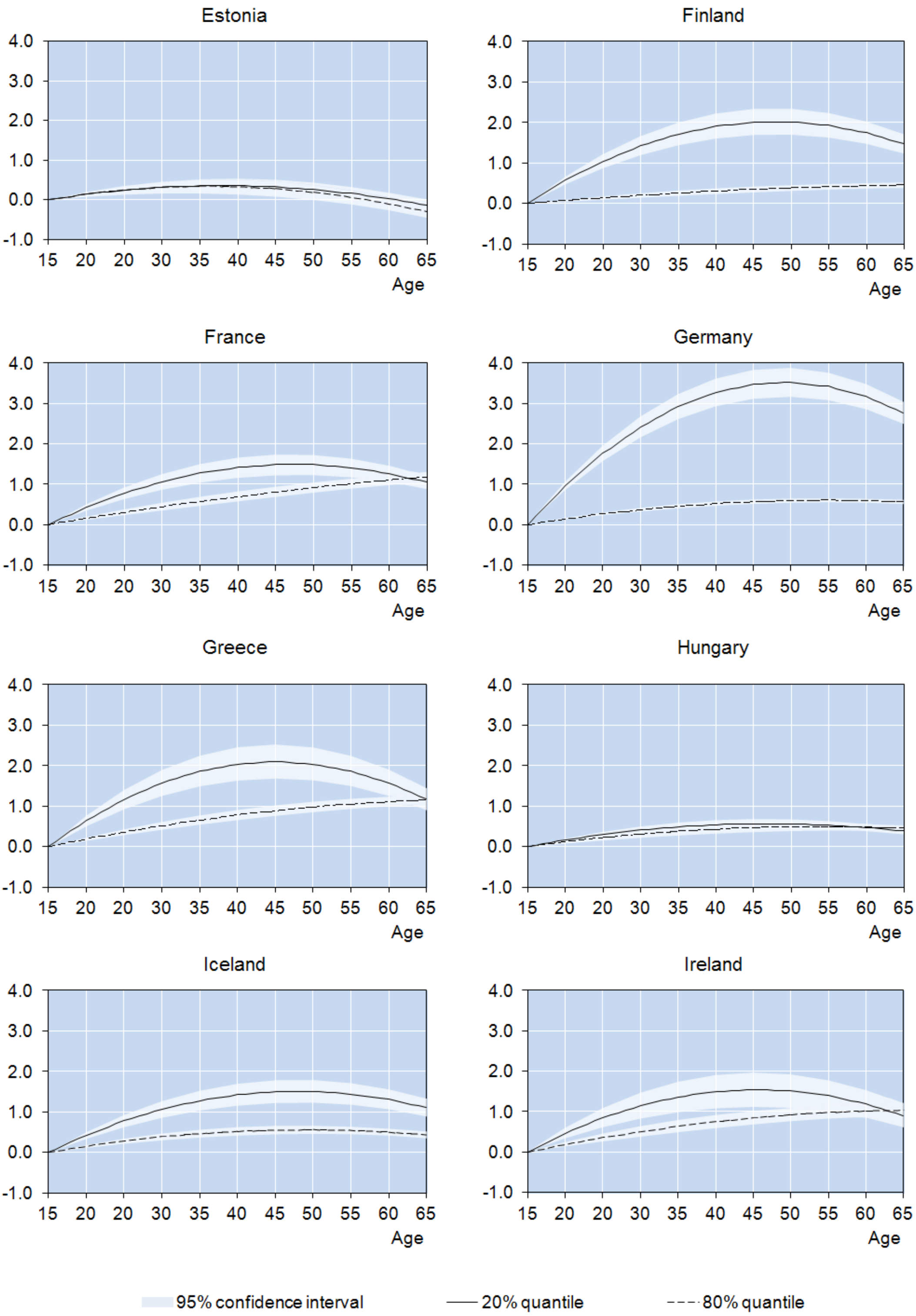


Figure A1. **Effect on log earnings of having a certain age relative to the age of 15,** *continued*

Unconditional quantile regression estimates (baseline)

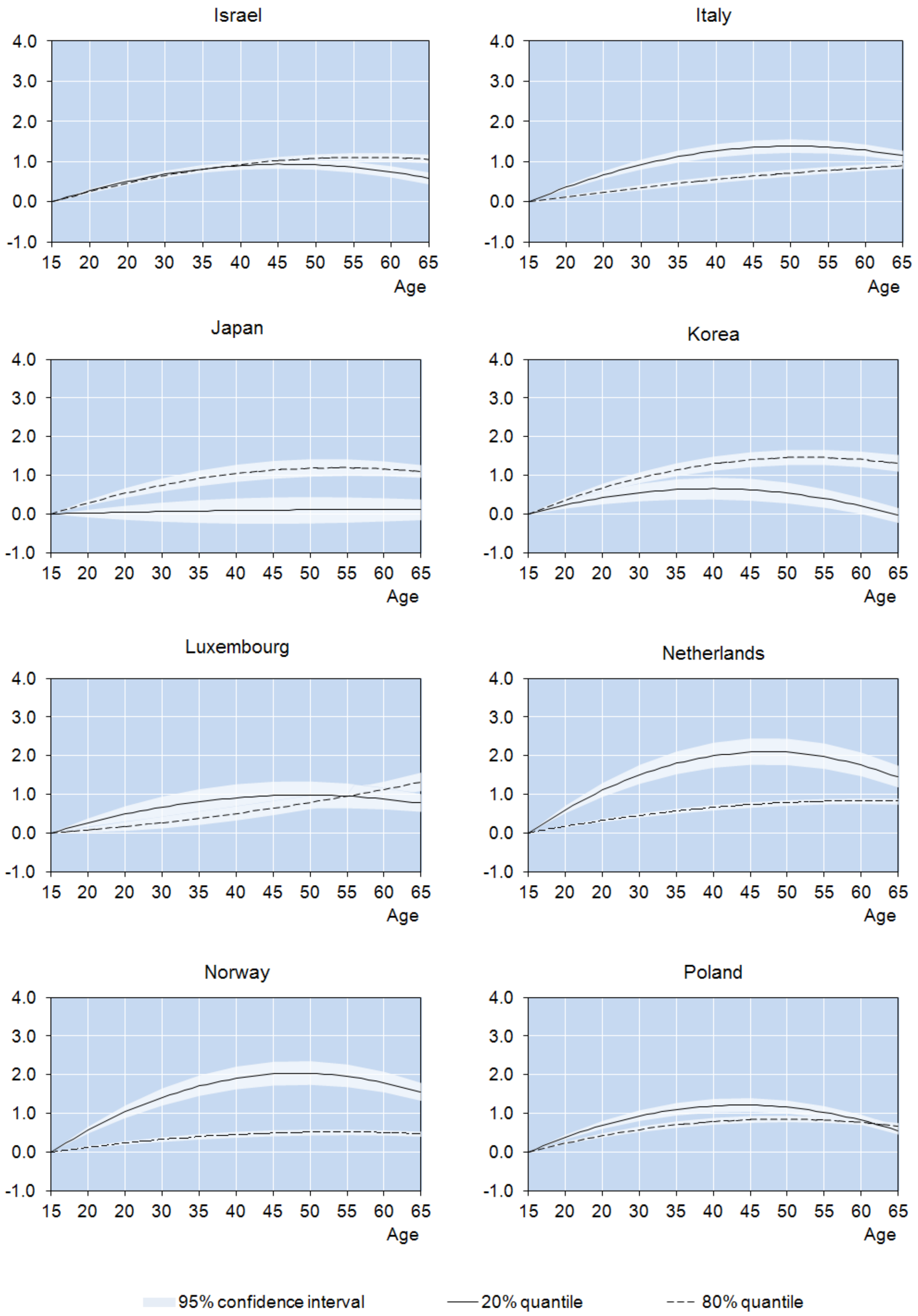


Figure A1. **Effect on log earnings of having a certain age relative to the age of 15,** *continued*

Unconditional quantile regression estimates (baseline)

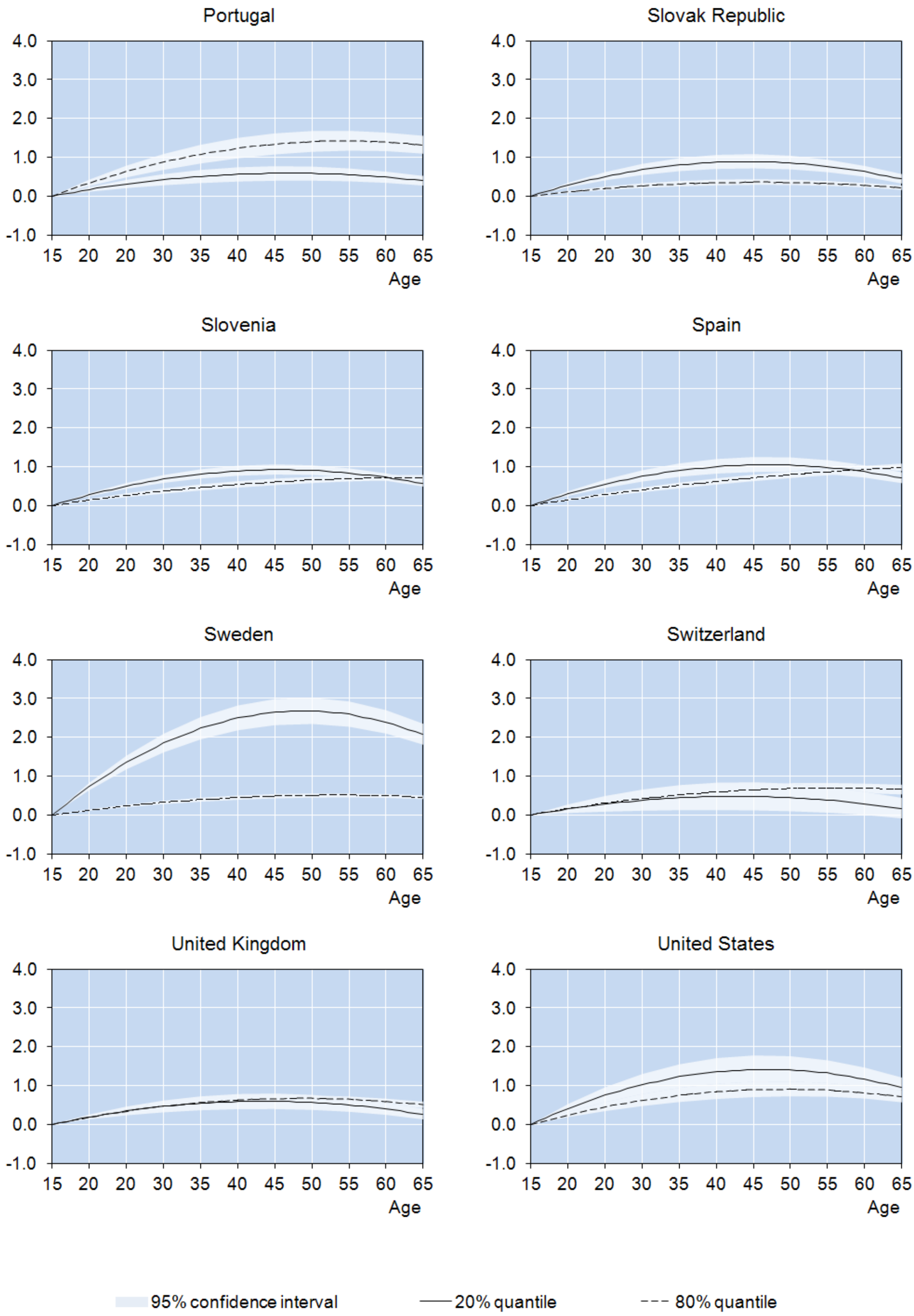


Figure A2. **Effect on log earnings of being a woman (relative to being a man)**

Unconditional quantile regression estimate (baseline)

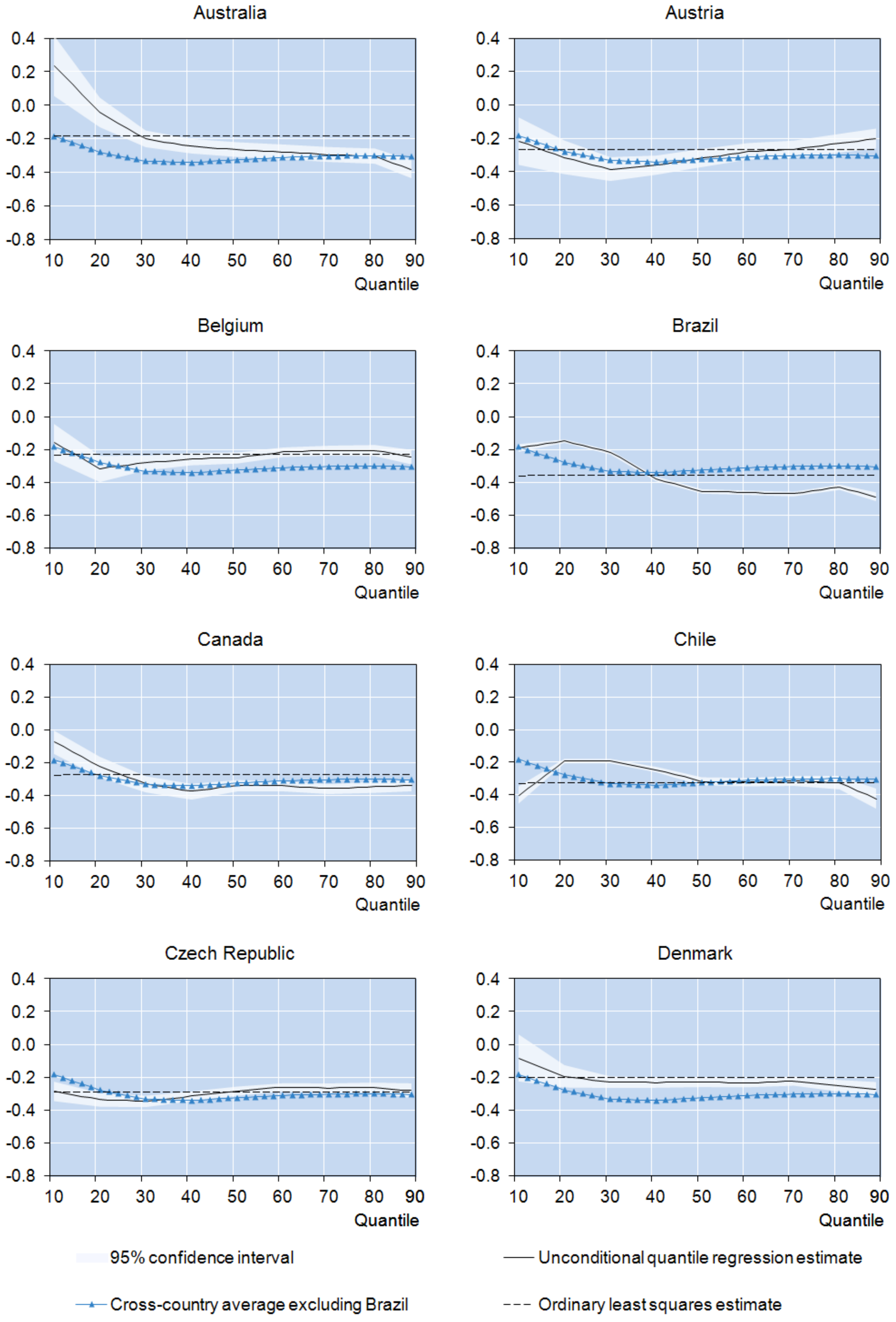


Figure A2. **Effect on log earnings of being a woman (relative to being a man),** *continued*

Unconditional quantile regression estimate (baseline)

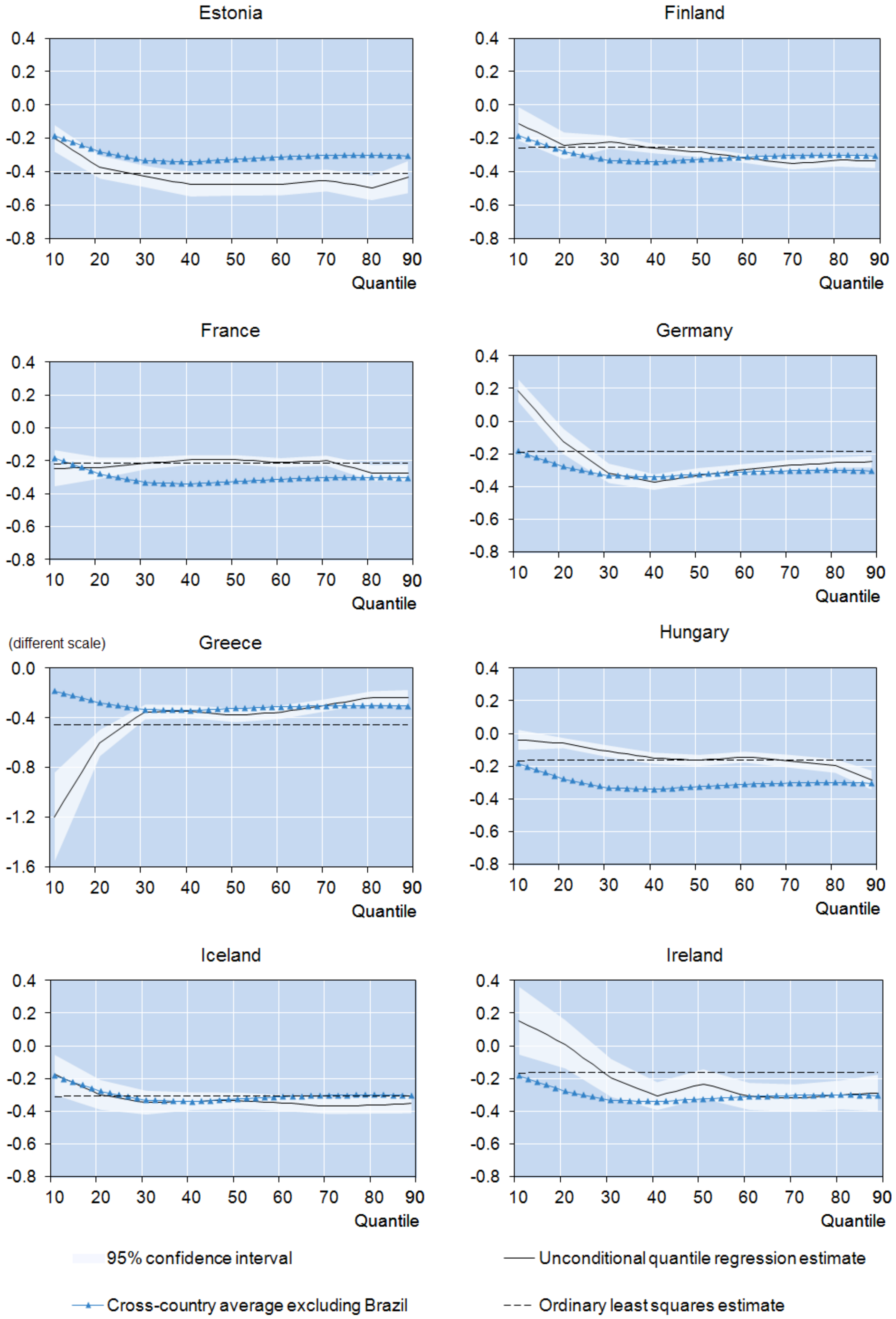


Figure A2. **Effect on log earnings of being a woman (relative to being a man),** *continued*

Unconditional quantile regression estimate (baseline)

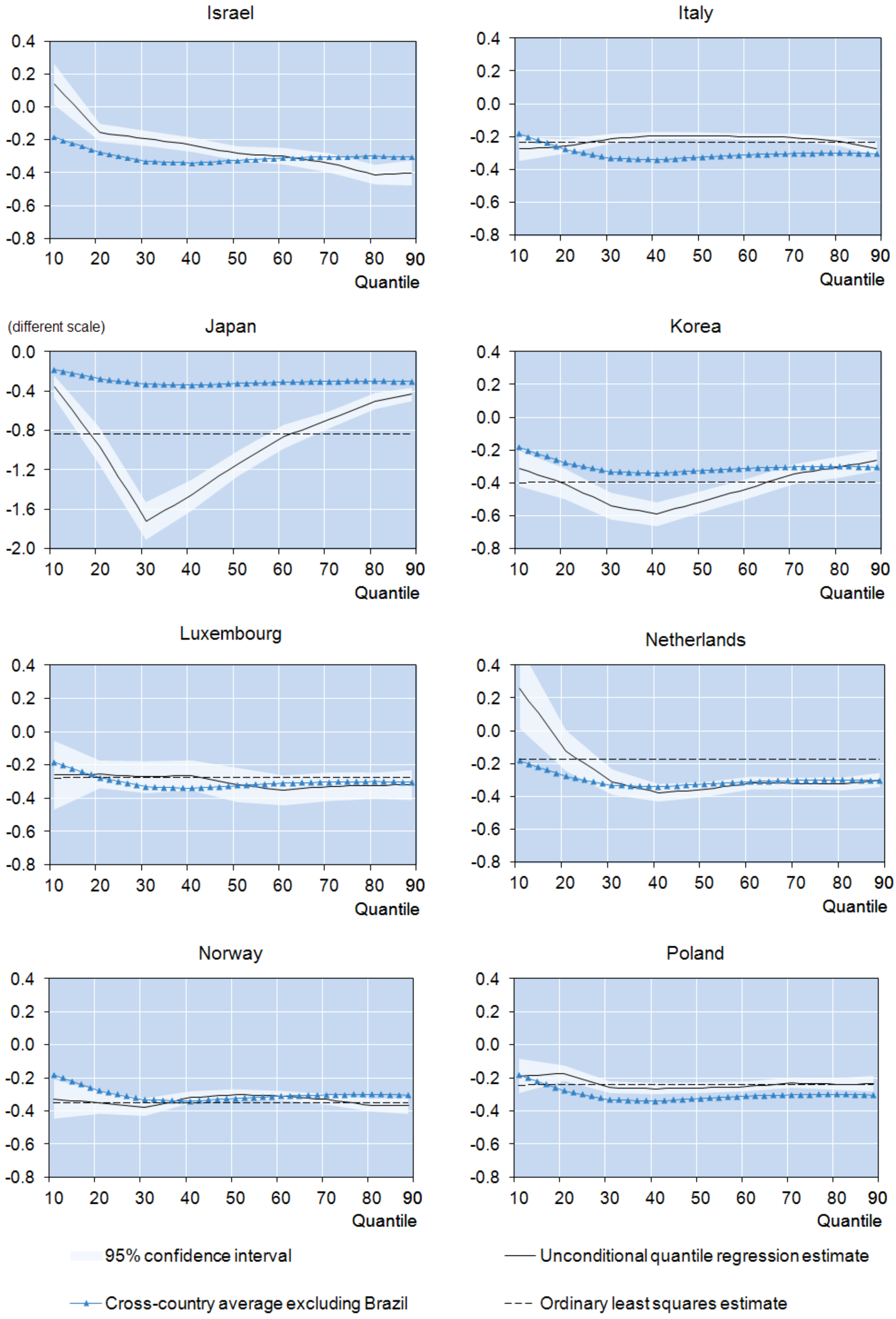


Figure A2. **Effect on log earnings of being a woman (relative to being a man),** *continued*

Unconditional quantile regression estimate (baseline)

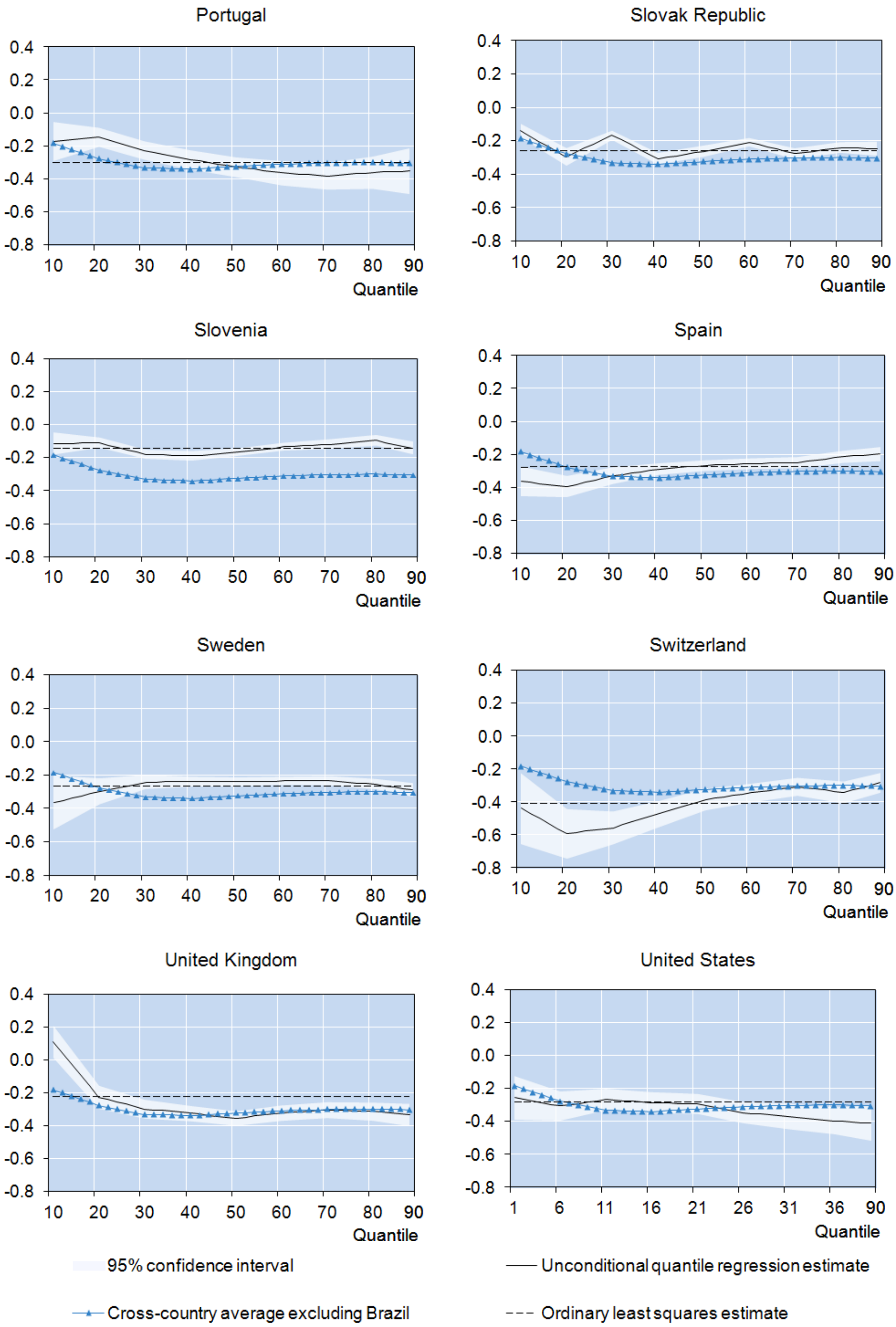


Figure A3. **Effect on log earnings of raising the share of workers with a certain education level by 1%**

Unconditional quantile regression estimate (baseline)

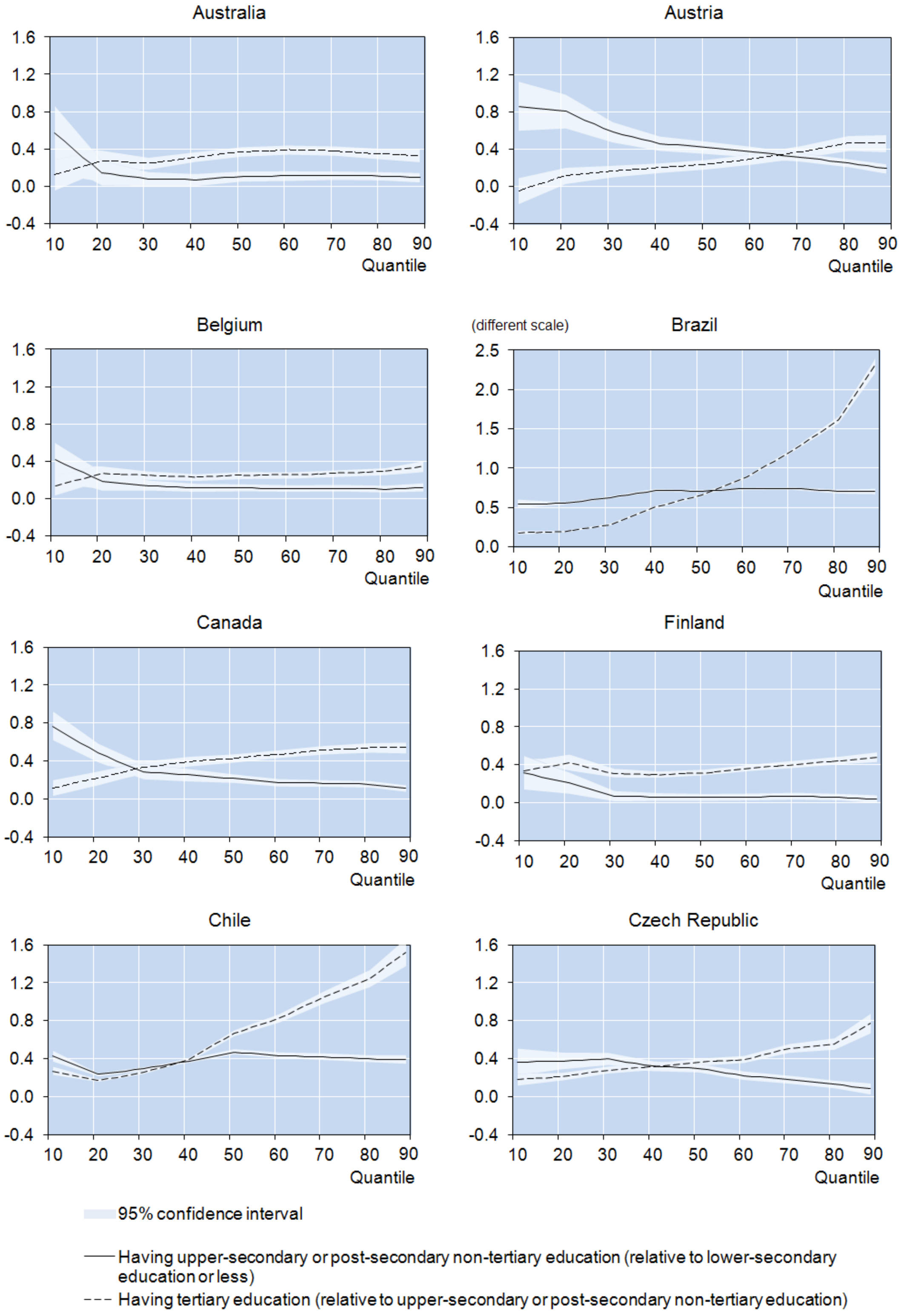


Figure A3. **Effect on log earnings of raising the share of workers with a certain education level by 1%,** *continued*

Unconditional quantile regression estimate (baseline)

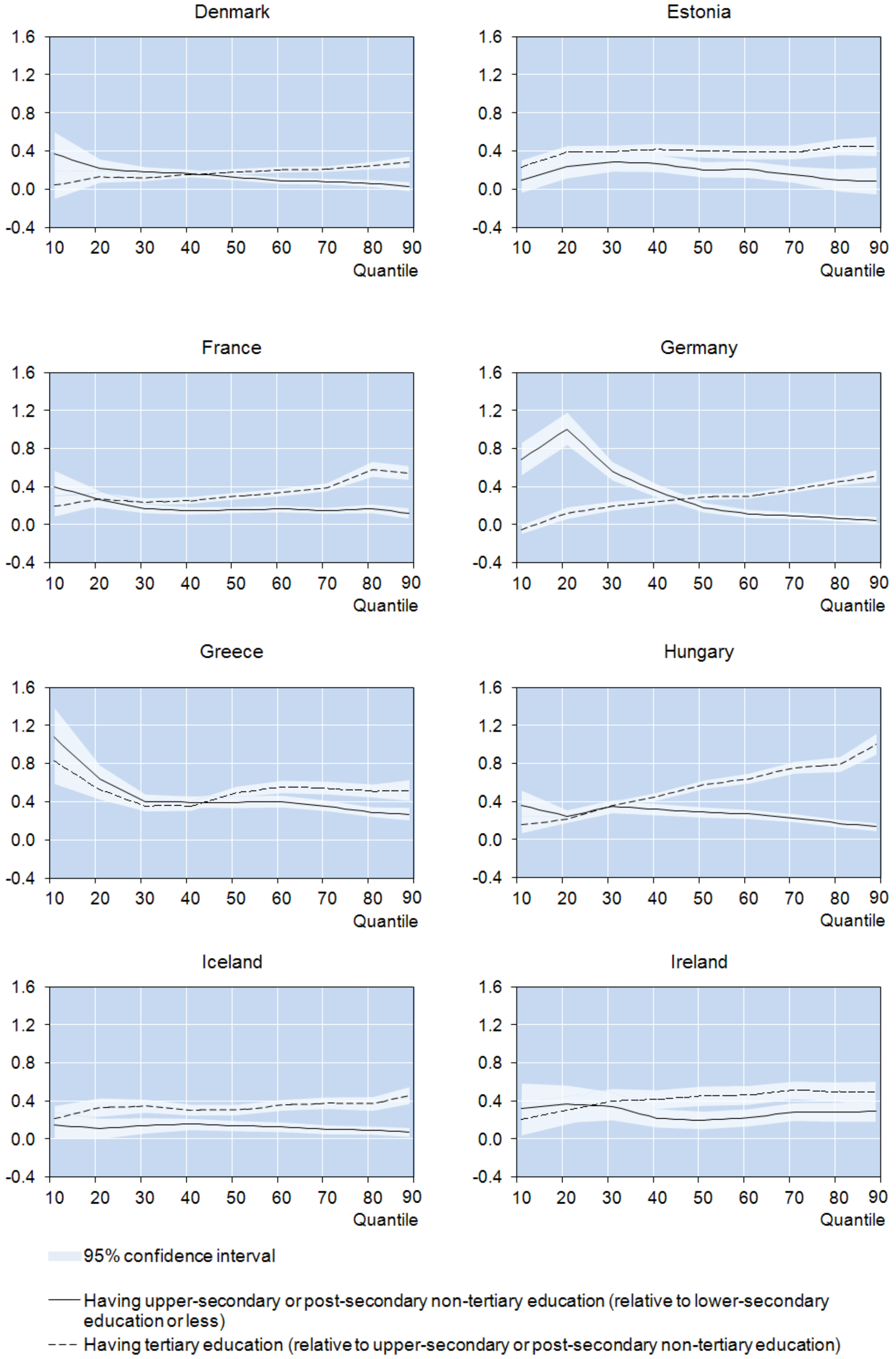


Figure A3. **Effect on log earnings of raising the share of workers with a certain education level by 1%,** *continued*

Unconditional quantile regression estimate (baseline)

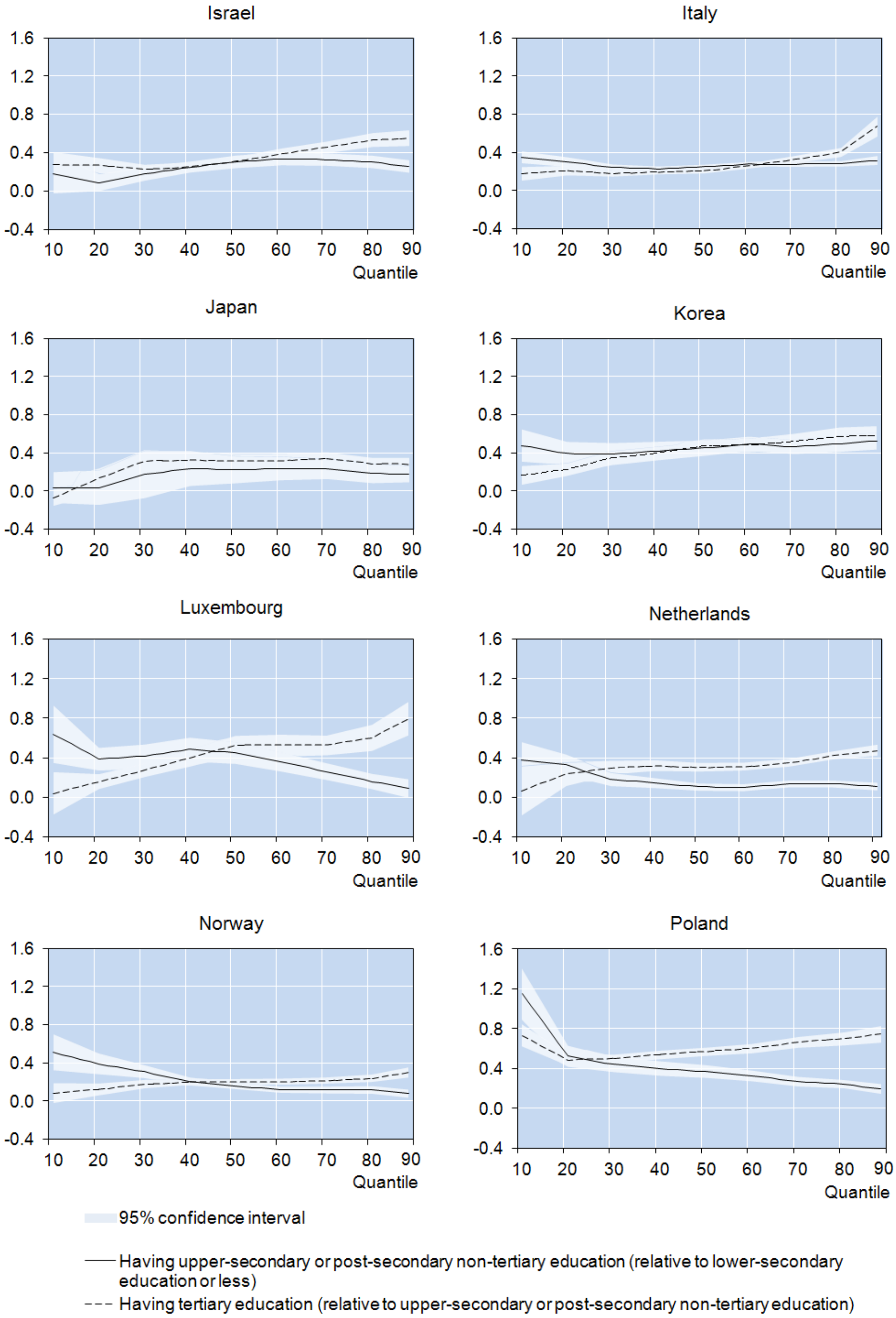


Figure A3. **Effect on log earnings of raising the share of workers with a certain education level by 1%,** *continued*

Unconditional quantile regression estimate (baseline)

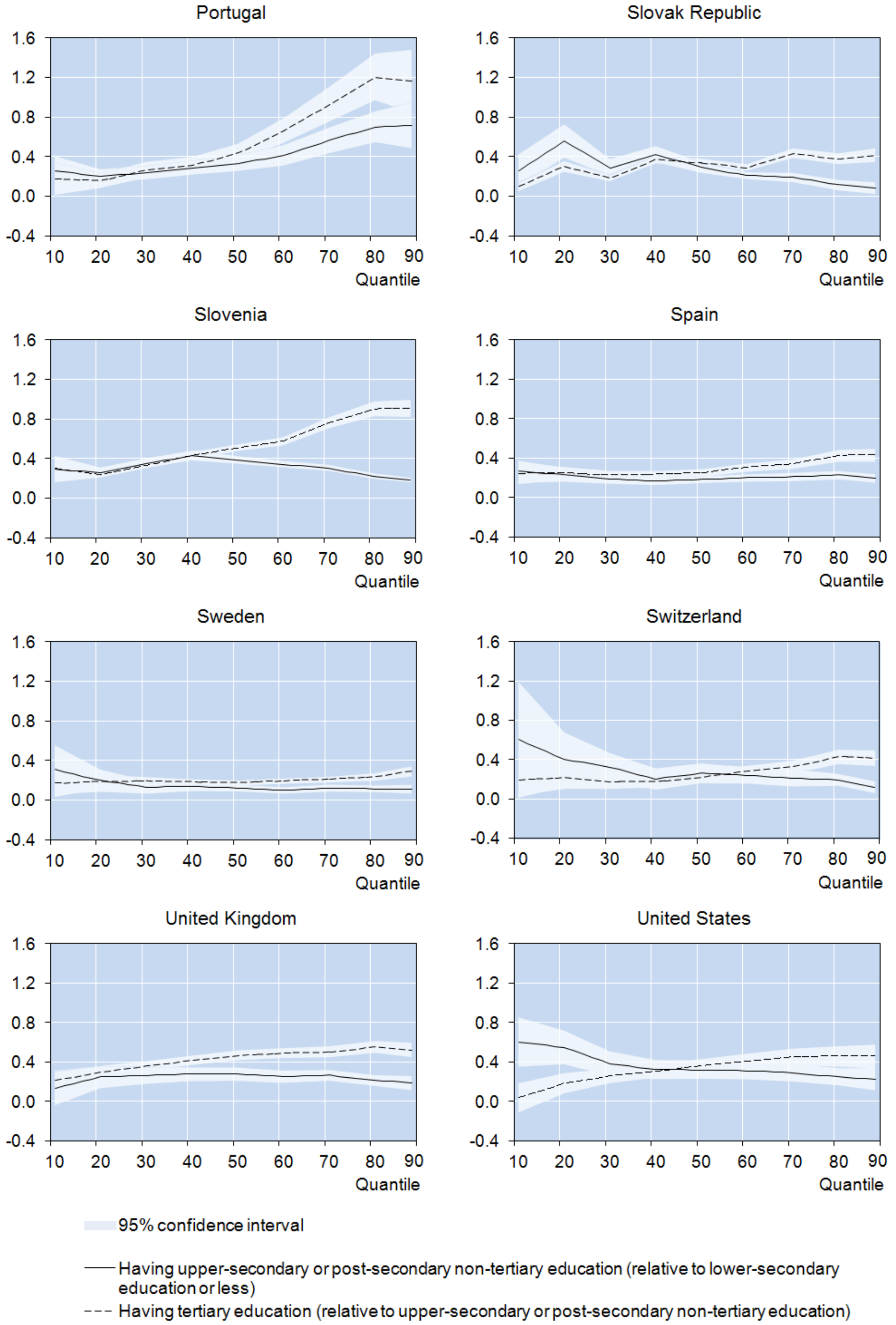


Figure A4. **Effect on earnings (in per cent) of a rise in hours worked by 1%**

Unconditional quantile regression estimate (baseline)

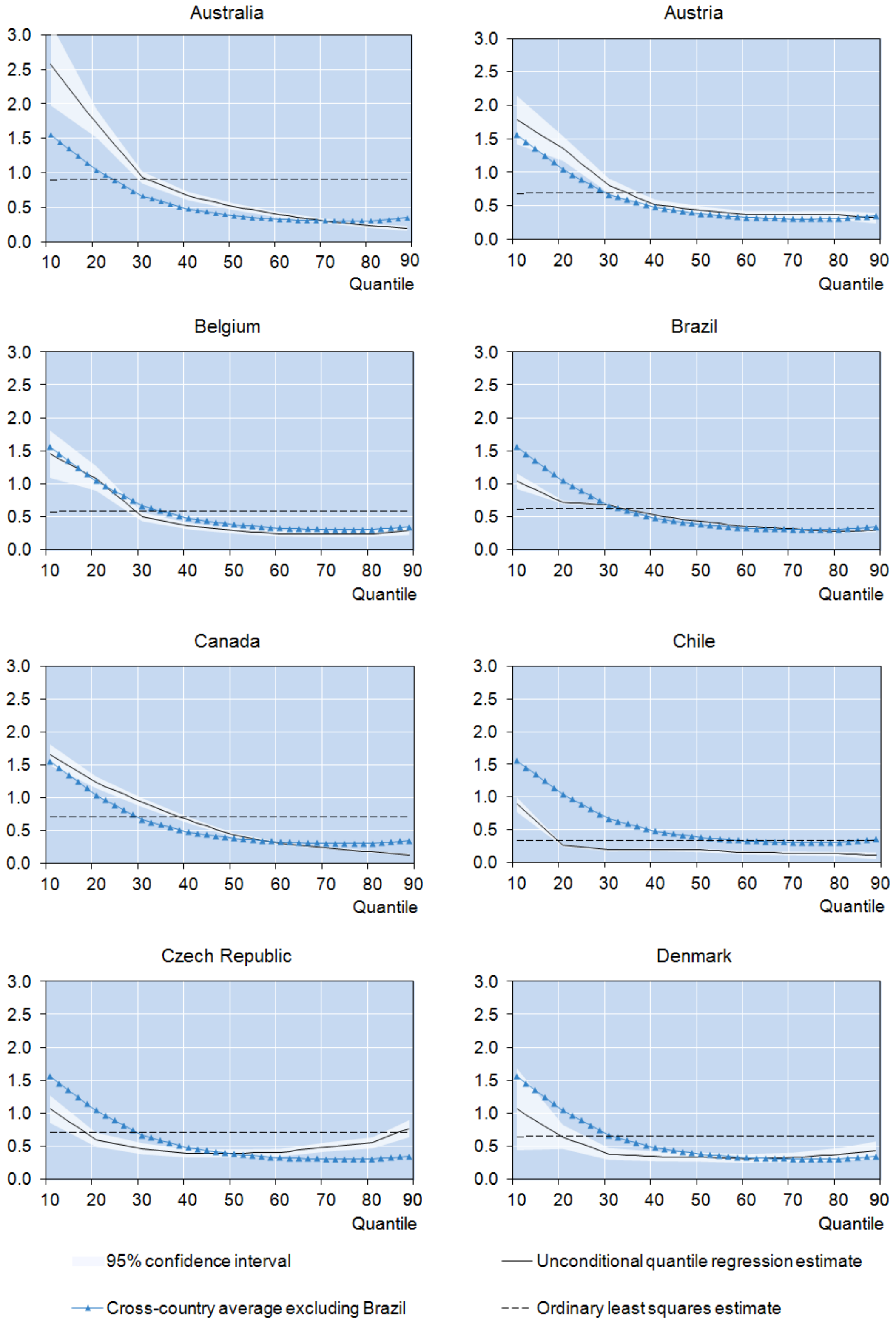


Figure A4. **Effect on earnings (in per cent) of a rise in hours worked by 1%**, *continued*

Unconditional quantile regression estimate (baseline)

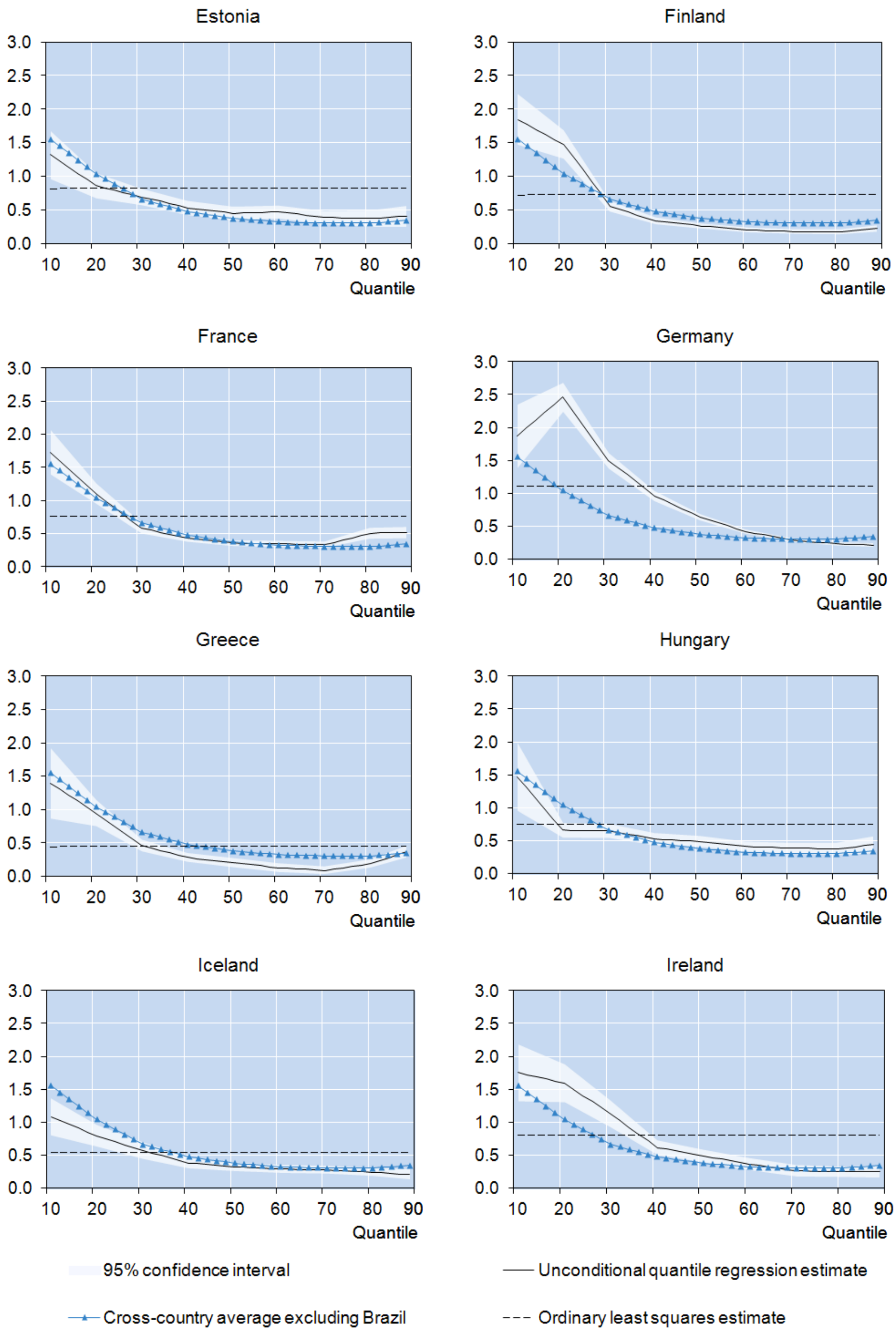


Figure A4. **Effect on earnings (in per cent) of a rise in hours worked by 1%**, *continued*

Unconditional quantile regression estimate (baseline)

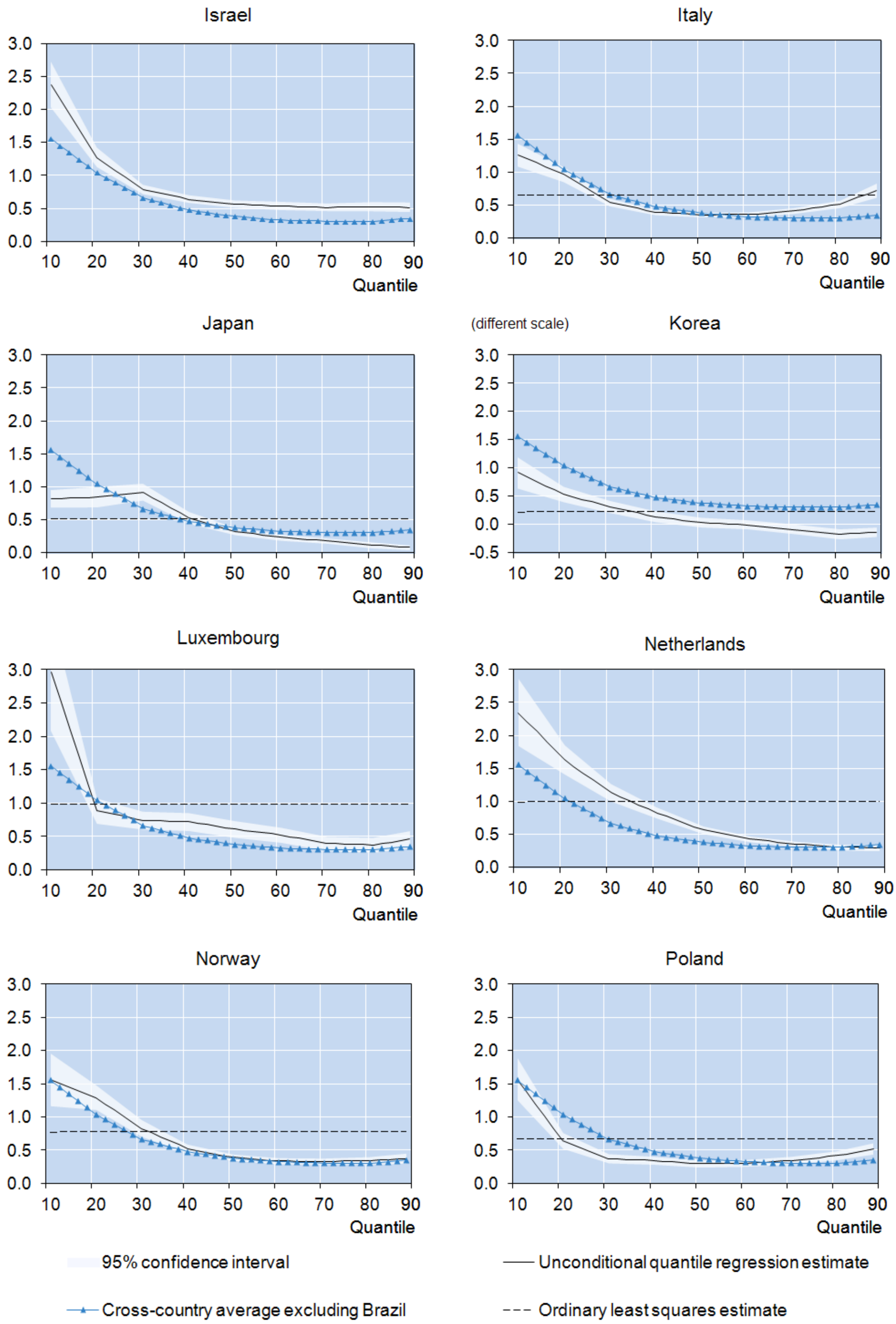


Figure A4. **Effect on earnings (in per cent) of a rise in hours worked by 1%**, *continued*

Unconditional quantile regression estimate (baseline)

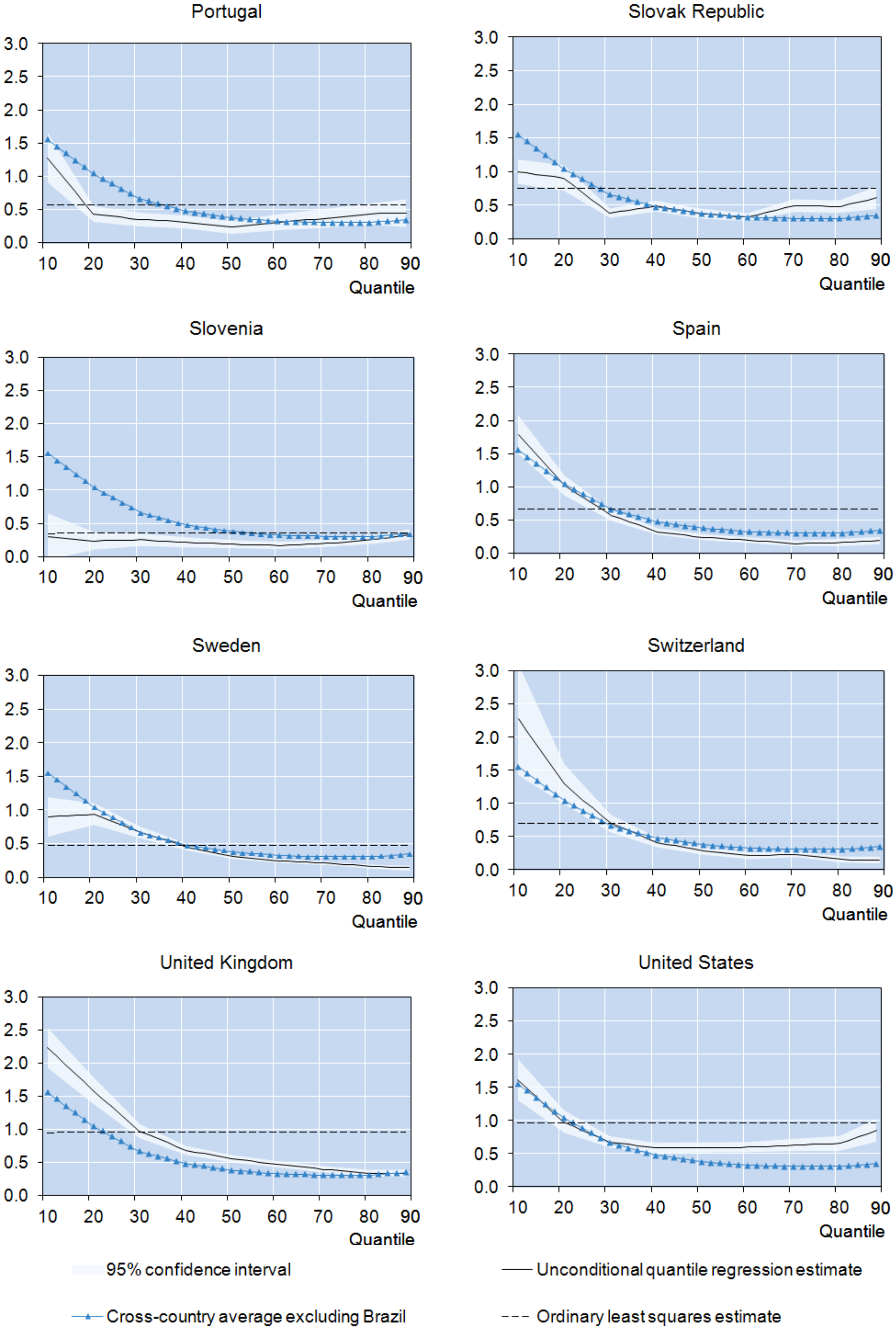


Figure A5. **Effect on log earnings of being foreign-born**

Unconditional quantile regression estimate

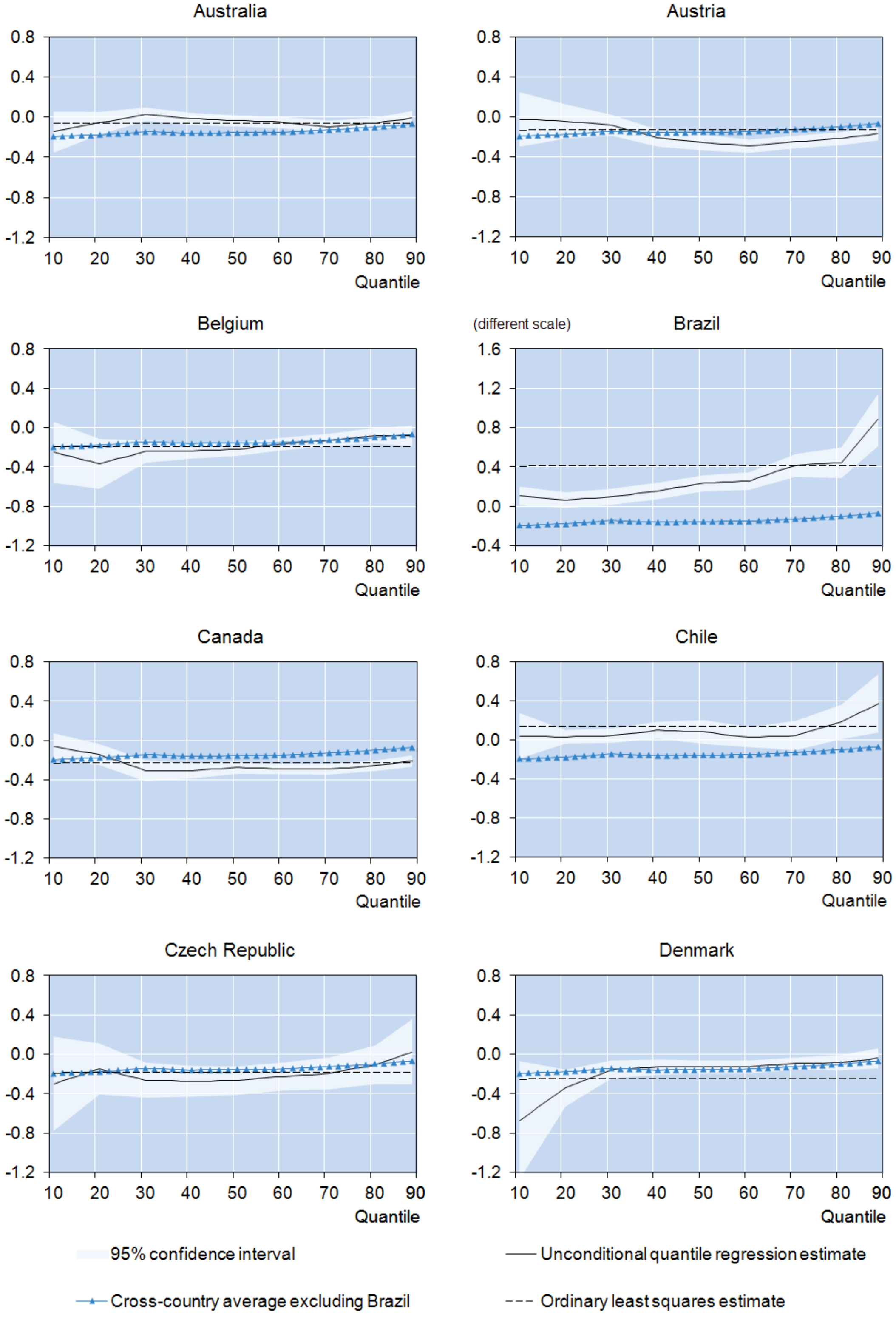


Figure A5. **Effect on log earnings of being foreign-born,** *continued*

Unconditional quantile regression estimate

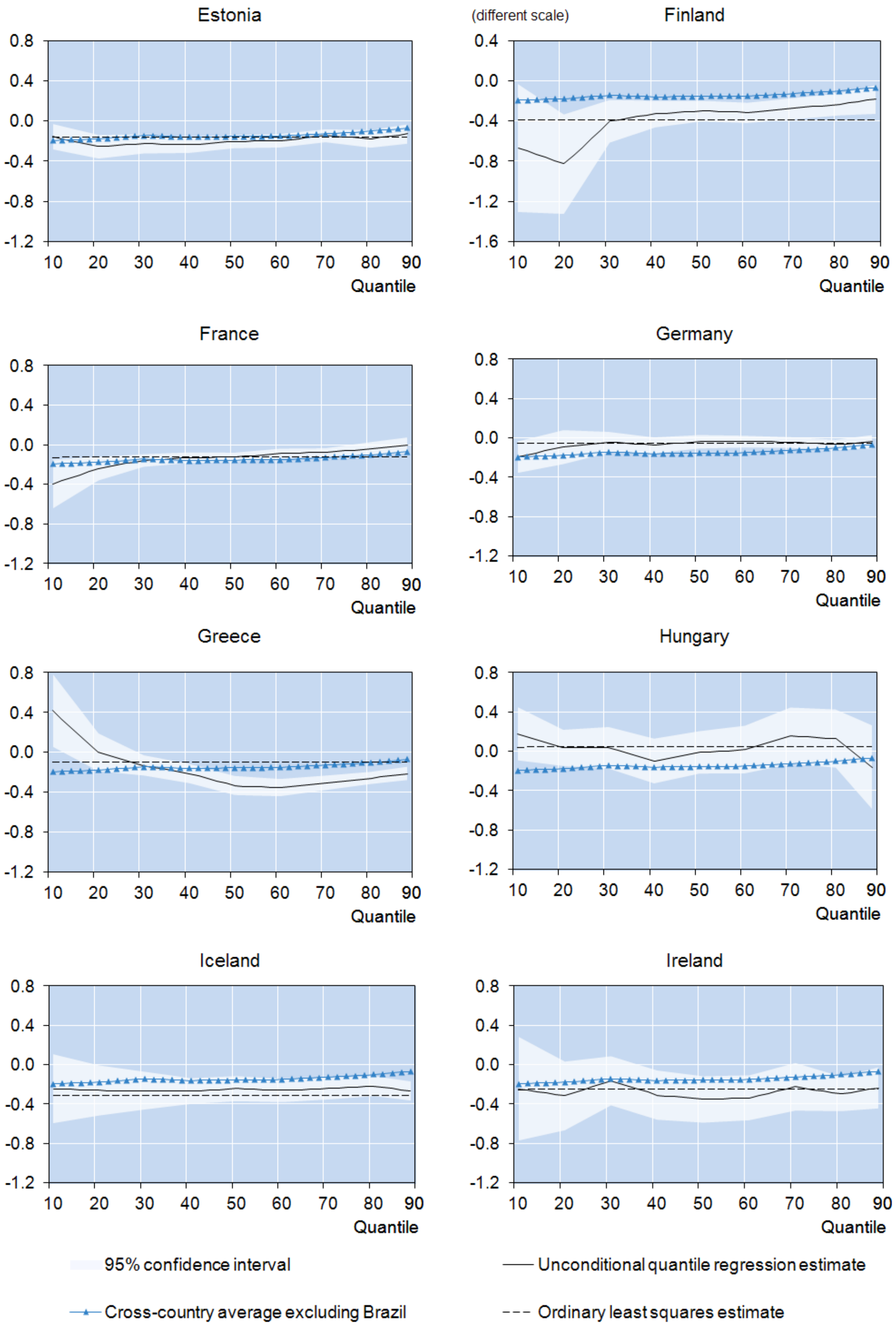


Figure A5. **Effect on log earnings of being foreign-born,** *continued*

Unconditional quantile regression estimate

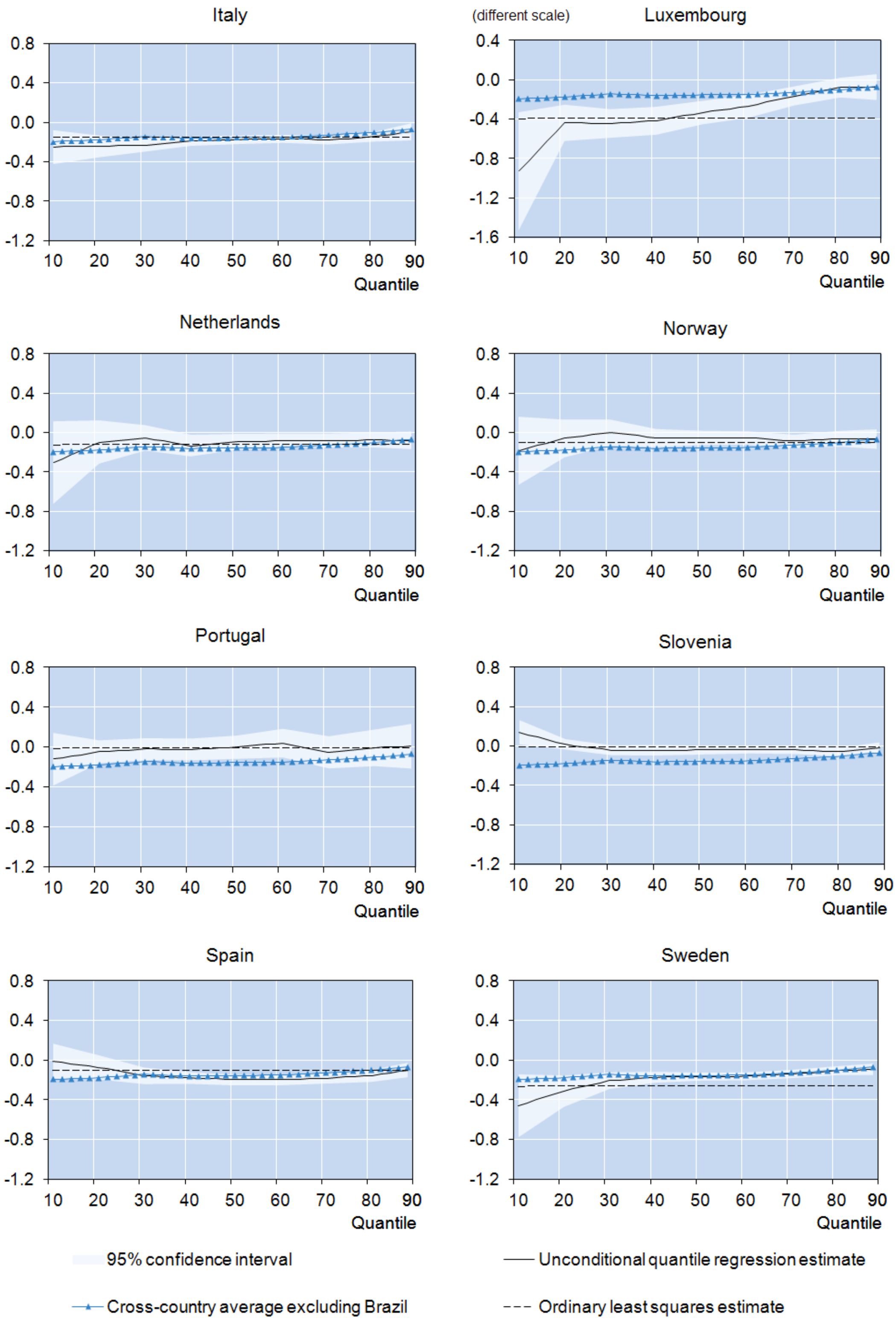


Figure A5. **Effect on log earnings of being foreign-born,** *continued*

Unconditional quantile regression estimate

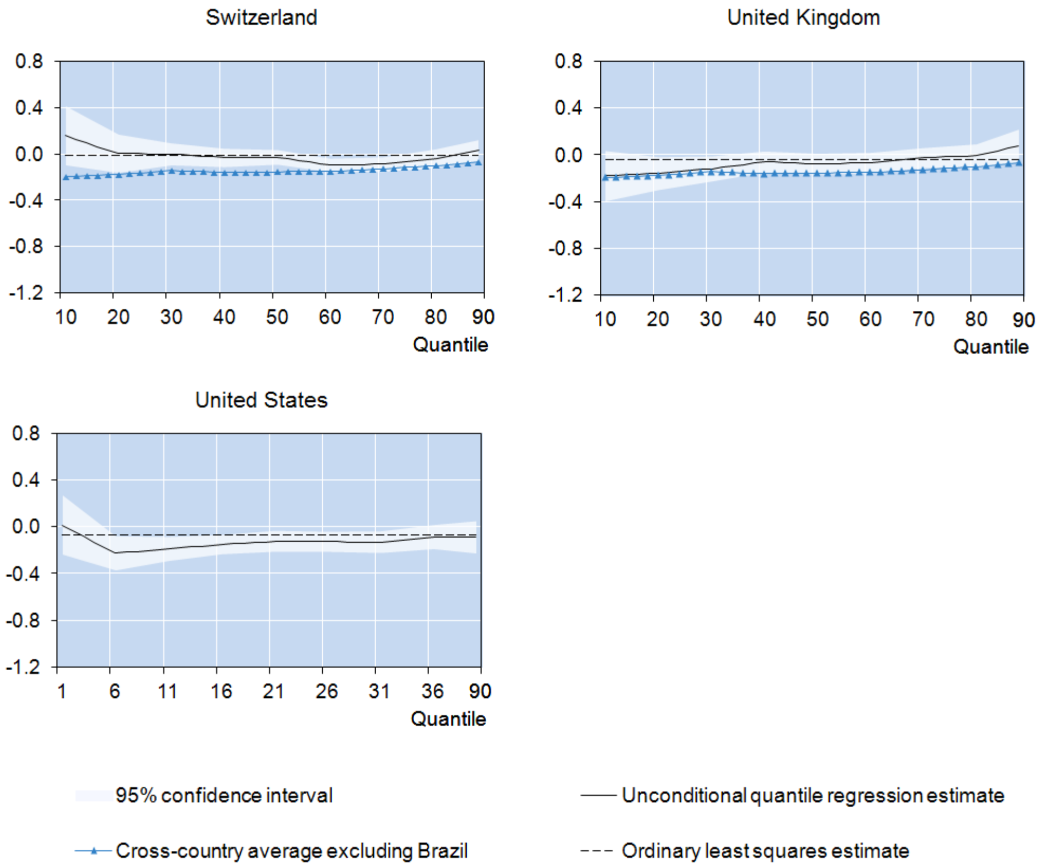


Figure A6. **Effect on log earnings of having a certain number of years of work experience relative to no experience**

Unconditional quantile regression estimate

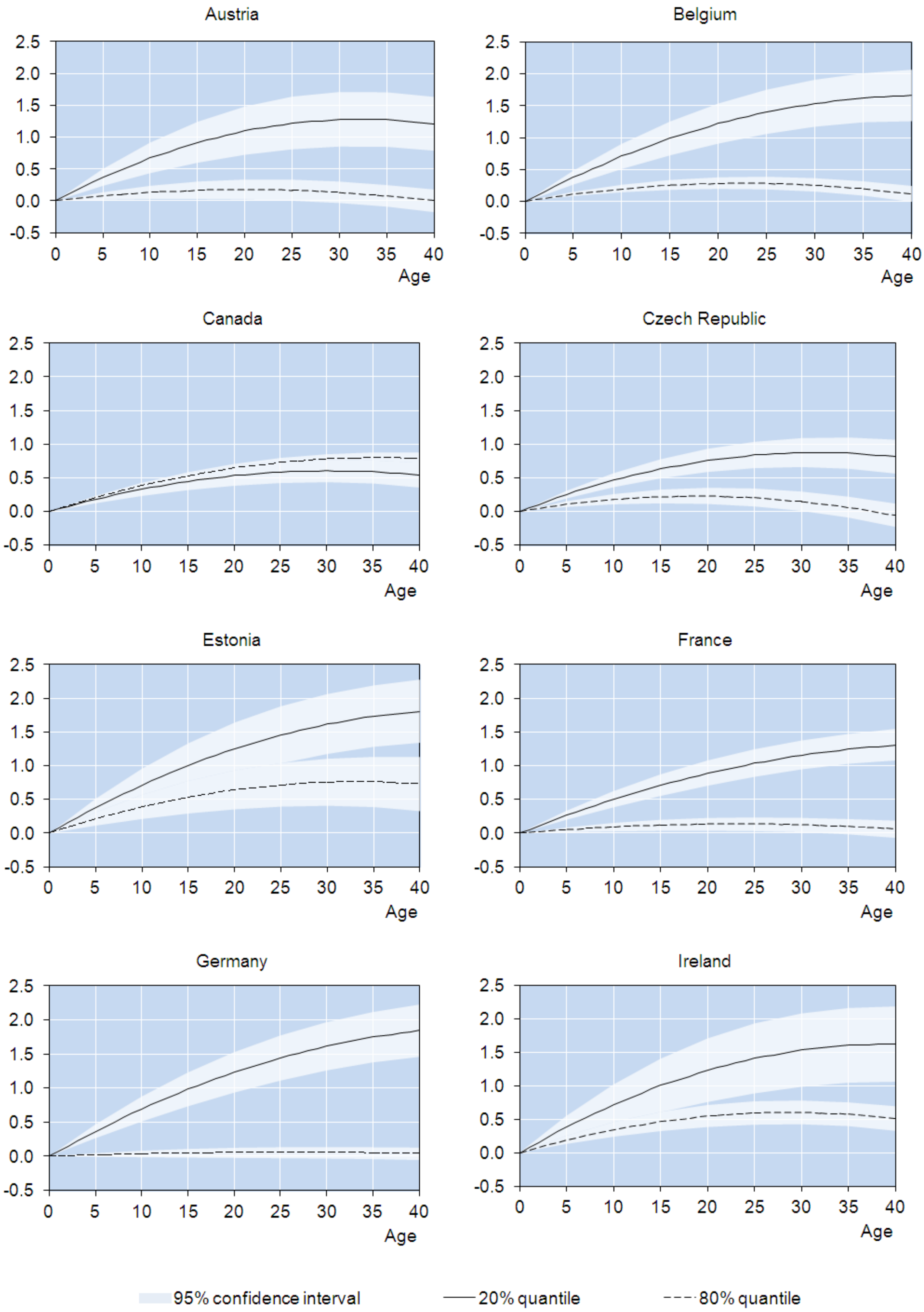


Figure A6. **Effect on log earnings of having a certain number of years of work experience relative to no experience,** *continued*

Unconditional quantile regression estimate

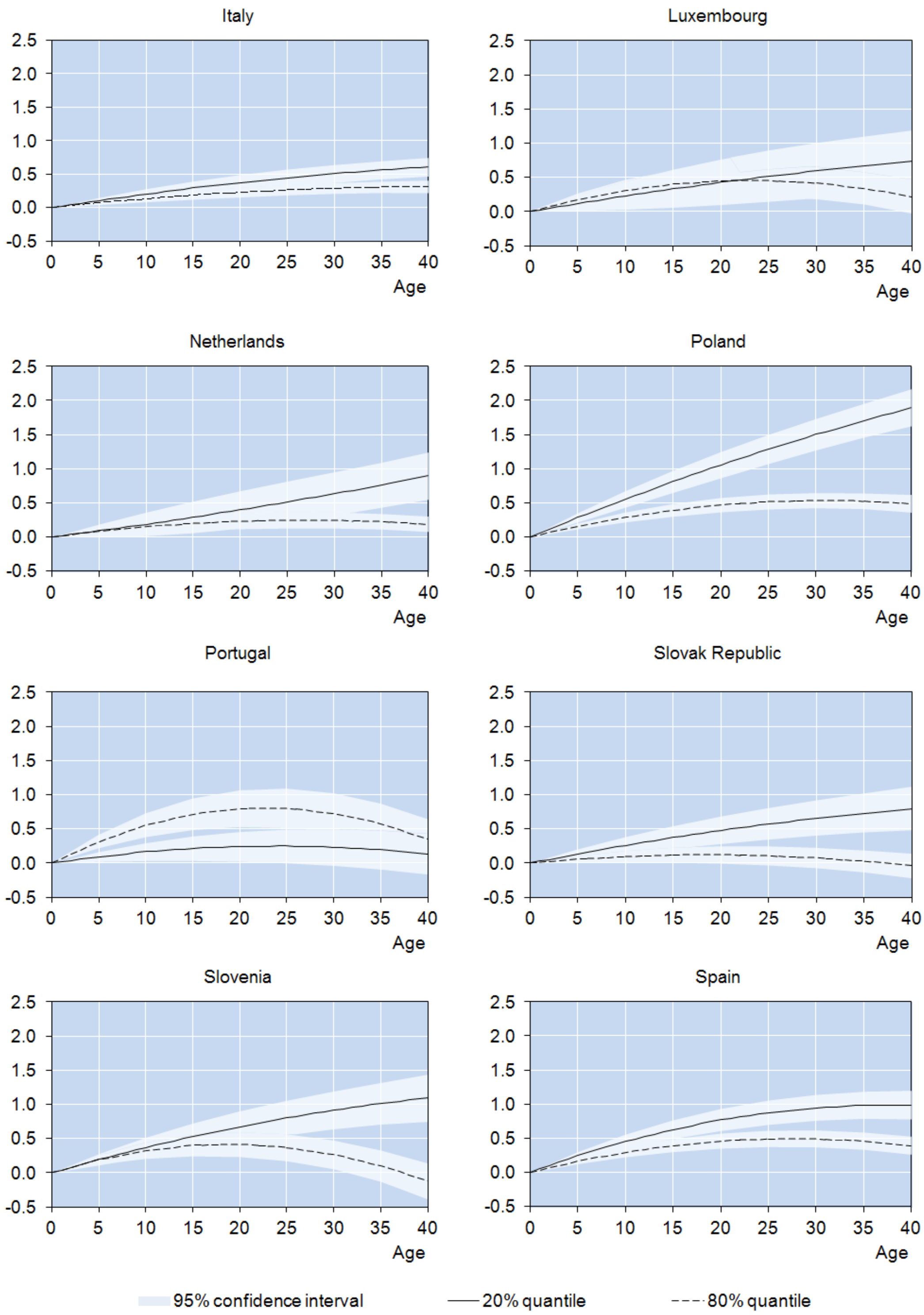


Figure A6. **Effect on log earnings of having a certain number of years of work experience relative to no experience,** *continued*

Unconditional quantile regression estimate

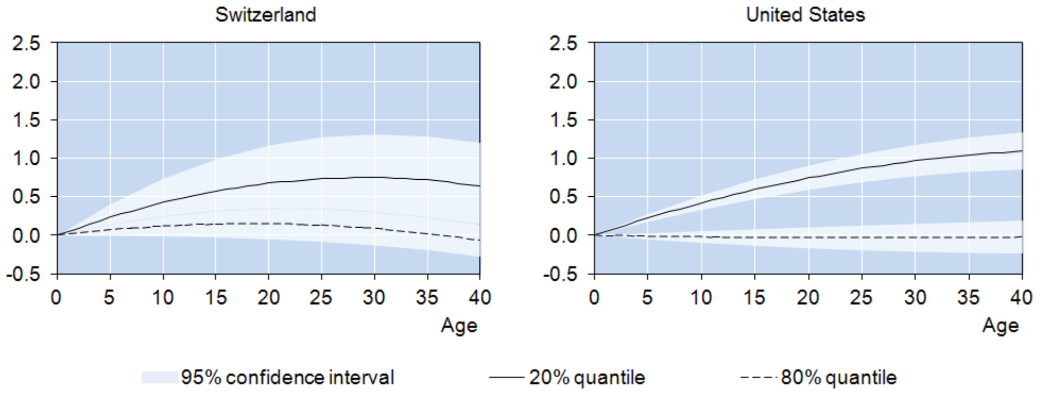


Figure A7. **Effect on log earnings of having a temporary contract (relative to having a permanent contract)**

Unconditional quantile regression estimate

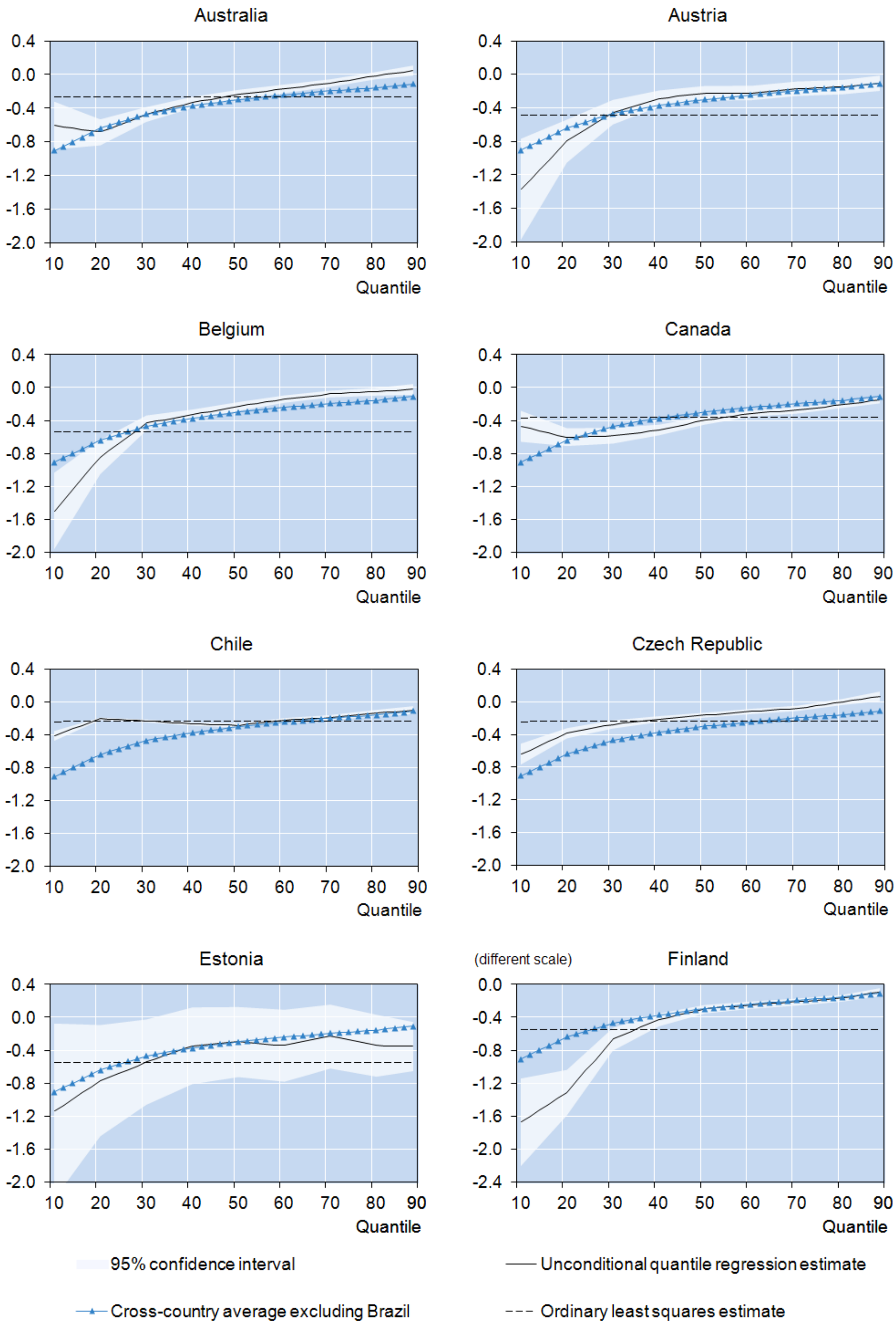


Figure A7. **Effect on log earnings of having a temporary contract (relative to having a permanent contract)**, *continued*

Unconditional quantile regression estimate

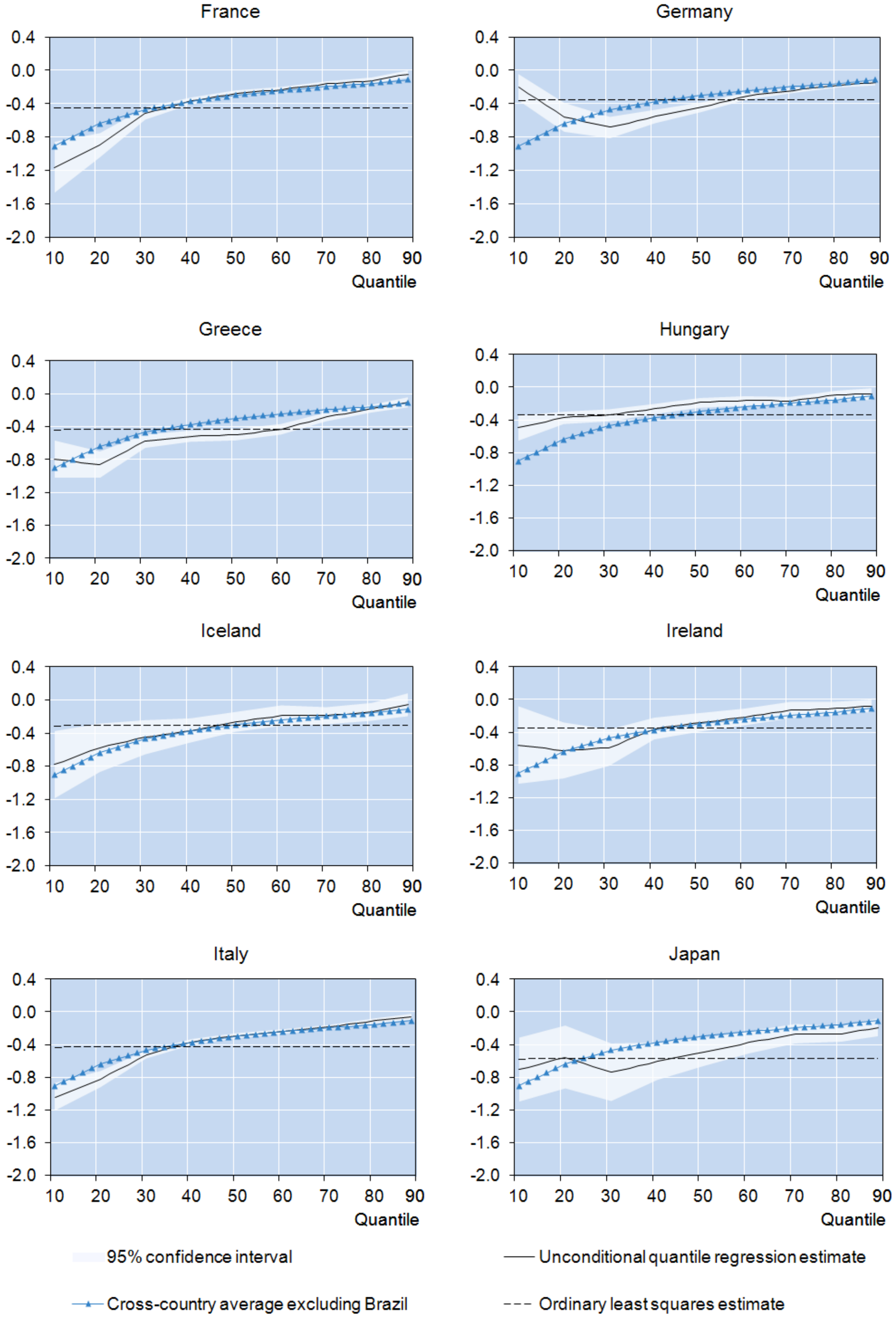


Figure A7. **Effect on log earnings of having a temporary contract (relative to having a permanent contract)**, *continued*

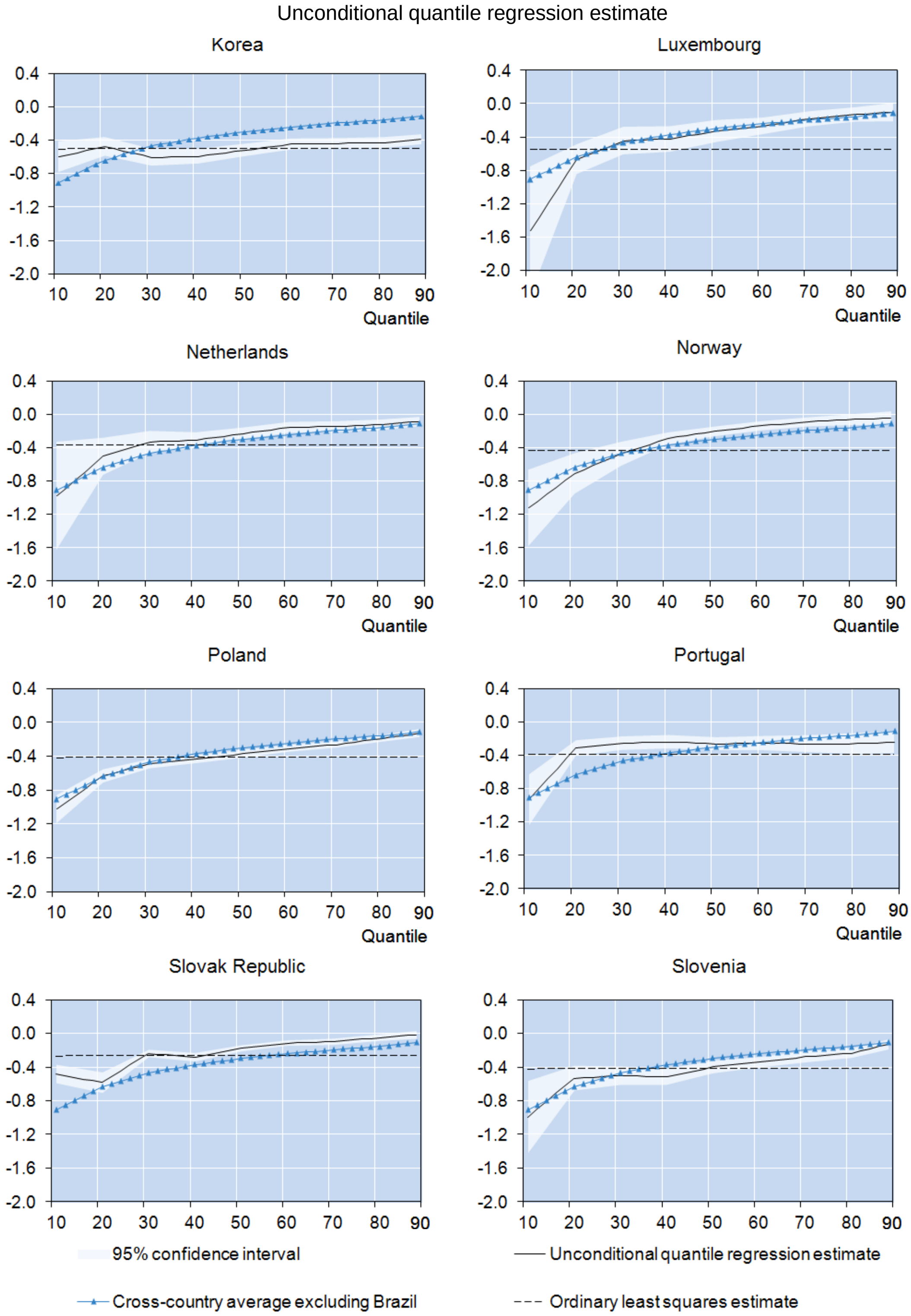


Figure A7. **Effect on log earnings of having a temporary contract (relative to having a permanent contract)**, *continued*

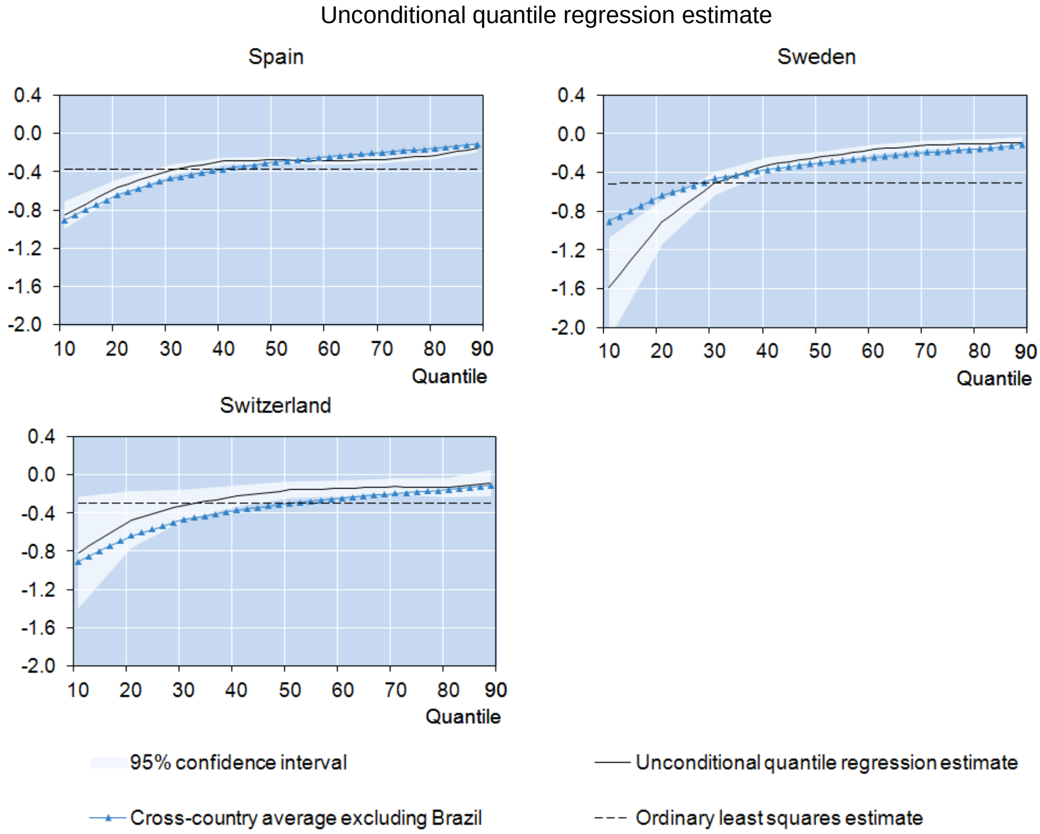


Figure A8. **Effect on log earnings of being self-employed (relative to having a permanent contract)**

Unconditional quantile regression estimate

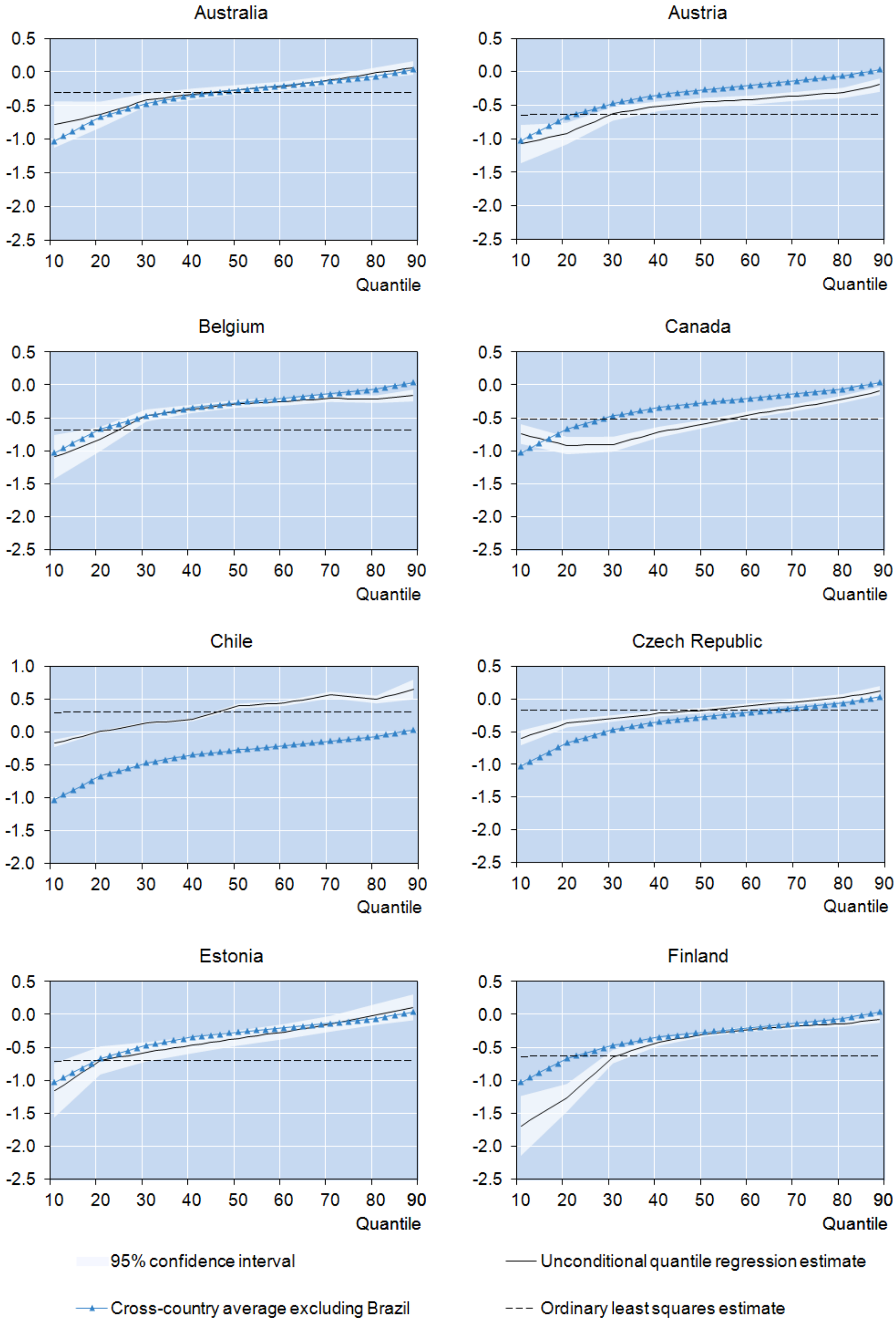


Figure A8. **Effect on log earnings of being self-employed (relative to having a permanent contract),** *continued*

Unconditional quantile regression estimate

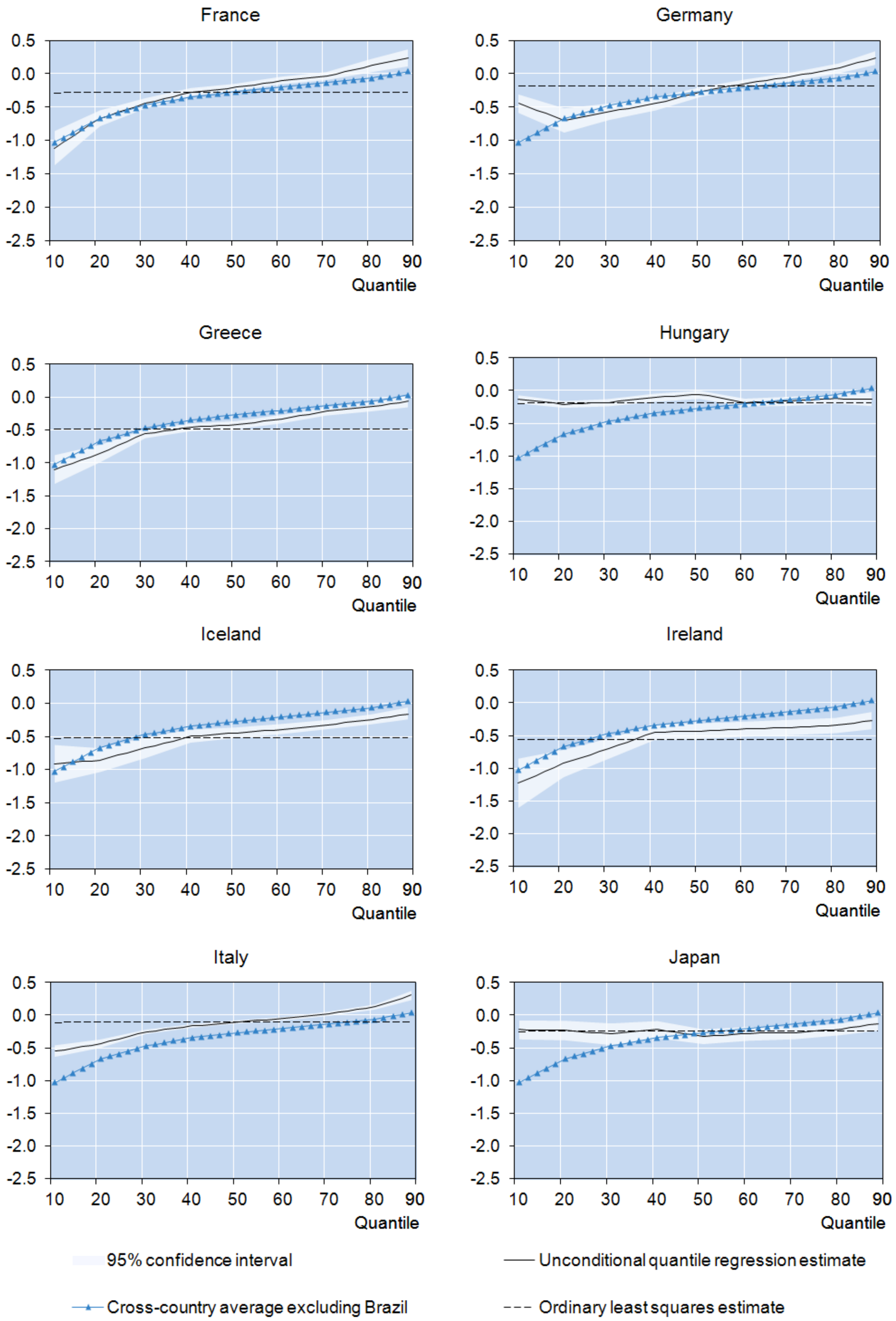


Figure A8. **Effect on log earnings of being self-employed (relative to having a permanent contract),** *continued*

Unconditional quantile regression estimate

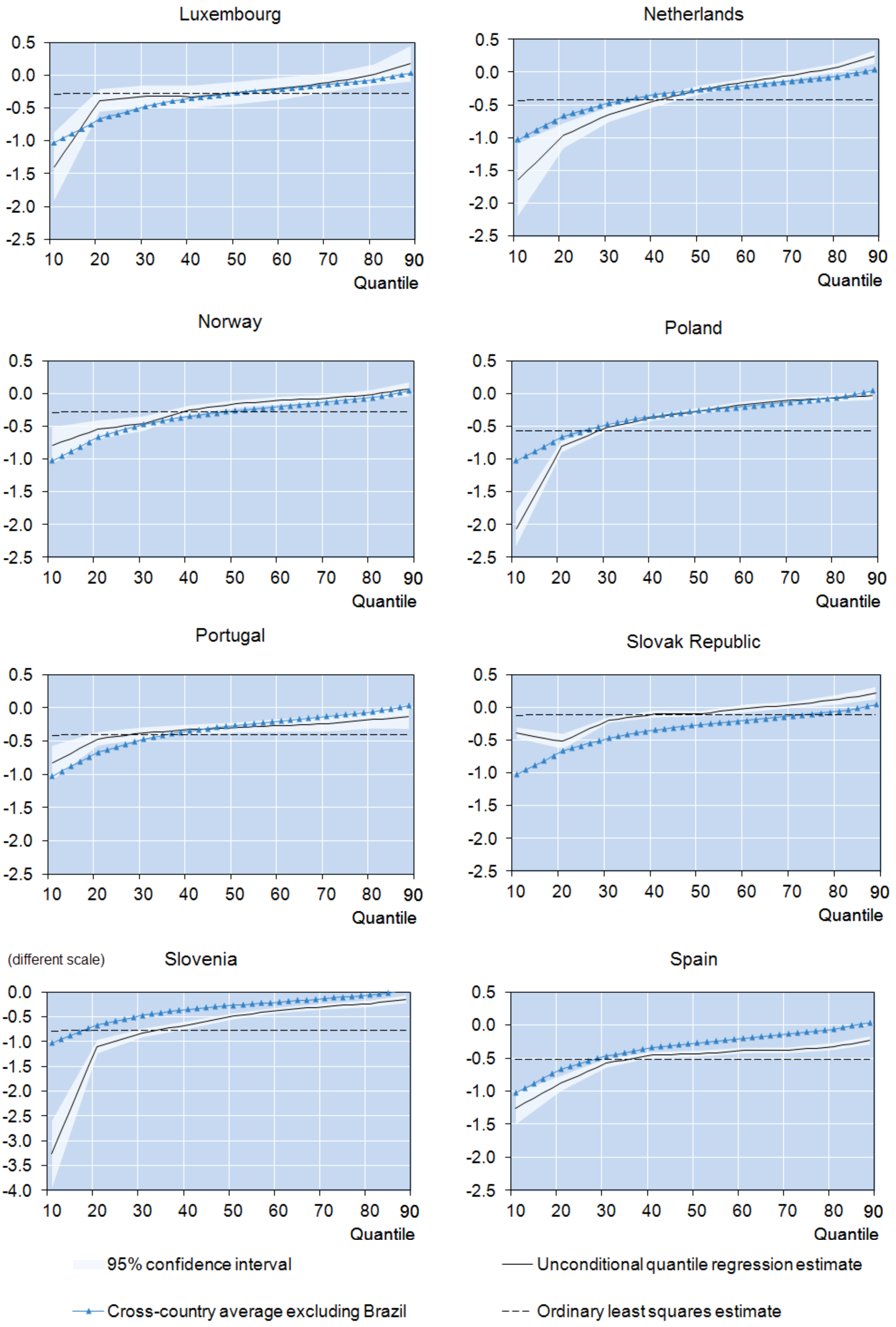


Figure A8. **Effect on log earnings of being self-employed (relative to having a permanent contract),** *continued*

Unconditional quantile regression estimate

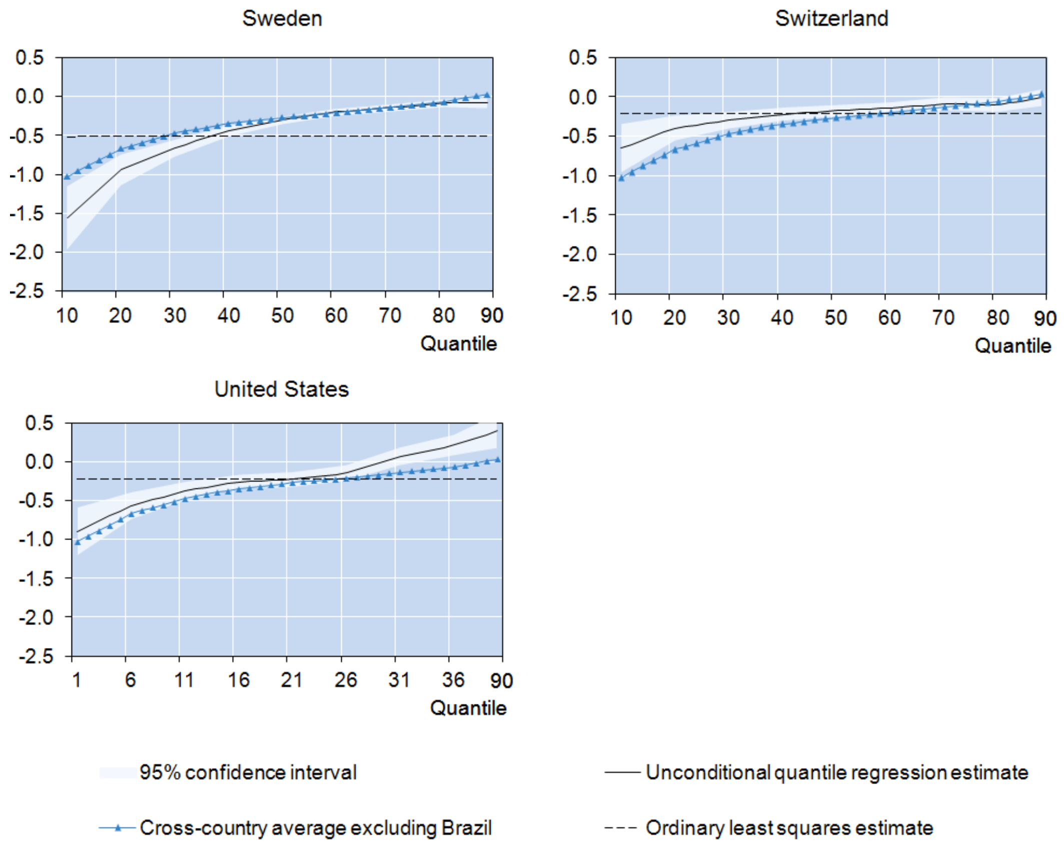


Figure A9. **Effect on log earnings of working for a public employer**

Unconditional quantile regression estimate

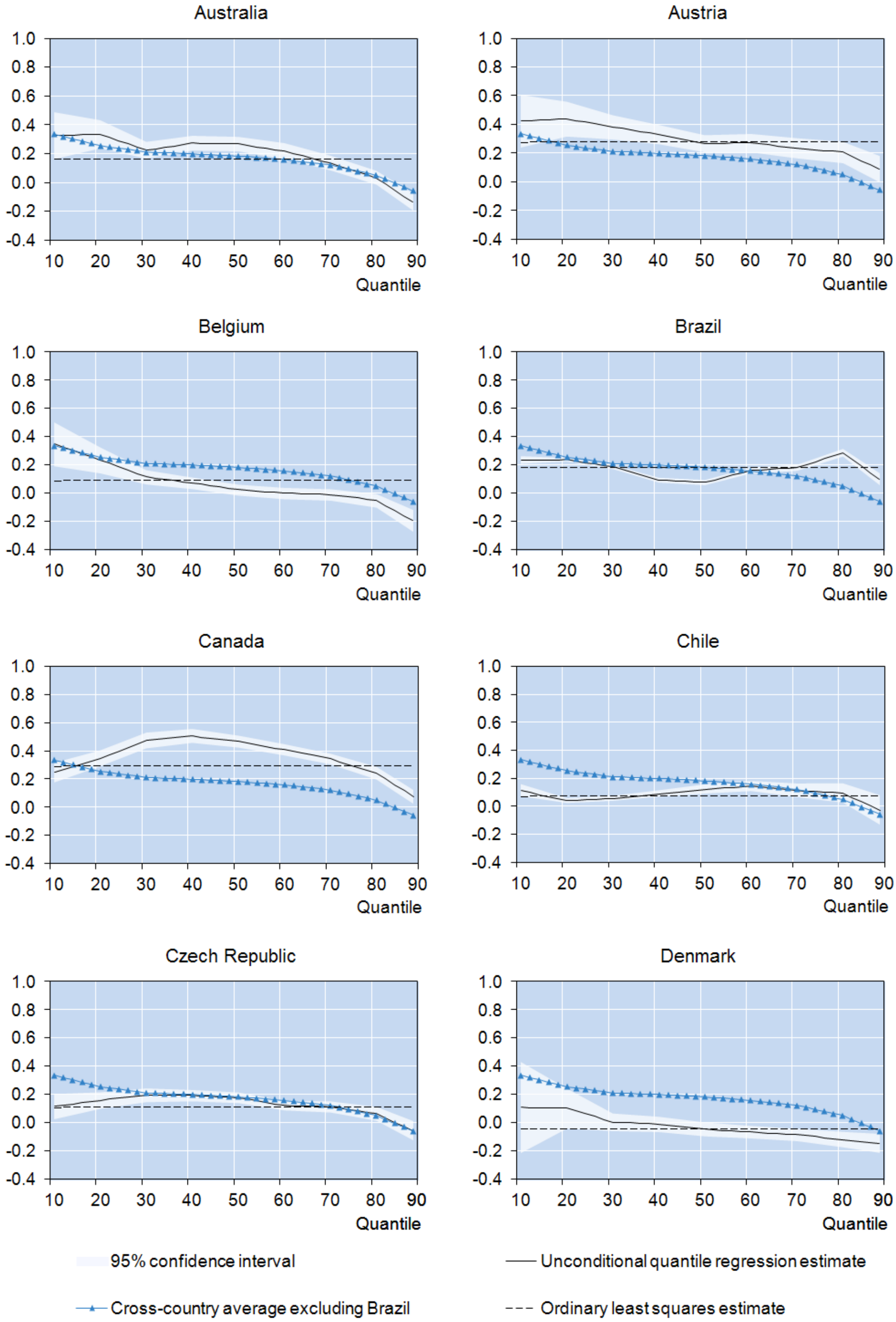


Figure A9. **Effect on log earnings of working for a public employer,** *continued*

Unconditional quantile regression estimate

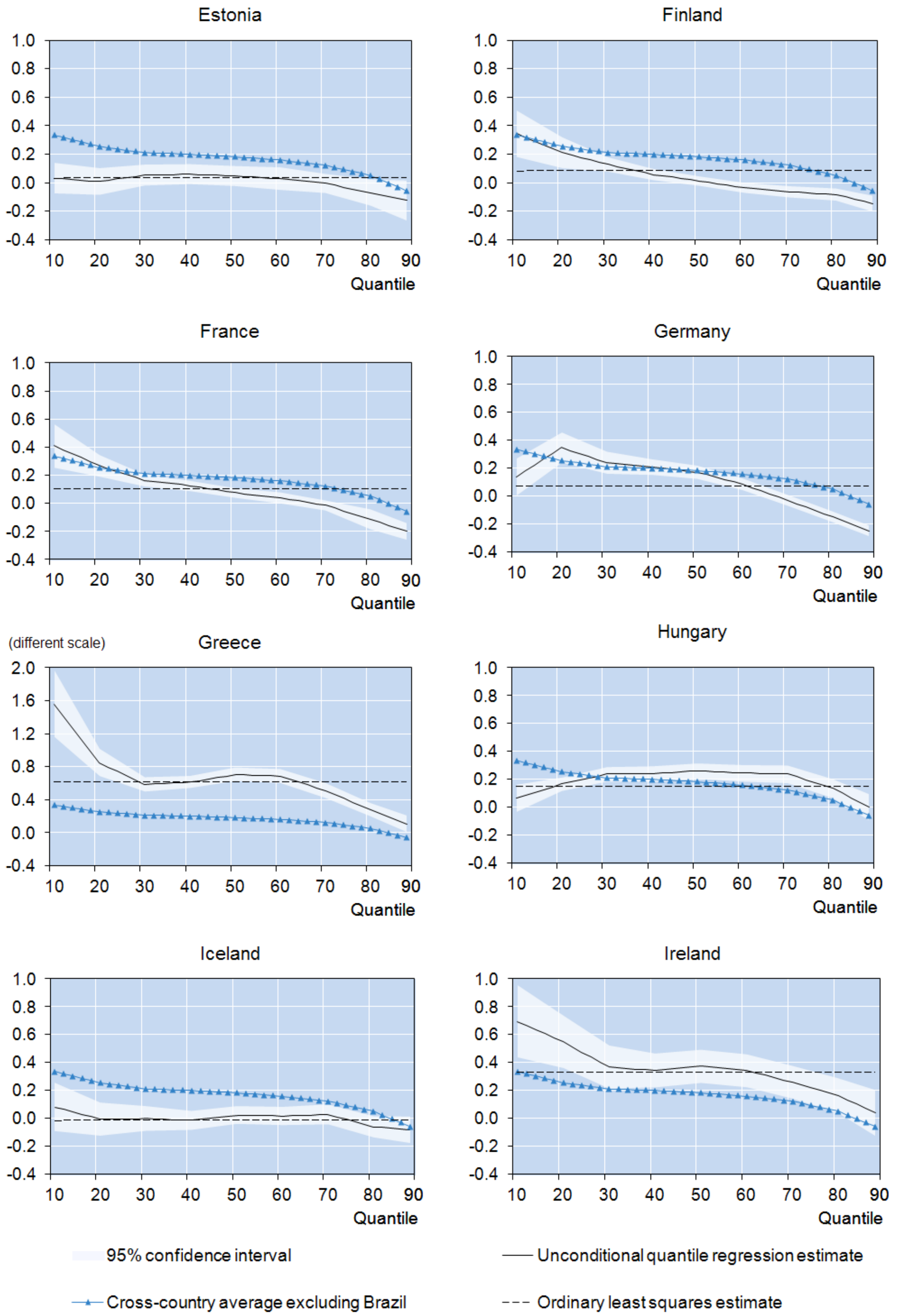


Figure A9. **Effect on log earnings of working for a public employer,** *continued*

Unconditional quantile regression estimate

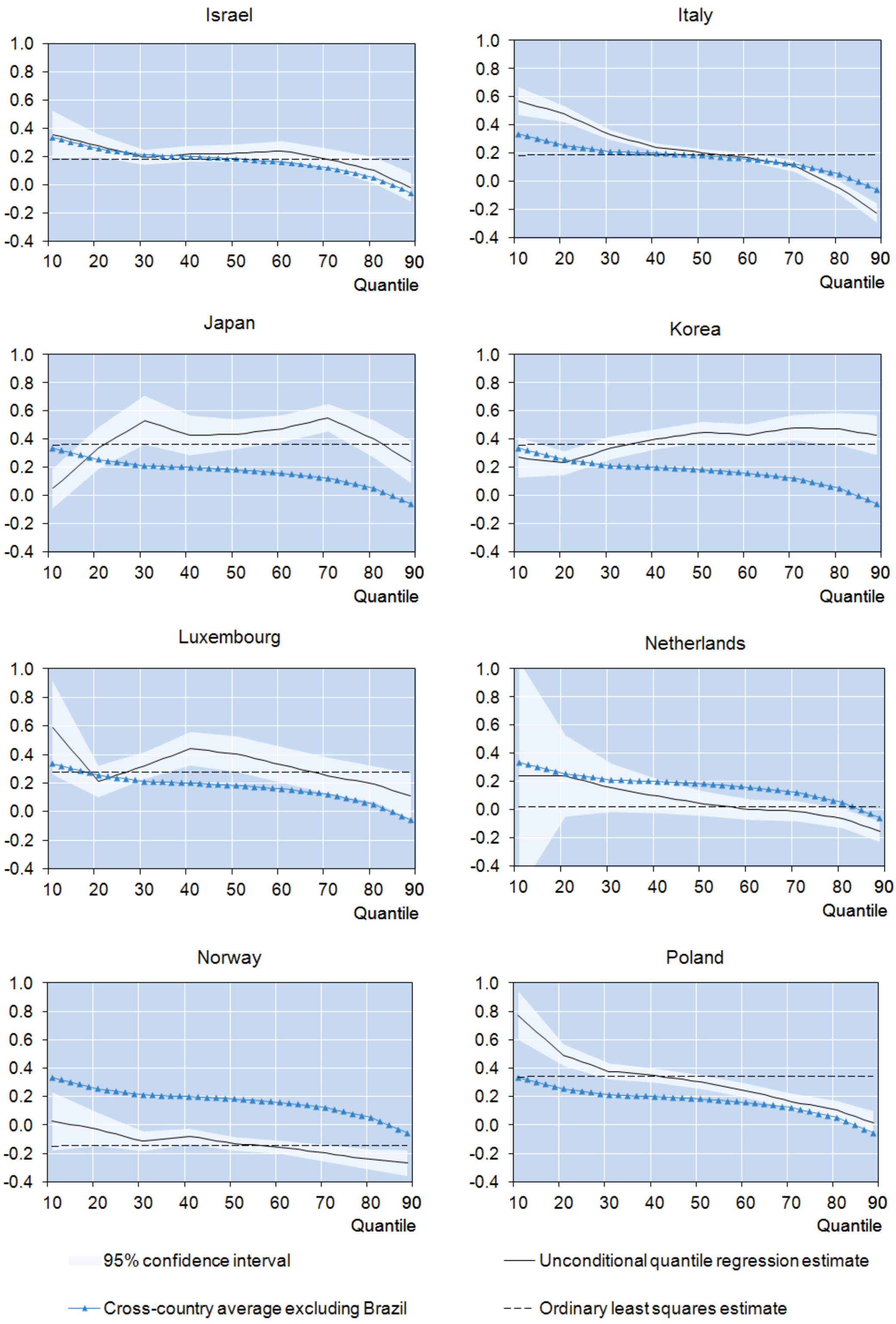


Figure A9. **Effect on log earnings of working for a public employer,** *continued*

Unconditional quantile regression estimate

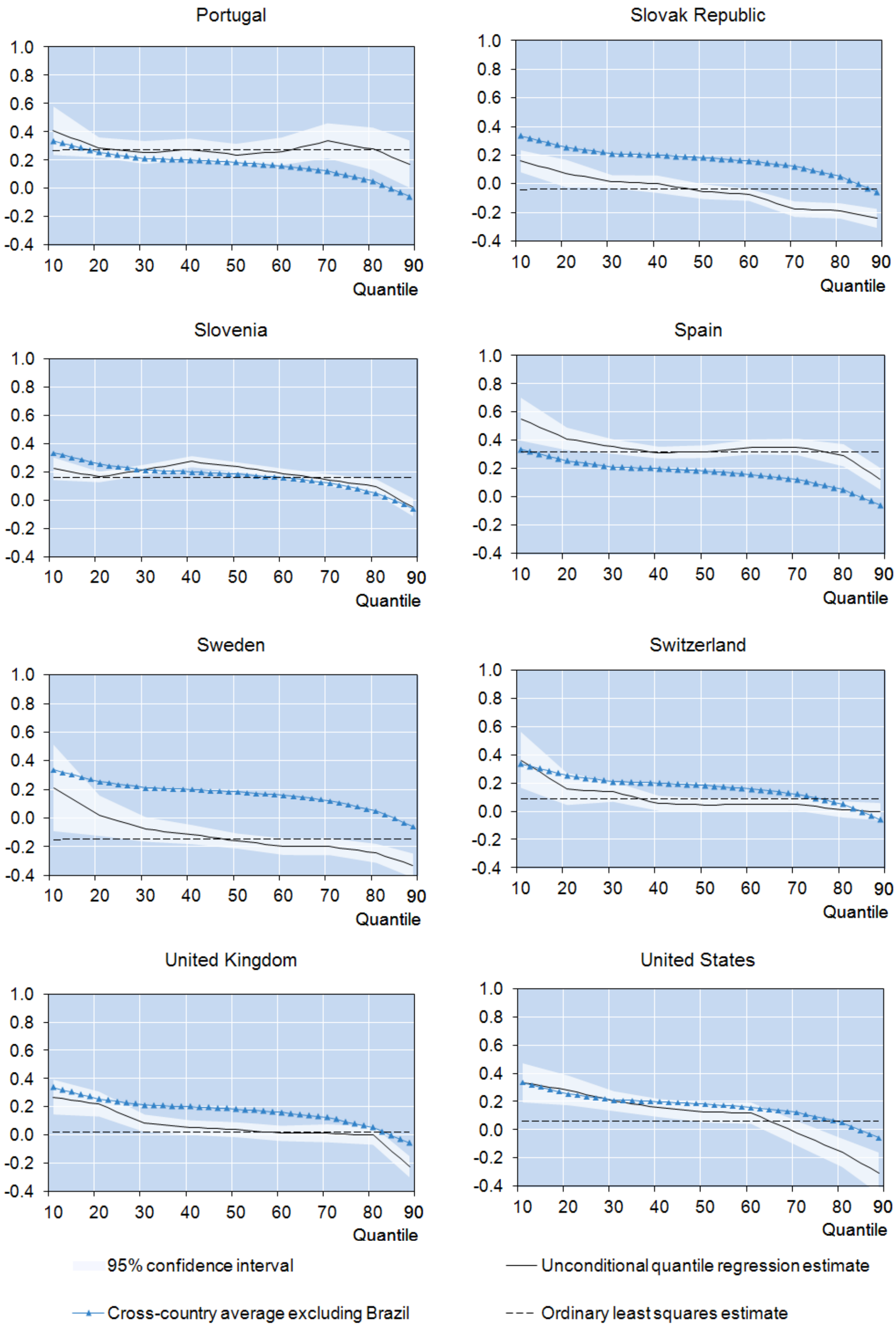
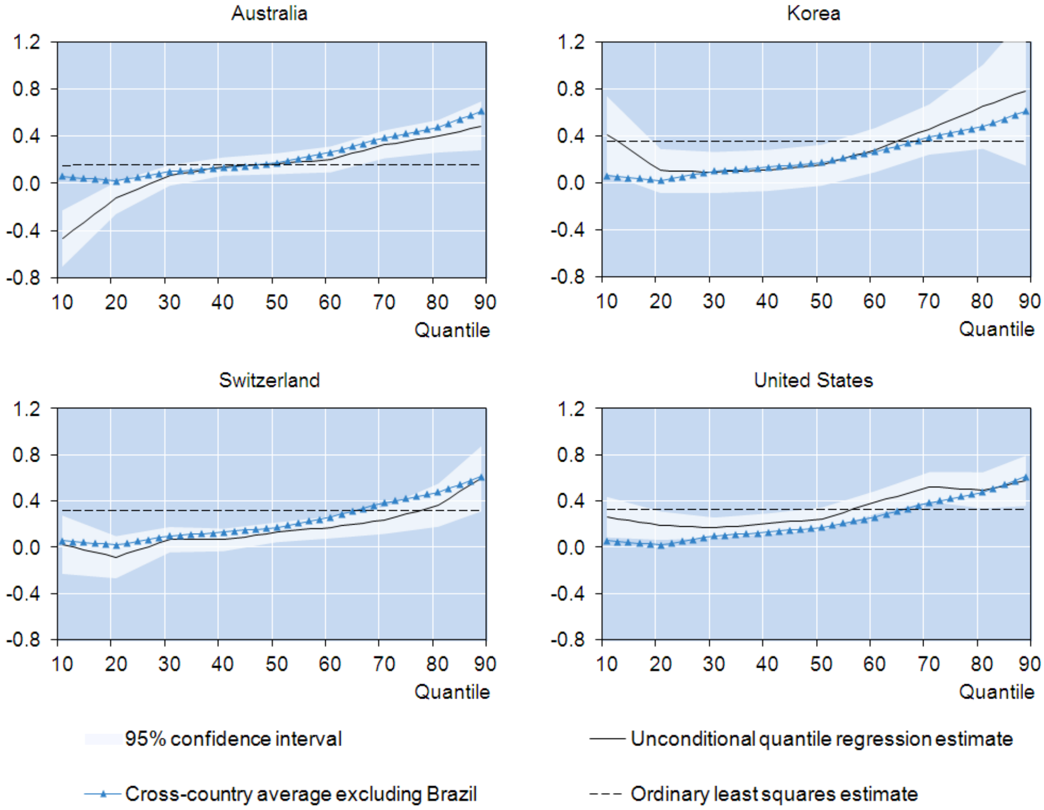


Figure A10. **Effect on log earnings of having a PhD (relative to any other tertiary degree)**

Unconditional quantile regression estimate



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