The multiple dimensions of selection into employment

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Abstract

A vast literature on gender wage gaps has examined the importance of selection into employment. However, most analyses have focused only on female labour force participation and gaps at the median. The Great Recession questions this approach both because of the major shift in male employment that it implied but also because women's decisions to participate seem to have been different along the distribution, particularly due to an "added worker effect". This paper uses the methodology proposed by Arellano and Bonhomme (2017) to estimate a quantile selection model over the period 2007-2018. Using a tax and benefit microsimulation model, I compute an instrument capturing the male selection induced by the crisis as well as female decisions: the potential out-of-work income. Since my instrument is crucially determined by the welfare state, I consider three countries with notably different benefit systems – the UK, France and Finland. My results imply different selection patterns across countries and a sizeable male selection in France and the UK. Correction for selection bias lowers the gender wage gap and, in most recent years, reveals an increasing shape of gender gap distribution with a substantial glass ceiling for the three countries.

Keywords: Gender wage gap, sample selection, quantile selection model, wage inequality, quantiles, selection, glass ceilings, sticky floors

JEL Classification: J31, J21, J16, C21

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1 Introduction

In high-income countries, women's investment in human capital, as well as their wages, labour force participation and employment aspirations, have progressively expanded over the past decades and converged towards those of men. However, this equalizing trend seems to have slowed down in recent years and disparities persist between and within countries, notably as far as the gender wage gap is concerned. While the selection of women into employment has been a major concern for decades, recent work has emphasized the importance of allowing for different degrees of selection along the wage distribution (Arellano and Bonhomme, 2017; Maasoumi and Wang, 2019). This paper aims to contribute to this literature, analysing the gender pay gap along the distribution of wages for three European countries (Finland, France and the United Kingdom), correcting for selection bias with a unique instrumental variable and capturing the impact of differences in the welfare state for both female and male selection.

The Great Recession had sizeable impacts on labour markets in Europe and the U.S., and while employment levels declined considerably everywhere, the structure of employment changes varied across countries both in terms of gender and skills. For example, both the financial and the construction sectors were badly hit, leading to major job losses in both sectors. These have traditionally been male-dominated sectors, and hence the observed employment changes imply that male selection biases are likely to have affected the evolution of the wage gap over the period. Moreover, these two sectors differ in the skill composition of the labour force they employ. As a result, depending on which has a larger relative weight in a country's employment structure, selection may be more important at the bottom or the top of the wage distribution. Then, correction for selection could impact the wage gap differently along the distribution and especially substantial glass ceiling and sticky floor observed in the literature (Arulampalam et al., 2007; Christofides et al., 2013). I try to answer such questions by considering how selection varies across the distribution in a setup that allows me to consider both male and female selection.

Accordingly, to analyze the features of wage inequality, I follow the method of Arellano and Bonhomme (2017) of quantile correction for sample selection and use the welfare system to assess for participation. One main challenge of labour market participation studies (and especially instrumental variable approaches) is that a good instrumental variable for men's labour supply is hard to find as men's working decisions may be motivated by different factors than women's.[1] The traditional participation variables used in the literature such as the number of young children or spouse's earnings, appear to be poor determinants of male participation and correlated with both male and female wages (Lundberg and Rose, 2000). To capture participation determinants of both men and women, I follow Blundell et al. (2003), using a measure of the opportunity cost of labour market participation and I simulate it for three tax and benefits frameworks. I compute the potential out-of-work income with the EUROMOD tax and benefits micro-simulation model. This variable, simulated as the income provided by the state if the worker stops working, is one of the key features of this empirical work.

Furthermore, the changes induced by the Great Recession have been particularly relevant in some European Union member states, where the recession lasted longer and its effects were more severe than in the U.S. As a response to the crisis, countries had different reactions to prop up the labour market, according to their welfare state regime. Three main welfare state regimes can be distinguished among developed countries based on government intervention, social capital, class equality, and other social factors (Esping-Andersen, 1990). These three types of welfare state have reacted differently to workers affected by the 2008 crisis and due to different legislation (in terms of employment protection or maternity leave for example), the type of welfare state has an impact on the female labour force. For instance, France, Finland and the United Kingdom have different systems in terms of labour market equality, social policy and the female employment rate. This diversity of societal frameworks in these three countries shows the interest of an empirical comparison. Hence, I use SILC data to investigate French, Finnish and UK gender wage gap evolution along the wage distribution and since the GR, as well as the underlying role of selection.

The findings from this exercise indicate a different sign of selection according to

[1]As mentioned in Mulligan and Rubinstein (2008).

the welfare state. While France exhibits a positive selection bias (i.e., the wages of employed workers are higher than the potential wages of the unemployed), the workforce is negatively selected in Finland and the UK (i.e., the wages of employed workers are lower than the potential wages of the unemployed). The considerable male selection bias in France and the UK sheds new light on the importance of male and female selection to correctly estimate gaps. The results also highlight that the median hides strong patterns at the tails of the distribution. In point of fact, correction for sample selection at the quantile level reveals the temporary French sticky floor hidden by its positive selection bias. Furthermore, a higher gender gap at the top of the wage distribution for the three countries is observed, illustrating glass ceiling patterns. Correcting for sample selection reduces the gender wage gap and highlights that the gender wage gap would be reduced at full employment and labour force participation rates.

This paper contributes to at least three distinct lines of research. First, my research relates to the literature on selection bias and gender gaps. Controlling the bias resulting from non-random sample selection is an important issue in wage analysis. Selection can arise when there is a self-selection of individuals in the labour market (Heckman, 1974) or an important demand-side selection like the one induced by the GR. Therefore, a narrower gender pay gap does not necessarily mean more gender equality in the labour market. The gender gap may decline in countries with lower female employment where participation in the labour market appears to be non-random and may lead to a selection bias. Indeed, as long as data on wages are available only for a self-selected group of labour force participants, this decrease in the gender pay gap may be due to the absence of women with low wage characteristics in the observed wage distribution (Blau and Kahn, 2003). Olivetti and Petrongolo (2008) emphasize the importance of selection bias to explain the gender wage gap (and especially its negative correlation with the employment gap). Consequently, controlling for selection bias becomes crucial for examining gender inequality from a cross-country perspective, mainly because compositional changes may lead to misleading conclusions. Furthermore, Mulligan and Rubinstein (2008) point out that selection correction might be fundamental for meaningful comparisons of the gender wage gap over time. Hence, most of the evidence in this literature focuses on correction for female selection but little is known about the impact of recent male selection on the gender wage gap. Dolado et al. (2020) have examined the impact of the Great Recession on wages and the employment gap and find an intensification of the selection of men in the labour market whereas the selection of women is mitigated. Using an instrumental variable, inspired by that of Blundell et al. (2003) and Arellano and Bonhomme (2017), I capture specific welfare system incentives for both men and women and overcome issues generated by traditional instruments (Huber and Mellace, 2014). I contribute to this literature by providing evidence that correction for male selection is also important in cross country studies on gender wage gaps.

Second, this paper relates to a large empirical literature that explores the evolution of the gender wage gap along the distribution. The papers aforementioned focus on the median or mean wage gap but many researchers have also studied the degree to which gender pay gaps might vary across wage distribution. Quantile regression is introduced by Koenker and Bassett (1978), followed Buchinsky (1994) and Chamberlain (1994) who were the first to study empirically the effect of predictor variables on the distribution of wage with quantile regression. Later, Arulampalam et al. (2007) explored the gender pay gaps with quantile regression and the method of Mata and Machado (2005) for eleven European countries. The authors find evidence of glass ceilings and to a lesser extent, evidence of sticky floors for some countries. While some studies compare European gender wage gaps along the distribution and especially the glass ceiling and sticky floor, they do not control for selection bias throughout the distribution (Christofides et al., 2013). In addition, to my knowledge, there is no comparative study analysing the gender wage gap corrected for sample selection at the quantile level. This paper aims to fill that gap in this empirical literature. This paper is also the first study using out-of-work income as an instrumental variable for more than one country.

Finally, my research contributes to the strand of literature on quantile selection models. Buchinsky (1998) was the first to focus on a methodology to solve the sample selection bias along the distribution of wages. Picchio and Mussida (2011) use the Oaxaca-Blinder decomposition to study selection-corrected gender pay inequality on the Italian labour market and Albrecht et al. (2009) extends the procedure of Mata and Machado (2005) for the same purpose with data from the Netherlands. Biewen et al. (2020) also create a quantile selection model with a new approach transforming the original quantile regression model with an empirical application in Germany. Based on the recommendations of Huber and Melly (2015), Arellano and Bonhomme (2017) develop a new method using the cumulative distribution function to correct for selection into employment for the period 1978-2000. Recently, Maasoumi and Wang (2019) and to a lesser extent Blau et al. (2022) use the method of Arellano and Bonhomme (2017) for an analysis of the gender wage gap evolution in the context of the US, and under different measures. Dolado et al. (2020) also use the same method to study the impact of the Great Recession on selection patterns in a European framework. Yet, economic contributions about the selection correction in a quantile framework for wage analysis purposes are still sparse and have been applied only at the country level. Moreover, one of the big difficulties in the sample selection literature has been finding a way of controlling for male selection. To this end, bridging the gap between these three strands of the literature, this paper applies the method of Arellano and Bonhomme (2017) to study the gender wage gap evolution for each decile and between European countries, correcting for both male and female selection.

The rest of the paper is structured as follows. I first provide a general description of the method developed by Arellano and Bonhomme (2017) in section 2, before depicting the data and the construction of the instrumental variable (section 3). Then in section 4, the results of the study are discussed. Section 5 presents the robustness analysis and section 6 the conclusion.

2 Empirical Strategy

2.1 A quantile selection model

The empirical strategy is based on Arellano and Bonhomme (2017) estimation procedure of the quantile selection model. The authors develop a three-step estimation method allowing correction for sample selection in a nonlinear model. Let us consider the following nonlinear quantile regression model:

$$Y^* = q(U, X),$$

where Y^* is the outcome (wages in this framework), U the error term, $q()$ the quantile function and X the covariates. Selection bias affects the estimates when the sample from (Y^*, X) is nonrandom, and then the function $q()$ cannot be estimated with the ordinary least squares method. For example, sample selection occurs when the outcome Y^* is only observed when the indicator of labour market participation is equal to one. Hence, in this design, sample selection arises because wages are only observed for those employed. It implies that potential outcomes equal the latent wages if the individual participates in the labour market:

$$Y = Y^* \text{ if } D = 1.$$

The binary selection indicator D is modelled as

$$D = 1\{V \leq p(Z)\},$$

where $p(Z)$ is a propensity score[2] (estimated through a probit selection equation) and U and V denote error terms, B excluded covariates and $Z = (B, X)$.

The main substantive assumption of the model is the exclusion restriction: (U, V) is jointly statistically independent of Z given X. With $Z = (B, X)$, (U, V) must be jointly independent of B given X. The specific feature of the instrument used in this framework is linked to this exclusion restriction assumption. Indeed, the instrument should affect the probability of participating in the labour market without impacting the wage of workers. However, the independence of the excluded regressors traditionally used to study female selection (i.e. partner's income or the presence of young children) and potential wages is questionable, threatening the identification strategy. Following

[2]**Propensity score**: The propensity score $p(Z) = Pr(D = 1|Z)$ describes the selection probability of individuals with characteristics Z.

the exclusion restriction assumption, I build an instrument whose determinants are exogenous to the latent wage equation: the potential out-of-work income. The latter is the benefits that individuals would receive from the state if they became unemployed, the opportunity cost of labour market participation.

Under the set of assumptions detailed by Arellano and Bonhomme (2017),[3]

$$\begin{aligned} Pr(Y^* \leq q(\tau, x)|D = 1, Z = z) &= Pr(U \leq \tau|V \leq p(z), Z = z) \\ &= G_x(\tau, p(z)), \quad \forall \tau \in (0, 1), \end{aligned} \tag{1}$$

with $G_x(\tau, p) = C_x(\tau, p)/p$ representing the conditional copula of U given V (assessing the dependencies between them). Equation (1) allows then, by shifting percentile ranks, to recover the quantile function Q with the conditional copula G.

2.2 Estimation

The estimation strategy relies on a semiparametric methodology. We consider a linear quantile pattern $q(\tau, x) = x'\beta_\tau$ for all $\tau \in (0, 1)$ and $x \in X$.

The conditional copula is now denoted

$$G(\tau, p; \rho) = \frac{C(\tau, p, \rho)}{p},$$

where ρ is the dependence parameter vector whose sign indicates whether the selection is positive or negative.

The framework developed by Arellano and Bonhomme (2017) supposes a non-additive conditional quantile as suggested by Huber and Melly (2015) since quantile curves are mostly non-additive in the propensity score $p(Z)$ and covariates X. Hence, if τ is in (0,1) and ρ does not depend on covariates, then the non-additivity is verified

[3]Other assumptions: 1) **Unobservables**: (U, V) are supposed to follow a bivariate cumulative distribution function (copula) denoted $C_x(u, v)$. 2) **Continuous outcomes:** The conditional cumulative distribution function is markedly increasing. Thus, $C_x(u, v)$ is increasing u. With $C_x(u, v) = F_{y|X}(y|x)$. 3) **Propensity score**: The propensity score $p(Z) = Pr(D = 1|Z)$ describes the selection probability of individuals with characteristics Z.

except if U and V are uncorrelated or if all coefficients of the estimator, except the intercept, are not correlated with the quantiles.

Implementation

In this paper, I specify the copula as a member of the one-parameter Frank family (Frank, 1979).[4] Frank copula belongs to a parametric family with a single parameter ρ capturing negative and positive dependence between U and V and indicating the sign of the selection. It then has a useful interpretation for the comparison of selection patterns between countries. I let the copula parameter be gender-specific to assess the selection of men and women independently.

A three step method

The estimation method can be summarized in three main steps. First, I estimate the propensity score of participation, then the parameters of the cumulative function distribution (Copula) and to finish, the quantile parameters.

Propensity score The estimation of the propensity score, $\hat{\theta}$ is achieved through maximum likelihood with a probit selection equation.

The copula The copula parameter ρ is computed based on a Generalized Method of Moments as follows

$$\hat{\rho} = \text{argmin}_{c \in C} || \sum_{i=1}^{N} \sum_{l=1}^{L} D_i \phi(\tau_l, Z_i)[1\{Y_i \leq X_i' \hat{\beta}_{\tau l}(c)\} - G(\tau_l, p(Z_i; \hat{\theta}); c)||$$

with

$$\tau - 1 < \tau_2 ... \tau_L$$

a finite grid on (0,1), and $\phi(\tau, Z_i)$ denoting the instrument functions. In this paper, copula parameters are estimated with the *arhomme* command in Stata (Biewen and Erhardt, 2021), using the command options to refine the copula parameter grid search.

[4]There are several families of copulas that can be used for specifications (Gaussian, Frank, Gumbel, etc.). I adopt the choice of the Frank copula which is widely used in empirical work (Arellano and Bonhomme, 2017; Maasoumi and Wang, 2019). The Gaussian copula is estimated as a robustness check and its dependence parameters are presented in the Robustness analysis section.

Quantile parameters Once copula and propensity score are estimated, the computation of each τ quantile regression coefficient, $\hat{\beta}_\tau$, is achieved as follows:

$$\hat{\beta}_\tau = \text{argmin}_{b\in\beta} \sum_{i=1}^{N} D_i[\hat{G}_{\tau i}(Y_i - X_i'b)^+ + (1-\hat{G}_{\tau i})(Y_i - X_i'b)^-] \quad \forall\tau \in (0,1)$$

with $\hat{G}_{\tau i} = G(\tau, p(Z_i, \hat{\theta}), \hat{\rho})$ allowing to correct for selection the ranks of the latent distribution, $a^+ = max(a, 0)$ and $a^- = max(-a, 0)$. Hence, to correct the sample selection, the check function is rotated depending on the importance of the selection bias.

3 Data

3.1 SILC Data

I focus on three European countries, each with a different welfare state profile:[5] France (conservative welfare state), Finland (social-democratic welfare state) and the United Kingdom (liberal welfare state). France, Finland and the United Kingdom were chosen mainly because each has a different type of welfare state. However, while the choice of Finland to represent the social-democratic welfare state could be questioned, it was motivated by the small samples in the SILC for other potentially suitable countries such as Sweden. Data for France, Finland and the United Kingdom are drawn from the European Statistics on Income and Living Conditions (EU-SILC). Formerly ECHP, EU-SILC is an unbalanced household-based panel survey, widely used in gender wage gap studies in Europe.[6] SILC has the advantage of containing a consistent set of annual information standardised and harmonized across these countries during the period 2007-

[5]Using a composite index of work-family policies and wage-setting institutions (Christofides et al., 2013) also distinguish France, Finland and the United Kingdom as different types of states. France is broadly regulated, Finland is highly regulated and the United Kingdom is largely unregulated. Christofides et al. (2013) base their index on (i) the availability of formal child care for children under 3 for more than 30 h a week, (ii) maternity pay entitlement (the product of length and generosity), (iii) the extent to which part-time employment for family, children and other reasons is possible, (iv) the extent to which working times can be adjusted for family reasons and (v) the extent to which whole days of leave can be obtained without loss of holiday entitlement for family reasons.

[6]See, amongst others, Arulampalam et al. (2007); Olivetti and Petrongolo (2008); Christofides et al. (2013); Dolado et al. (2020).

2018,[7] making cross country comparisons possible. The survey gives information both at the household and the individual level. Both household and individual sections allow me to obtain essential information on the family composition and labour market characteristics, required for the wage and participation equation.

The sample is restricted to individuals aged 23-59 at the survey date, excluding individuals in full-time education or military service or who are self-employed. Self-employed people are usually excluded in empirical work on the gender wage gap (Olivetti and Petrongolo, 2008; Christofides et al., 2013; Arellano and Bonhomme, 2017). However, a shift from employment to self-employment could be another source of selection bias. Estimations with a sample including the self-employed are presented in the Robustness analysis section. Following the recommendations of Iacovou et al. (2012), I use the EU-SILC longitudinal dataset for this cross-national analysis to correct for the reference period mismatch between income and non-income information. All monetary variables are deflated, converted to Euro (for the UK and Finland) and expressed in Purchasing Power Parity (PPP) following the guidelines for EU-SILC provided by Mack et al. (2020).[8]

Table 1: Descriptive statistics

	Labour force participation rate						**Employment rate**					
	France		**Finland**		**United-Kingdom**		**France**		**Finland**		**United-Kingdom**	
	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females
2007-2010	76	68	80	75	78	69	69	61	71	69	75	65
2011-2013	78	70	78	72	86	74	70	63	68	66	75	65
2014-2018	78	71	80	75	86	75	70	64	68	66	81	71

Notes: The labour force participation rates are calculated as the labour force divided by the total working-age population (i.e. people aged 15 to 64). Employment rates are calculated as the ratio of the employed to the working-age population. Labour force participation rates and employment rates are computed using EU-SILC data, these statistics are similar to those of the OECD, available at the following link: OECD Labour force participation rate and OECD employment rate listed in the table 14 of the Appendix section.

Information about labour force participation rates and employment rates is provided in Table 1. Table 1 shows that male selection is sizeable, especially for France, and increased following the Great Recession in the UK. One can also notice that the

[7] EU-SILC longitudinal dataset covers the period before the global financial crisis, since 2004. However, EUROMOD, tax and benefit microsimulation model, is only available from 2007 for Finland.

[8] Explanatory material about the sample construction and variables descriptions is available in the Appendix.

employment gaps differ by country. The highest female participation rates and the lowest gender gaps are found in Finland. Gender differences in labour force participation and employment rates are higher in the United Kingdom but with higher female employment rates than in France. Tables 12 and 13 in the Appendix report the descriptive statistics for unemployed and employed individuals. Comparison between Tables 12 and 13 indicates that employed individuals do not have the same characteristics as unemployed ones, highlighting the importance to correct for selection.

3.2 Instrumental Variable

The first step of Arellano and Bonhomme (2017)'s method is to estimate the propensity score through a probit model. The literature traditionally uses the presence of young children or partner's income as the main excluded regressor in the wage equation (Heckman, 1974; Mulligan and Rubinstein, 2008; Maasoumi and Wang, 2019). This exclusion restriction implies that a valid instrument would not affect potential wages while impacting the probability of participating. Although both variables, young children and partner's income are popular, this choice is questionable. On the one hand, the empirical relationship between these instruments and the labour force participation decision is not as strong for men as for women. Table 11 in the Appendix shows that the presence of young children does not significantly impact male labour market participation in Finland and the United Kingdom. On the other hand, for both men and women, the partner's-income and presence-of-young-children variables also seem to violate the assumption of independence of the excluded instrument and potential wages (Huber and Mellace, 2014) due to the assortative mating (Ciscato et al., 2020) and child penalty (Kleven et al., 2019).

To overcome these issues, I chose another instrument variable. Following Blundell et al. (2003) and Arellano and Bonhomme (2017), I use a measure of potential out-of-work welfare income as exclusion restriction. The amount of welfare a worker could have if he or she stops working has an impact on the labour market participation because it represents the opportunity cost of being employed. Furthermore, this IV is a function of the household composition (the number of parents, the number of children and their age). Yet, the demographic composition of the household seems to be an important determinant of women's participation in the labour market (Maasoumi and Wang, 2019). This instrument consists of the value of benefits (tax deducted) a person could earn from the welfare system if she became unemployed. This simulated instrument has been shown by Arellano and Bonhomme (2017) to be a strong determinant of labour market participation for both men and women.[9]

In this paper, the construction of this variable is different to the one created in Blundell et al. (2003) and then used by Arellano and Bonhomme (2017). The latter used the Institute of Fiscal Studies (IFS) tax and welfare-benefit simulation model for the UK to create a variable based on housing benefits and unemployment benefits unrelated to work history for the period 1978-2000. Their instrument, reflecting the opportunity cost of labour market participation, also include a small amount of income from investment. Since the measure of out-of-work income will serve to identify the labour force participation decision, variation in the components of out-of-work income must be as exogenous to the decision to work or the level of wages as possible. Hence, I do not consider income from investment.[10]

Although my instrument measure is similar to that of Arellano and Bonhomme (2017), it differs in several ways. Since taxation creates incentives or disincentives to engage in paid work, I add the taxes simulation. The amount and the composition of the tax system can influence employment decisions through the income tax threshold, the unit of taxation and marital tax relief (Alesina et al., 2011; Ichino et al., 2019). Also differing from the aforementioned authors, I choose to consider family benefits and to have a specific simulation for both partners when married. While the amount of welfare was the same for both partners in the IV of Blundell et al. (2003), I simulate welfare considering the income of the partner (and other members of the household) unchanged to capture gender-specific strategies of labour market participation within

[9]Moreover, I check the independence of the excluded regressor and potential wages with the statistical test developed by Huber and Mellace (2014). Results of the test are available in Table 7 in the Robustness analysis section. Using the method detailed by Huber and Mellace (2014), I fail to reject the validity of the IV for the three countries.

[10]Huber and Mellace (2014) find that with non-employment income IV computed as the sum of dividends, interest, and rent, the exclusion restriction assumption and the additive separability of the errors assumption are violated.

the household. As women usually earn less than their husbands, and both partners' incomes are considered for the calculation of some benefits, benefits are expected to be lower if the wife stops working compared to the husband. However, since Huber and Mellace (2014) test results on partner's income as an IV point to a violation of the exclusion restriction, I decided not to add the partner's income to the amount of potential out-of-work income. Lastly, similarly to the instrument of Blundell et al. (2003), I also consider housing benefits as well as unemployment benefits unrelated to work history. I then simulate this out-of-work income variable for the period 2007-2018, using the EUROMOD tax and benefit model, for three different countries: France, Finland and the United Kingdom.

3.3 Tax and benefit microsimulation

Another reason why these data have been chosen is the construction of this instrument. I simulate the out-of-work income variable with EUROMOD, the tax-benefit microsimulation model for the European Union, which is itself based on EU-SILC microdata. EUROMOD is the static tax-benefit microsimulation model for European countries, developed by the Institute for Social and Economic Research, University of Essex. The EUROMOD model simulates specific components of each welfare system of European Union countries, taxes and benefits. EUROMOD enables cross-country comparability thanks to policy systems coded according to a common framework based on a harmonized set of protocols. Another main feature of EUROMOD is the possibility to compute benefits at the individual level. This is particularly important since it allows us to determine accurately which individuals are entitled to receive benefits, whereas, in simulation models, these are usually allocated to adults present in the household. Besides, EUROMOD has the advantage of simulating in separate variables the different taxes and benefits, while considering non-cumulation and threshold rules.

Table 10 in the Appendix summarizes all the taxes and benefits included in the simulation of the out-of-work income variable for the French, the UK and the Finnish policy system. Within the benefits simulated for this variable, there are housing benefits, family benefits and unemployment benefits unrelated to work history. The latter is of considerable importance as it enables the instrument to be exogenous to the wage equation, which would not be the case if I considered benefits related to the previous wage. Indeed, only unemployment benefits unrelated to work history can be considered in the construction of the IV given that the identifying assumptions as contributory benefits are correlated with the wage equation.[11]

4 Results

Using the quantile selection model developed by Arellano and Bonhomme (2017), I model the evolution of log hourly wages controlling for individual characteristics and correcting for selection bias. I first comment results of the probit estimation before discussing the selection patterns arising from the estimation. Then for each country, I compare the distribution of the evolution of wages corrected and uncorrected for the selection bias. I will also discuss the evolution of inequality, both between countries and along the wage distribution. In the last subsection, I will illustrate how addressing selection may affect quantile regression estimations with the comparison of quantile regression un-corrected and corrected for selection.

4.1 Probit model

As explained above, the first step of the Arellano and Bonhomme (2017) method is the estimation of the propensity score of participation by probit models. The control variables include the number of years spent in employment (experience) and its second-order polynomial term, a set of regional dummies when available,[12] linear, quadratic, and cubic time trends, health characteristics, marital status, education (tertiary level diploma) and the number of children split by age categories.[13] As discussed earlier, the

[11]Disability benefits, as well as sickness benefits, are not considered in the out-of-work income variable for the same reason, they are correlated with the wage equation. However, I control for health characteristics in both participation and wages estimations.

[12]Information about regions are only available for France and Finland in the SILC data but these additional controls do not impact the specification. For further details about the covariates and their construction, see the Appendix section.

[13]I control for the number of children aged under or equal to 3, between 4 and 6, between 7 and 10, between 11 and 15, and between 16 and 17.

main excluded regressor is the potential out-of-work income. Following Arellano and Bonhomme (2017), I estimate selection patterns through probit models for the overall period (2007-2018), using time trend control variables based on the year.[14] As selection patterns are different for men and women, estimations are also gender-specific.

First stage results of the effects of out-of-work income on labour market participation in Table 2 shows the strong significant impact of the instrument for every period and every country. Hence, the instrumental variable has a strong impact on the labour market participation of both men and women. In Finland and the United Kingdom, the coefficient is negative, denoting the disincentive effect of welfare on labour market participation, in line with results of Arellano and Bonhomme (2017). However, potential out-of-work income has a positive and significant impact on employment for both French men and women. A possible explanation could be that the Great Recession is a demand shock, implying that the benefits would help to escape a poverty trap. Besides, these results are consistent with the findings of Gurgand and Margolis (2008) who observe in France that almost all welfare beneficiaries would gain from being employed relative to staying on welfare. In the last two decades, the French government has created several incentives for employment, guaranteeing that by entering the labour market, the worker does not lose in terms of benefits (Sicsic, 2018, 2020).[15] As we will see below, this French specificity in the sign of the instrument coefficient's in the probit model has no impact on the selection specification since the sign and magnitude of the French selection is the same with the traditional instrumental variable and my instrument (See Table 8).

[14]As a large literature documented the cyclicality of labour force participation, selection patterns for three periods over the business cycle (Great recession (2007-2010), sovereign debt crisis (2011-2013), and the recovery period (2014-2018)) can be found in the Appendix section.

[15]The *RSA activité* and *Prime pour le retour à l'emploi (PPE)* (today *"Prime d'activité"*) are two employment incentives schemes whose objective is to ensure that working more increases disposable income. Both are employment conditional benefits, increasing work incentives (OCDE, 1999).

Table 2: The effects of out-of-work income on labour market participation

	France		Finland		United Kingdom	
	Males	Females	Males	Females	Males	Females
Out-of-work income	0.061***	0.083***	-0.051***	-0.074***	-0.103***	-0.130***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.005)
Number of children (age under or equal 3)	0.029	-0.370***	0.162***	-1.036***	0.042**	-0.516***
	(0.022)	(0.017)	(0.031)	(0.026)	(0.020)	(0.014)
Number of children (age between 4 and 6)	0.034	-0.188***	0.141***	-0.104***	0.041*	-0.369***
	(0.024)	(0.017)	(0.029)	(0.020)	(0.022)	(0.014)
Number of children (age between 7 and 10)	0.033*	-0.145***	-0.002	-0.084***	-0.037**	-0.239***
	(0.019)	(0.014)	(0.023)	(0.018)	(0.018)	(0.012)
Number of children (age between 11 and 15)	-0.022	-0.154***	0.054***	0.035**	-0.099***	-0.149***
	(0.016)	(0.012)	(0.019)	(0.016)	(0.016)	(0.011)
Number of children (age between 16 and 17)	0.021	-0.166***	0.120***	0.054**	-0.043	-0.112***
	(0.028)	(0.021)	(0.031)	(0.025)	(0.028)	(0.020)
Observations	44,944	50,456	29,498	34,616	47,964	58,971
Pseudo R-squared	0.1527	0.1563	0.1464	0.1916	0.2476	0.1911

Notes: First-stage results of the effects of out-of-work income and the number of children split by age categories on employment with a probit model estimation. Other covariates in the participation equation include experience and its polynomial term, a set of regional dummies for France and Finland, linear, quadratic, and cubic time trends, health characteristics, marital status and education (tertiary level diploma). Standard errors in parentheses. *, ** and *** denote statistical significance at 10, 5, and 1 percent levels.

4.2 Selection patterns

Table 15 in the Appendix reports some features of the estimated propensity score, respectively, for males and females, France, Finland and the UK. The propensity score captures the probability that one person is in employment given her initial characteristics. It should be noticed that the mean and the median hide strong inequality at the bottom of the distribution, especially in Finland.

Table 3 reports the dependence parameter, ρ, indicating the sign and the magnitude of the selection. A negative ρ in Table 3 denotes a positive selection in the labour market, while a positive ρ denotes a negative selection in the labour market. A positive selection bias means that the wages of employed individuals are higher than the potential wages of the unemployed. In contrast, a negative selection bias means that the market wages of employed individuals are lower than the potential market wages of the unemployed. The selection pattern observed in Table 3 indicates that while selection is significantly negative in the UK and for Finnish females, it is significantly positive in France.

Table 3: Selection parameter and its signs

	France		**Finland**		**United Kingdom**	
	Males	Females	Males	Females	Males	Females
ρ	-1.9974***	-0.7235**	0.7235	2.0926***	1.4248***	2.1960***
	[-3.0528 ; -0.9420]	[-1.3284 ; -0.1187]	[-0.7404 ; 2.1874]	[1.1240 ; 3.0616]	[0.5046 ; 2.3450]	[1.3258 ; 3.0662]
Sign of the selection	Positive	Positive	Negative	Negative	Negative	Negative
Spearman correlation	-0.3164	-0.1198	0.1198	0.3300	0.2313	0.3444

Notes: Frank copula estimation. The dependence parameter, ρ, captures the dependence between U and V, the two error terms. A negative ρ indicates positive selection into employment and vice versa. Standard errors are computed based on subsampling. Sample size is chosen as a constant (1000) plus the square root of the sample size, following Arellano and Bonhomme (2017). *, ** and *** denote statistical significance at 10, 5, and 1 percent levels.

Confidence intervals in Table 3 show that, except for Finland, male selection is significant and considerable. In contrast with the findings of Arellano and Bonhomme (2017), who find a small positive selection in the UK for the period 1978-2000[16], my results indicate that workers are negatively selected into the labour force in the UK for the period 2007-2018. This shift in selection bias in the UK between these two periods may arise from the effects of the Great Recession. In fact, the Great Recession impacted high skilled sectors such as finance. Table 16 in the Appendix displays selection patterns

[16] Arellano and Bonhomme (2017) find a rank correlation of -0.24 for married males, and of -0.79 for singles, with 95% confidence intervals of $(-0.35; -0.06)$ for married males and $(-0.84; -0.42)$ for singles, respectively. For females, Arellano and Bonhomme (2017) find a rank correlation of -0.17 for married ones, and of -0.08 for singles. The confidence intervals for the correlation coefficients are $(-0.30; -0.01)$ for married females, and $(-0.24; 0.16)$ for singles.

varying with time estimated for three different business phases and reports no significant selection bias for the period closest to that of Arellano and Bonhomme (2017), 2007-2010. In point of fact, results in table 16 shows that the negative selection in the UK is driven by the most recent years, denoting a recent shift in the selection pattern. Moreover, Dolado et al. (2020) observe an added-worker effect, explaining the female shift toward a negative selection. The added worker effect appears when less-skilled women, who were previously inactive, enter the labour market to help restore household income levels as male breadwinners become jobless (Lundberg, 1985). The same added worker effect could also explain the female negative selection bias in Finland. Finnish male selection may not have been impacted due to the higher job destruction rate among low-skilled workers following the crisis (Dolado et al., 2020). My results with a stronger female negative selection bias compared with men in the UK are consistent with those of Arellano and Bonhomme (2017) with less positive selection into employment for women than for men. In addition, the negative selection in the UK and Finland are congruent with the descriptive statistics in Table 13 indicating that around 40 % of Finnish unemployed females and unemployed in the UK are highly educated. These findings are also consistent with those of Mueller (2017) for the US indicating a negative labour market participation bias in recessions due to the high cyclicality of separations for high-wage workers.

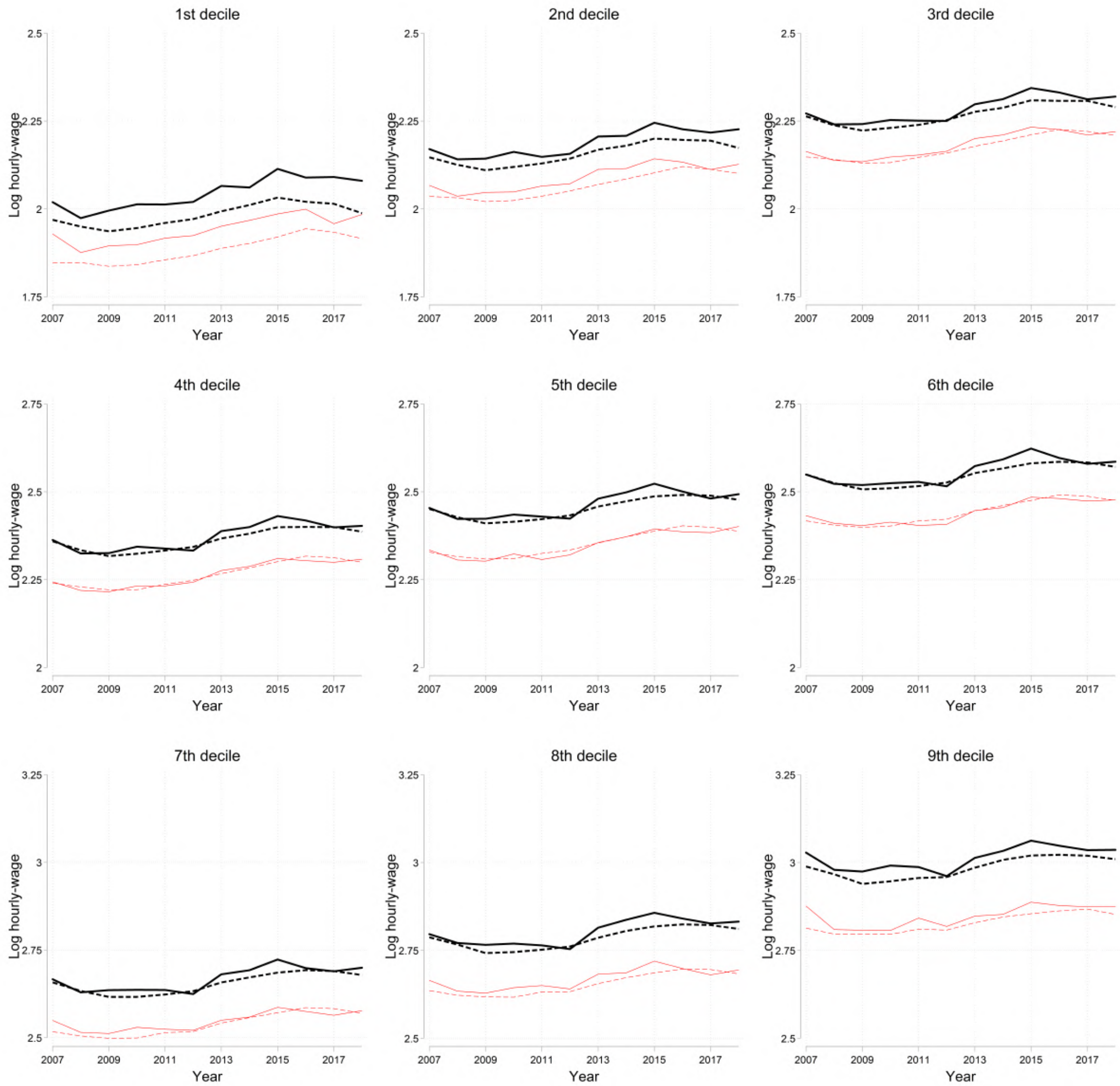
4.3 Wage distribution

Figure 1, 2 and 3 plot the distribution of log wages corrected and uncorrected for selection when controlling for observable characteristics. Female wages are represented in thin red lines and male wages in thick black lines. The distribution of log wages conditional on employment is represented by solid lines while the selection corrected distribution is represented by dashed lines. The selection-corrected distribution has been derived with the method of Mata and Machado (2005)[17] from the estimation of the quantile regression coefficient using the method of Arellano and Bonhomme (2017).

Figure 1 for France highlights the relevance of the sample selection correction all over

[17] Mata and Machado (2005)'s method is briefly summarized in the Appendix.

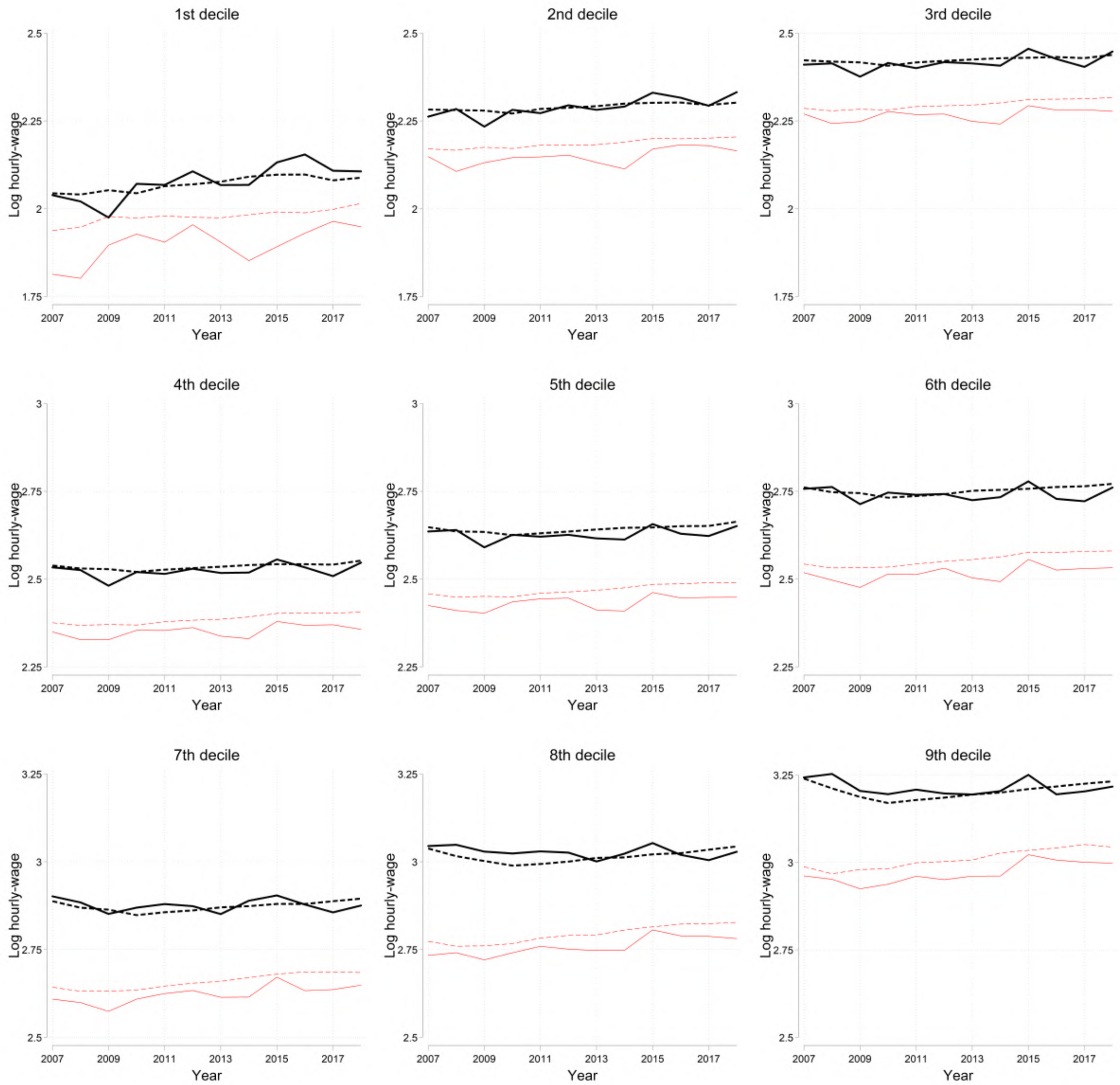
the wage distribution. While the correction for selection bias does not seem important for the analysis of wages at the median of the wage distribution, it has a strong impact on the wages at the tails of the distribution, especially at the bottom. At the bottom of the distribution, the correction for the positive selection slows wage growth.



Notes: EU-SILC data for 2007-2018. Quantiles of log-hourly wages, conditional on employment (solid lines) and corrected for selection (dashed). Male wages are plotted with thick black lines (top lines in each graph), while female wages are in thin red lines (bottom lines).

Figure 1: Wage quantiles according to the gender and sample correction in France

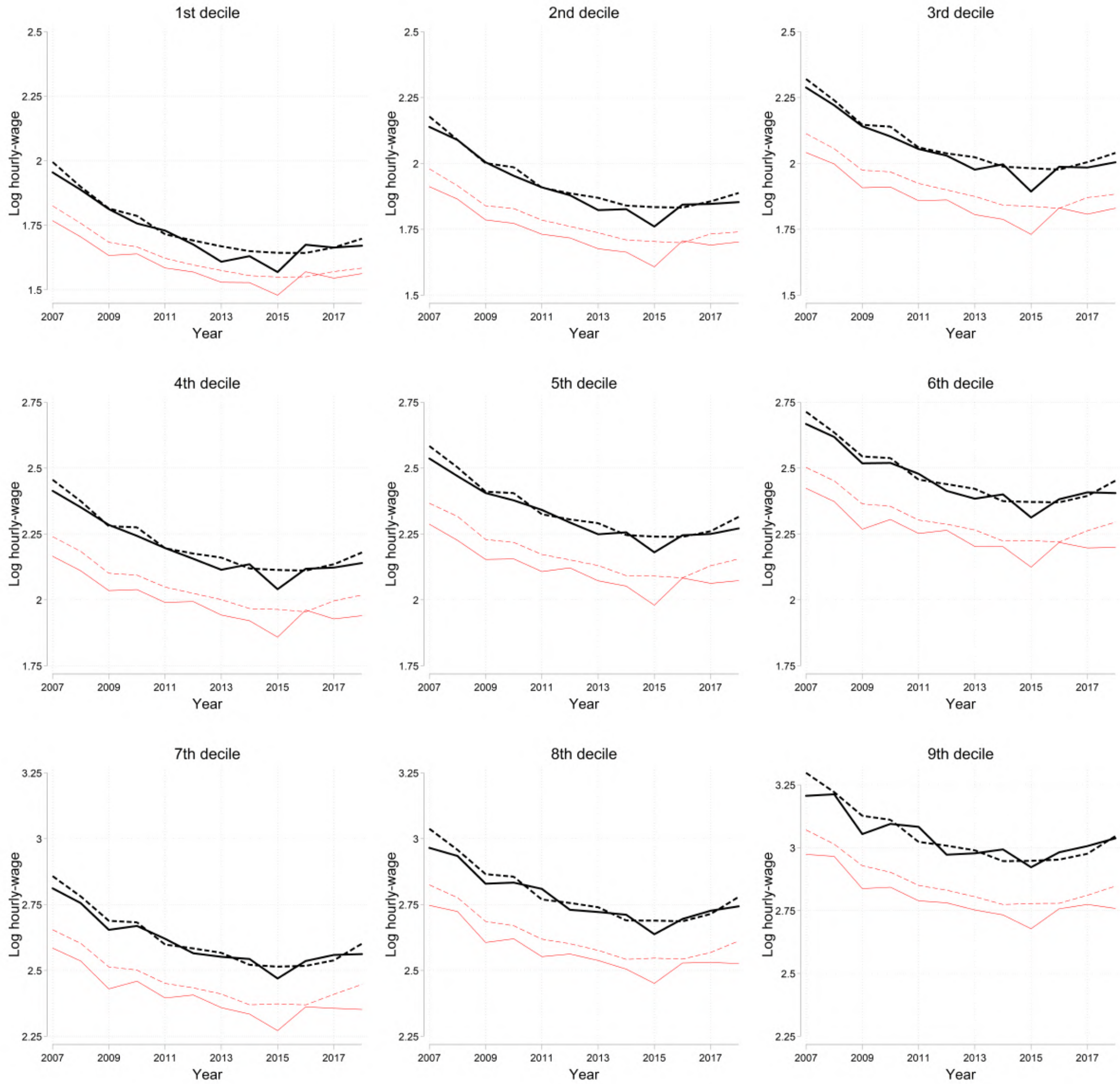
Figure 2 for Finland shows an important negative selection bias for women all along the wage distribution. In contrast, male selection in Finland is weak and impacts marginally the distribution of wages. This negative selection considerably impacts the female measure of wages at the bottom of the distribution.



Notes: EU-SILC data for 2007-2018. Quantiles of log-hourly wages, conditional on employment (solid lines) and corrected for selection (dashed). Male wages are plotted with thick black lines (top lines in each graph), while female wages are in thin red lines (bottom lines).

Figure 2: Wage quantiles according to the gender and sample correction in Finland

In Figure 3 for the UK, we can see that the correction for sample selection slows the decline in female wages in the UK. The female negative selection, more important than that of males, decreases the gender wage gap all along the distribution as illustrated in Figure 3.



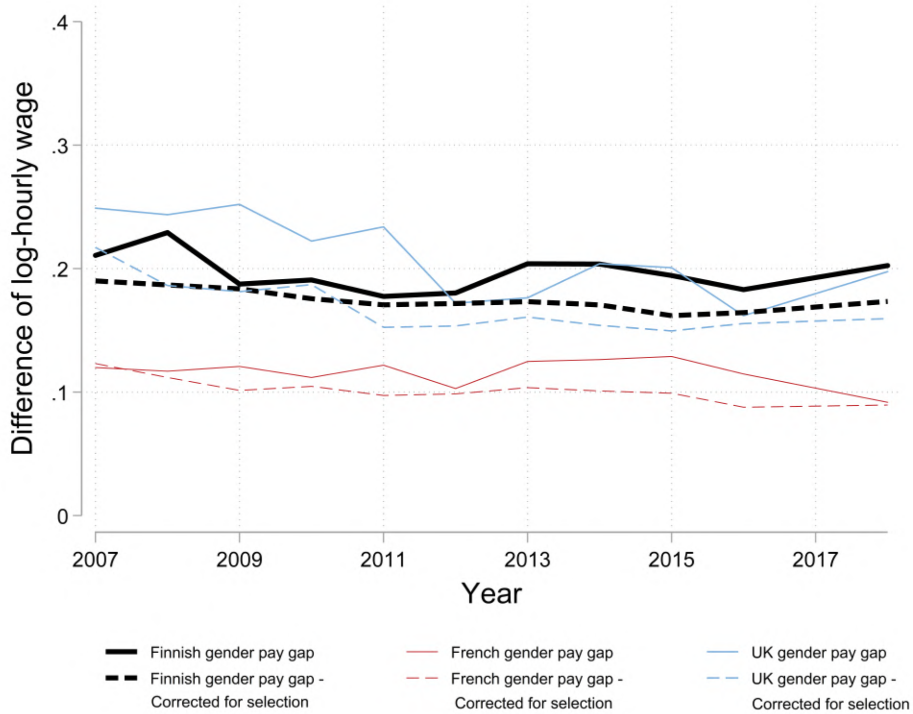
Notes: EU-SILC data for 2007-2018. Quantiles of log-hourly wages, conditional on employment (solid lines) and corrected for selection (dashed). Male wages are plotted with thick black lines (top lines in each graph), while female wages are in thin red lines (bottom lines).

Figure 3: Wage quantiles according to the gender and sample correction in the United Kingdom

Figure 1 shows an important positive male selection in France and 3 a negative male selection in the UK, different along the wage distribution, suggesting that not considering it would lead to a downward biased estimation of wage inequality. Moreover, the female negative selection in Finland and the UK is stronger than the male selection, causing a reduction in the corrected gender wage gap, compared to the uncorrected one. In comparison, in France, it is the stronger male selection which induces a lower corrected gender gap.

4.4 The dynamics of wage gaps

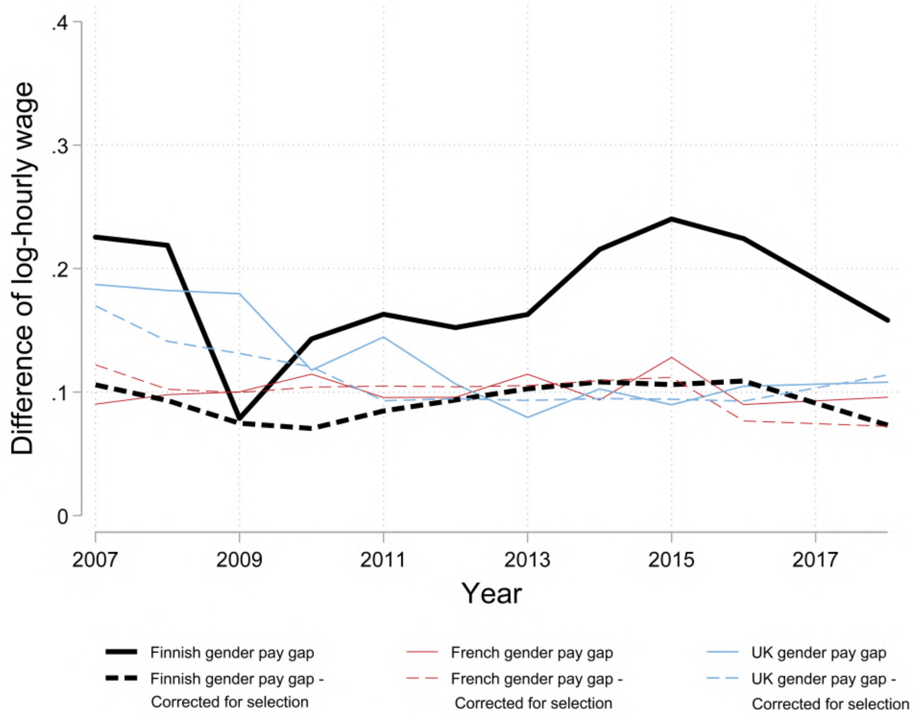
Figure 5, 4, 6 plot the gender wage gap according to the country for the median, first and ninth decile. The solid lines and the dashed lines stand for the gender pay gap uncorrected and corrected for selection respectively. Once again, the importance of a quantile study is highlighted by the median in Figure 4. Observing only the median would lead us to the conclusion that France is more egalitarian than Finland and the UK and that the Finnish corrected gap has converged towards the UK. Correcting for the selection bias leads to a smaller gender wage gap as illustrated in Figure 4. For example, correcting for sample selection declines the median gender difference in log-wages in 2007 in the UK from 25% to 21%. We have previously seen that these findings are driven by the female negative selection in the UK and Finland. It implies that the median gender wage gap would be reduced in the UK and Finland if non-working women were employed.



Notes: EU-SILC data for 2007-2018. Median of log-hourly wages, conditional on employment (solid lines) and corrected for selection (dashed). Finnish gender wage gap is in thick black lines, French in thin red lines and UK in mid-thick blue lines.

Figure 4: Gender wage gap at the median

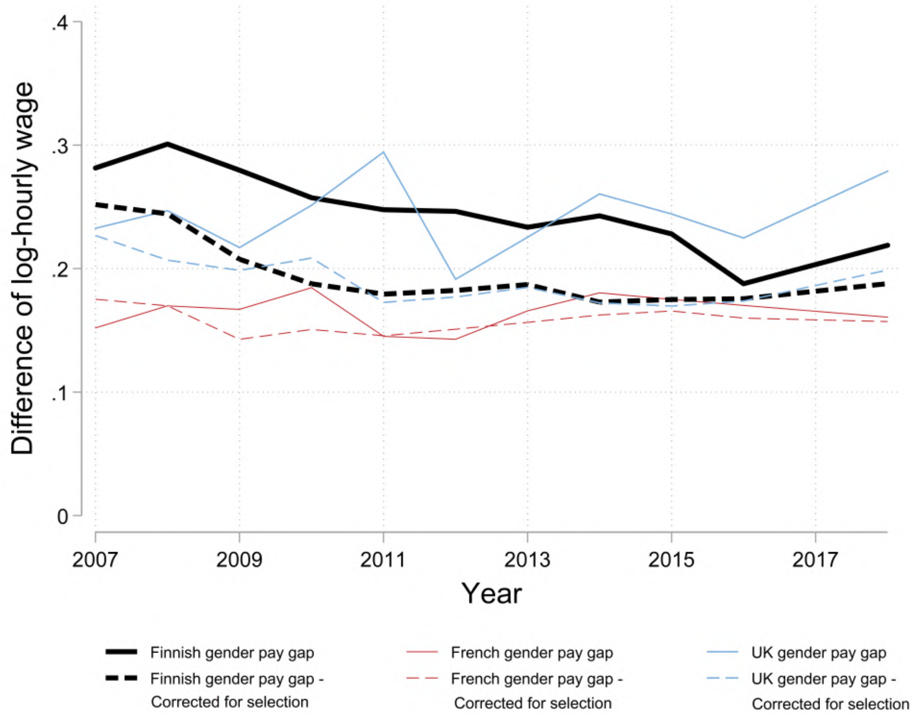
Figure 5 plots the gender wage gap at the first decile of the wage distribution. The Finnish gender wage gap seems to have dropped sharply with the crisis. Since there is no fall in the corrected gender gap, this trend could simply be reflecting the added worker effect. Furthermore, the correction of the sample selection bias indicates a decreasing gender wage gap in the UK, hidden with the observed adjusted wages. Correction for sample selection emphasizes a different trend. While the uncorrected wage gap indicates a convergence over time between France and the UK, the corrected gender wage gap shows a convergence between France and Finland. Selection considerably affects the gender wage gap at the bottom of the distribution in Finland, which was reduced by almost 8% in 2018. In 2007, correction for sample selection plummeted the gap from more than 20% to 10%. However, if correction for selection plunges the gender wage gap in Finland markedly, it has a mixed effect in the UK and France.



Notes: EU-SILC data for 2007-2018. First decile of log-hourly wages, conditional on employment (solid lines) and corrected for selection (dashed). Finnish gender wage gap is in thick black lines, French in thin red lines and UK in mid-thick blue lines.

Figure 5: Gender wage gap at the 1^{st} decile

Figure 6 shows the strong impact of selection at the top of the distribution in Finland and the UK. Correction for selection reveals a drop in the gender wage gap at the top until 2015, in the UK and Finland. This trend is driven by the negative female selection bias in those two countries, indicating that women with high wage characteristics do not participate in the labour market. Their participation in the labour market would reduce the glass ceiling in Finland and the UK, as illustrated in Figure 6. In contrast, selection has a mixed effect on the French gender gap that remains stable over time. Finland is the country where correcting for selection has the bigger impact on the wage gap. Finland is a social-democratic welfare state denoted as the more egalitarian welfare state explaining the fact that once corrected, the gap drops sharply.



Notes: EU-SILC data for 2007-2018. Ninth decile of log-hourly wages, conditional on employment (solid lines) and corrected for selection (dashed). Finnish gender wage gap is in thick black lines, French in thin red lines and UK in mid-thick blue lines.

Figure 6: Gender wage gap at the 9$^{\text{th}}$ decile

4.5 Inequality along the wage distribution

So far, we have explored differences in the gender wage gap between countries, according to the decile. But this is not the only dimension of the selection corrected gender gap. In particular, a comparison of the magnitude of the gender wage gap along the distribution could inform us about the existence of a sticky floor or a glass ceiling. In this section, I show that there is a glass ceiling in France, Finland and the UK and that the gender gap is decreasing with time.

Figure 7, 8 and 9 plot the gender wage gap along the wage distribution for each year for France, Finland and the UK, respectively. These three figures show once again, that correction for selection at the median hides a strong pattern at the tails. The three figures denote a different impact of correction depending on the quantile and the country but also over time.

Figure 7 shows that in France, where the selection is positive, the adjusted gender wage gap is under-estimated at the beginning of the period when non-corrected. However, in most recent years, correction for sample selection lowers the French gender wage gap. Besides, until 2015, the French corrected gender gap along the distribution is illustrated by a U shape, with higher inequality at the tails, representing a sticky floor and glass ceiling effect. But, recently, the sticky floor, characterized by higher inequality at the bottom is disappearing once the gap is corrected for selection. It implies that, in France, if unemployed women participated in the labour market, the French sticky floor would vanish. Moreover, lately, the shape of the French wage gap distribution has become similar to the one in the UK and Finland, with an increasing pattern of its shape. This increasing pattern reflects the presence of a glass ceiling, referring to higher inequality at the top of the distribution (90th percentiles).

Notes: EU-SILC data for 2007-2018. Distribution of log-hourly wages in France, conditional on employment (solid lines) and corrected for selection (dashed).

Figure 7: Annual distribution of the French gender wage gap

Both in the UK and Finland, the adjusted non-corrected gender wage gap is overestimated compared to the gap corrected for selection, all along the wage distribution and for every year (see Figures 8 and 9). The Finnish sticky floor for the uncorrected gap is due to the large negative selection for Finnish women. Differences between the corrected and uncorrected gap at the tails of the Finnish distribution highlight the importance of correction for sample selection. In addition, correcting for selection enables us to observe this increasing shape for those two countries, every year. This corrected gender gap demonstrates that Finland and the UK have a shape of wage gap distribution that remains stable over time.

Notes:EU-SILC data for 2007-2018. Distribution of log-hourly wages in Finland, conditional on employment (solid lines) and corrected for selection (dashed).

Figure 8: Annual distribution of the Finnish gender wage gap

The heterogeneity in the impact of selection along the distribution represented in Figure 9 for the different years in the UK can reflect its liberal welfare regime, where employment protection is lower than in the conservative and democratic countries.

Notes: EU-SILC data for 2007-2018. Distribution of log-hourly wages in the United Kingdom, conditional on employment (solid lines) and corrected for selection (dashed).

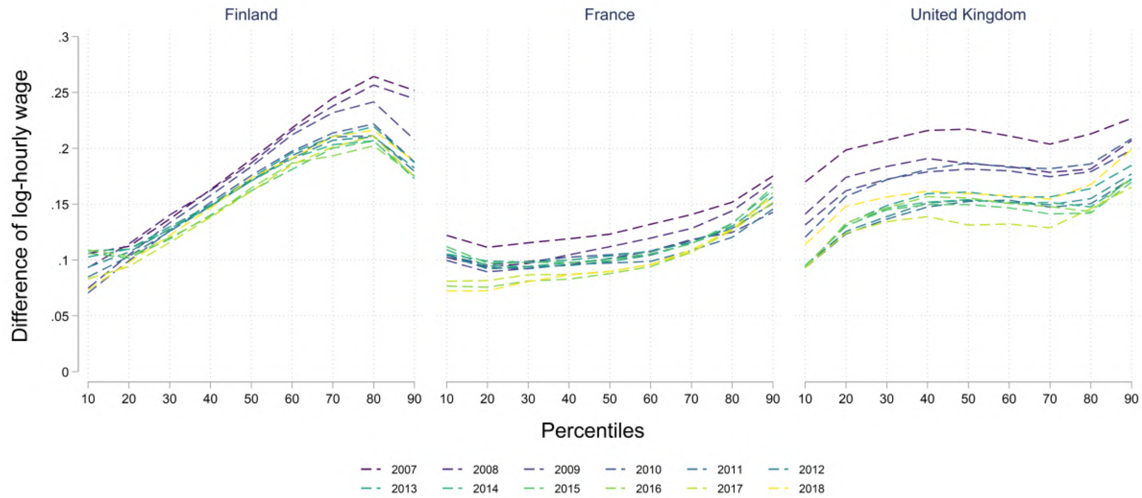
Figure 9: Annual distribution of the gender wage gap in the United Kingdom

Distributions of the selection corrected gender gap for the three countries are represented in Figure 10.[18] At the bottom, the gap has recently become similar for the three countries, with a gap of around 10% for the first decile. Moreover, the gap has diminished over time, especially at the top in Finland and all over the distribution in the UK and France.

Distributions of the selection-corrected gender gap in the Figure 10 are consistent with the findings of Christofides et al. (2013) who find a sticky floor in France and a glass ceiling in the UK and Finland in 2006.[19] Shapes of the distributions according to the country are also similar to the one found by Arulampalam et al. (2007) for the period 1995-2001.

[18]In the Appendix, Table 11 shows the distributions of the uncorrected gender gap.

[19]From the 2007 EU Statistics on Income and Living Conditions (EU-SILC) dataset for the 2006 reference year.



Notes: EU-SILC data for 2007-2018. Distribution of log-hourly wages, corrected for selection.

Figure 10: Distribution of the selection-corrected gender gap

4.6 Quantile regression

Tables 4 and 5 display the quantile regression results for men and women, controlling for selection and not controlling for selection, respectively. Comparison between these two tables enables us to observe the impact of observed characteristics on both men and women if the unemployed had participated in the labour market.

First, it should be noted that controlling for selection has a slight impact on the coefficients of the number of children split by age categories, as well as the marital status for males of the three countries. Indeed, these variables are not at the source of the male selection bias and thus, impact only marginally the wages once corrected for selection.

However, in Finland and in the UK where the female selection is negative, correcting for selection rises the coefficients, especially at the top. It implies that more women with high wage characteristics and children (or married) do not participate in the labour market in Finland and the UK. Consequently, if married women, as well as those with children and those with high wage characteristics, participated in the labour market, it would reduce the gender gap. In contrast, in France, due to the positive female selection bias, it would widen the gender wage gap if non-employed women participated in the labour market. These findings are consistent with the lowest level of women's employment at the bottom, as a result of policies that encourage mothers to remain in the home because of costly childcare. In Finland and the UK, it is mothers with high-income characteristics who stay at home probably because of the difficulties of combining a career and children. For the UK, these results are consistent with the liberal model where alternatives to the labour market are limited.

Table 4: Selection corrected quantile regression

	France						Finland						United Kingdom					
	Men			Women			Men			Women			Men			Women		
	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile
Number of children (age under or equal 3)	0.002	-0.001	**-0.033*** **	-0.013	**0.028*** **	**0.022** **	**-0.031* **	**-0.020*** **	**-0.026** **	**-0.305*** **	**0.057* **	**0.123*** **	**-0.015* **	-0.005	0.020	**-0.044* **	**0.063*** **	**0.188*** **
	(0.009)	(0.005)	(0.009)	(0.014)	(0.005)	(0.010)	(0.017)	(0.007)	(0.012)	(0.076)	(0.034)	(0.030)	(0.009)	(0.008)	(0.014)	(0.025)	(0.012)	(0.021)
Number of children (age between 4 and 6)	-0.007	0.003	-0.001	-0.000	**0.012** **	**0.019** **	**0.028** **	**0.021*** **	**0.036*** **	**0.049*** **	**0.018** **	0.003	0.004	**0.028*** **	**0.071*** **	0.005	**0.043*** **	**0.111*** **
	(0.009)	(0.005)	(0.009)	(0.014)	(0.005)	(0.009)	(0.014)	(0.007)	(0.012)	(0.019)	(0.008)	(0.013)	(0.011)	(0.008)	(0.015)	(0.013)	(0.010)	(0.021)
Number of children (age between 7 and 10)	0.006	**0.010** **	**0.018** **	-0.019	**0.014*** **	**0.024*** **	0.006	0.005	0.010	**0.026* **	0.009	0.005	-0.009	**0.022*** **	**0.060*** **	**-0.043*** **	0.008	**0.086*** **
	(0.009)	(0.005)	(0.007)	(0.012)	(0.004)	(0.007)	(0.011)	(0.006)	(0.009)	(0.013)	(0.006)	(0.011)	(0.010)	(0.006)	(0.013)	(0.009)	(0.007)	(0.017)
Number of children (age between 11 and 15)	-0.009	**0.010** **	**0.027*** **	**-0.054*** **	**0.010*** **	**0.024*** **	**0.021** **	0.001	0.001	**0.018** **	**0.009** **	0.007	-0.007	**0.025*** **	**0.059*** **	**-0.028*** **	**-0.015*** **	**0.030*** **
	(0.007)	(0.004)	(0.007)	(0.011)	(0.003)	(0.006)	(0.010)	(0.005)	(0.008)	(0.009)	(0.004)	(0.008)	(0.010)	(0.006)	(0.012)	(0.007)	(0.006)	(0.011)
Number of children (age between 16 and 17)	0.017	**0.018** **	**0.044*** **	**-0.052** **	**0.021*** **	**0.019* **	0.014	0.003	0.016	0.002	-0.006	0.000	0.002	0.001	0.027	**-0.030*** **	**-0.022** **	-0.001
	(0.012)	(0.007)	(0.011)	(0.021)	(0.006)	(0.010)	(0.016)	(0.009)	(0.013)	(0.017)	(0.008)	(0.014)	(0.016)	(0.010)	(0.020)	(0.010)	(0.010)	(0.020)
Marital status (single)	**-0.161*** **	**-0.105*** **	**-0.124*** **	-0.009	-0.001	**0.012* **	**-0.263*** **	**-0.092*** **	**-0.089*** **	**0.036* **	**0.032*** **	**0.025* **	**-0.109*** **	**-0.118*** **	**-0.124*** **	**-0.015** **	**-0.038*** **	**-0.020* **
	(0.017)	(0.006)	(0.009)	(0.010)	(0.005)	(0.007)	(0.050)	(0.012)	(0.021)	(0.019)	(0.007)	(0.014)	(0.011)	(0.010)	(0.019)	(0.007)	(0.006)	(0.012)

Notes: Results of the selection corrected quantile regression. Other covariates in the wage equation include experience and its polynomial term, a set of regional dummies for France and Finland, linear, quadratic, and cubic time trends, health characteristics and education (tertiary level diploma). Standard errors in parentheses. *, ** and *** denote statistical significance at 10, 5, and 1 percent levels.

Table 5: Uncorrected quantile regression

	France						Finland						United Kingdom					
	Men			Women			Men			Women			Men			Women		
	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile	First Decile	Median	Ninth Decile
Number of children (age under or equal 3)	-0.009	-0.004	**-0.031*** **	-0.002	**0.035*** **	**0.031*** **	**-0.030* **	**-0.019*** **	**-0.025** **	**-0.542*** **	**-0.059*** **	0.024	-0.016	-0.007	0.007	**-0.117*** **	0.011	**0.098*** **
	(0.009)	(0.005)	(0.009)	(0.013)	(0.005)	(0.010)	(0.017)	(0.007)	(0.010)	(0.030)	(0.009)	(0.017)	(0.010)	(0.007)	(0.012)	(0.010)	(0.007)	(0.013)
Number of children (age between 4 and 6)	-0.003	0.001	-0.002	0.007	**0.015*** **	**0.021** **	**0.032* **	**0.022*** **	**0.037*** **	**0.046** **	**0.012* **	0.007	0.003	**0.024*** **	**0.067*** **	-0.016	0.005	**0.044*** **
	(0.009)	(0.005)	(0.009)	(0.012)	(0.005)	(0.010)	(0.016)	(0.007)	(0.010)	(0.021)	(0.006)	(0.012)	(0.011)	(0.007)	(0.013)	(0.010)	(0.007)	(0.013)
Number of children (age between 7 and 10)	0.010	**0.011** **	**0.018** **	**-0.023** **	**0.018*** **	**0.025*** **	0.006	0.004	0.011	0.026	0.005	-0.000	-0.009	**0.018*** **	**0.053*** **	**-0.067*** **	**-0.016*** **	**0.043*** **
	(0.007)	(0.004)	(0.008)	(0.010)	(0.004)	(0.008)	(0.014)	(0.006)	(0.008)	(0.017)	(0.005)	(0.009)	(0.009)	(0.006)	(0.011)	(0.008)	(0.006)	(0.011)
Number of children (age between 11 and 15)	-0.006	**0.014*** **	**0.030*** **	**-0.041*** **	**0.015*** **	**0.026*** **	**0.020* **	0.003	0.003	0.020	**0.010** **	0.006	-0.012	**0.018*** **	**0.048*** **	**-0.036*** **	**-0.031*** **	0.006
	(0.007)	(0.004)	(0.007)	(0.008)	(0.003)	(0.006)	(0.012)	(0.005)	(0.007)	(0.013)	(0.004)	(0.008)	(0.009)	(0.006)	(0.010)	(0.007)	(0.005)	(0.009)
Number of children (age between 16 and 17)	**0.021* **	**0.015** **	**0.045*** **	**-0.048*** **	**0.022*** **	**0.022** **	0.016	0.001	0.013	-0.002	-0.001	0.004	0.004	-0.001	0.022	**-0.038*** **	**-0.029*** **	-0.020
	(0.011)	(0.006)	(0.011)	(0.013)	(0.006)	(0.011)	(0.020)	(0.008)	(0.012)	(0.021)	(0.006)	(0.012)	(0.015)	(0.010)	(0.017)	(0.011)	(0.008)	(0.015)
Marital status (single)	**-0.122*** **	**-0.085*** **	**-0.107*** **	-0.010	0.000	0.012	**-0.293*** **	**-0.102*** **	**-0.094*** **	0.024	**0.012* **	0.003	**-0.127*** **	**-0.142*** **	**-0.148*** **	**-0.023*** **	**-0.048*** **	**-0.040*** **
	(0.009)	(0.005)	(0.010)	(0.010)	(0.004)	(0.008)	(0.019)	(0.008)	(0.012)	(0.022)	(0.007)	(0.012)	(0.011)	(0.007)	(0.012)	(0.008)	(0.006)	(0.010)

Notes: Results of the quantile regression. Other covariates in the wage equation include experience and its polynomial term, a set of regional dummies for France and Finland, linear, quadratic, and cubic time trends, health characteristics and education (tertiary level diploma). Standard errors in parentheses. *, ** and *** denote statistical significance at 10, 5, and 1 percent levels.

As previously mentioned, each of the three countries corresponds to a different welfare state according to the Esping-Andersen (1990) classification. On the one hand, France, the conservative welfare state, has not undergone any important changes in its gender wage gap following the Great Recession. This is related to the substantial employment protection in place in conservative welfare states. On the other hand, the UK gender wage gap, in this liberal welfare state without much employment protection, was particularly impacted by the crisis but only temporarily. Lastly, Finland, the democratic welfare state has a gender gap that has diminished, once the selection is considered.

Following Esping-Andersen (1990), I find that each welfare state model is associated with a distinct labour market trajectory for women. My findings yield strong support for the hypothesis of a gender wage gap reflecting the pattern of institutions and policies, characterized by the type of welfare state (Christofides et al., 2013). It implied important dissimilarities following the Great Recession. However, in the most recent years, the shapes, and levels of the gap along the distribution have become more similar between the countries.

5 Robustness analysis

I first examine the underlying assumptions and robustness of my approach to correct for the selection bias. Then, I analyse the contribution of my instrument compared to the traditional one before investigating the role of self-employment in my findings.

5.1 Choice of the copula

The Frank copula is a logical choice given its interpretation advantages, but I assess the robustness of my results to the choice of the copula by reestimating the model with a Gaussian copula (another low-dimension copula). The Gaussian copula provides, as well as the Frank copula, comparable dependence parameters (the Spearman correlation coefficient). I calculate the Spearman correlation coefficient for both copula functions in table 6. Table 6 shows similar dependence parameters for the two copula functions.

Table 6: Spearman Correlation Coefficients for Different Copula Models

	France		Finland		United Kingdom	
	Males	**Females**	**Males**	**Females**	**Males**	**Females**
Frank Copula	-0.3164	-0.1198	0.1198	0.3300	0.2313	0.3444
Gaussian Copula	-0.3287	-0.1681	0.1822	0.3966	0.2336	0.3679

Notes: Frank and Gaussian copula estimation. The Spearman correlation of a copula (or rank correlation) measures the correlation between the ranks U and V.

5.2 Validity of assumptions

The choice of the instrument and the exclusion restrictions assumptions are important features of this paper. Since the out-of-work income instrumental variable is a function of household composition, the validity of the exclusion restriction assumption in this study could be questioned. Then, I offer arguments in support of my choices and the validity of these assumptions. The strength of the empirical relationship between the out-of-work income variable and female labour market participation as well as male participation has been demonstrated in the estimates in table 2. In addition, to assess the validity of my exclusion restriction, following Maasoumi and Wang (2019), I use the Huber and Mellace (2014) statistical test to validate this assumption. This method tests the joint satisfaction of both the exclusion restriction assumption and the additive separability assumption (For more details of this test, see Huber and Mellace (2014)).

Table 7: Huber and Mellace IV Tests in the Sample Selection Models

	France		**Finland**		**UK**	
	Test	**P-value**	**Test**	**P-value**	**Test**	**P-value**
Males	-0.1873	1	-2.2504	1	-2.9433	1
Females	-0.0395	1	-2.7761	1	-3.4623	1

Notes: Following the application of Huber and Mellace (2014) for non-labour income instrumental variable, the out-of-work income instrument is discretized (equal to one if out-of-work income is larger than the median value in the sample and zero otherwise).

Results in table 7 show a p-value equal to one and negative standardized mean constraints (indicating that constraints are not binding). I fail to reject the validity of the IV as an excluded regressor for the three countries. In comparison, table 17 in the Appendix section shows the results of D'Haultfœuille et al. (2021)'s test of exclusion restriction of the traditional instrumental variable (presence of young children). The statistical test developed by D'Haultfœuille et al. (2021) is valid for binary instruments only. In contrast with the findings in table 7 with the exclusion restriction test of the out-of-work income instrument, table 17 shows that we reject the null hypothesis of a satisfied exclusion restriction of the traditional instrumental variable.

5.3 Traditional instrumental variable

As explained earlier in subsection 3.2, one of the novel elements of this paper is the instrumental variable, the potential out-of-work income. This variable seems to be a stronger determinant of male labour market participation as shown in Table 2 than the number of young children (reported in Table 11 in the Appendix).

Moreover, Table 8 shows different selection patterns from Table 3. Indeed, the French selection pattern is similar using both IV, but the latter is different for Finnish and UK women. Hence, the choice of the instrument has an impact on the findings. As my specification includes the number of young children in the controls, one possible explanation could be that the traditional instrument variable, not controlling for young children in the wage equation fails to capture the important wage pattern caused by household composition. It should be noticed that the biggest change in comparison to Table 3 relates to the selection parameter for Finnish males and males in the UK, for which the instrument had no impact on participation (see Table 11 in the Appendix).

Table 8: Selection parameter and its sign with the traditional IV (presence of young children)

	France		**Finland**		**United Kingdom**	
	Males	**Females**	**Males**	**Females**	**Males**	**Females**
ρ	-2.3097***	-2.8540***	1.3734***	1.2068***	-3.9055***	-0.3151
	[-3.0716 ; -1.5478]	[-3.5398 ; -2.1682]	[0.39247 ; 2.3542]	[0.7519 ; 1.6618]	[-4.6873 ; -3.1236]	[-0.8979 ; 0.2676]
Sign of the selection	Positive	Positive	Negative	Negative	Positive	Positive
Spearman correlation	-0.3601	-0.4309	0.2233	0.1973	-0.5480	-0.0525

Notes: Frank copula estimation. Results of the quantile selection model with the presence of young children as instrument (i.e., having at least one child aged three or under). The dependence parameter, ρ, captures the dependence between u and v, the two error terms. A negative ρ indicates positive selection into employment and vice versa. Standard errors are computed based on subsampling. Sample size is chosen as a constant (1000) plus the square root of the sample size, following Arellano and Bonhomme (2017). *, ** and *** denote statistical significance at 10, 5, and 1 percent levels.

5.4 Self-employment

My analysis assumes that a shift from employment to self-employment cannot be another source of selection bias. Indeed, as most empirical work on gender wage gap (Olivetti and Petrongolo, 2008; Christofides et al., 2013; Arellano and Bonhomme, 2017), I exclude the self-employed from my sample. However, following the Great Recession, if those who were employed shifted towards self-employment, it could introduce another selection bias. Estimations with a sample including self-employed are presented in Table 9. Table 9 shows a selection parameter sign identical to Table 3.

Table 9: Selection parameter and its signs with a sample including self-employed individuals

	France		**Finland**		**United Kingdom**	
	Males	Females	Males	Females	Males	Females
ρ	-3.7917***	-0.8577 **	3.0205***	2.7647***	1.5045***	1.5832***
	[-4.7191 ; -2.8643]	[-1.5558 ; -0.1596]	[-0.7404 ; 2.1874]	[1.4418 ; 4.0876]	[1.7252 ; 4.3158]	[9.7647 ; 2.4017]
Sign of the selection	Positive	Positive	Negative	Negative	Negative	Negative
Spearman correlation	-0.5365	-0.1416	0.4512	0.4198	0.2435	0.2554

Notes: Frank copula estimation. The dependence parameter, ρ, captures the dependence between U and V, the two error terms. A negative ρ indicates positive selection into employment and vice versa. Standard errors are computed based on subsampling. Sample size is chosen as a constant (1000) plus the square root of the sample size, following Arellano and Bonhomme (2017). *, ** and *** denote statistical significance at 10, 5, and 1 percent levels.

6 Conclusion

This paper aims to measure the gender gap by focusing on heterogeneity in wages and selection into full-time employment, using a quantile selection model. Simulating an instrumental variable capturing the opportunity cost of entering the labour market, I measure the labour market participation of both men and women in France, Finland and the UK and assess the evolution of the selection-corrected gender wage gap along the distribution and over time.

The Great Recession has impacted the once marginal selection of men into the labour market. My results demonstrate that it is essential to also account for men's participation decisions as their employment patterns have been affected by the Great Recession and impact the estimation of the gender wage gap. I find a different sign of selection according to the welfare state, and a considerable male selection in France and the UK.

Moreover, the evolution of the corrected gender wage gap along the wage distribution shows the importance of correcting it beyond the median. This paper provides new insight into European comparisons as results corrected for selection bias reveal different patterns along the distribution. For the three countries, correcting for selection lowers the gender wage gap and enables us to perceive a similar increasing shape of the gender gap along the distribution, with a substantial glass ceiling.

This finding encourages us to further investigate selection patterns by discerning the intensity of engagement in paid work. In fact, many women in OECD countries work part-time, sometimes voluntarily due to household constraints. This paper focuses on the overall employment participation without distinguishing between part-time and full-time employment. Since women are usually more likely than men to work in a part-time job, a better understanding of the selection into the labour market at the intensive margin, rather than only at the extensive margin, is an important avenue for future research.

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7 Appendix

Table 10: Tax and benefits simulated in the out of work income variable

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
France												
Family benefits												
Mean tested birth grant (PN)	+	+	+	+	+	+	+	+	+	+	+	+
Mean tested benefit for young children (APJE/PAJE)	+	+	+	+	+	+	+	+	+	+	+	+
Mean tested benefit for large families (CF)	+	+	+	+	+	+	+	+	+	+	+	+
Mean tested benefit for lone parents (API)	+	+										
Universal child benefit (AF)	+	+	+	+	+	+	+	+	+	+	+	+
Supplement for free choice of activity (CLCA)	+	+	+	+	+	+	+	+	+	+	+	+
Family support allowance (ASF)	+	+	+	+	+	+	+	+	+	+	+	+
Income support												
Guarantee minimum income (RMI/RSA)	+	+	+	+	+	+	+	+	+	+	+	+
Housing benefits												
Mean tested housing benefit (AL)	+	+	+	+	+	+	+	+	+	+	+	+
Other benefits												
Activity allowance										+	+	+
Tax												
Personal income ta+ (IRPP)	-	-	-	-	-	-	-	-	-	-	-	-
Finland												
Family benefits												
Child benefit (lapsilisä)	+	+	+	+	+	+	+	+	+	+	+	+
Child home care allowance (kotihoidon tuki)	+	+	+	+	+	+	+	+	+	+	+	+
Income support												
Local authority income support/ social assistance (toimeentulotuki)	+	+	+	+	+	+	+	+	+	+	+	+
Housing benefits												
General housing allowance e (yleinen asumistuki)									+	+	+	+
Tax												
Personal income tax	-	-	-	-	-	-	-	-	-	-	-	-
United Kingdom												
Family benefits												
Child benefit	+	+	+	+	+	+	+	+	+	+	+	+
Child tax credit	+	+	+	+	+	+	+	+	+	+	+	+
Income support												
Social assistance	+	+	+	+	+	+	+	+	+	+	+	+
Housing benefits												
Housing benefits and local housing allowance	+	+	+	+	+	+	+	+	+	+	+	+
Other benefits												
Universal credit										+	+	+
Tax												
personal income tax	-	-	-	-	-	-	-	-	-	-	-	-
Other charge												
High income child benefit charge							-	-	-	-	-	-

Notes: These taxes and benefits are simulated using EUROMOD model (Version I2.0+) to create the potential out of work income. Simulations have been carried out at the individual level, considering the income of the partner unchanged and considering every individual as unemployed. Capital incomes are not considered in this simulation. The sign "+" denotes components added to the out-of-work income variable while the sign "-" denotes components subtracted.

Table 11: The effects of presence of young children on labour market participation

	France		Finland		United Kingdom	
	Males	**Females**	**Males**	**Females**	**Males**	**Females**
Presence of young children (age under or equal 3)	0.111***	-0.285***	0.028	-1.472***	-0.024	-0.616***
	(0.026)	(0.019)	(0.033)	(0.024)	(0.024)	(0.016)
Observations	44,944	50,456	29,498	34,616	47,964	58,971
Pseudo R-squared	0.1439	0.1363	0.1410	0.1787	0.2269	0.1563

Notes: First-stage results of the effects of the presence of young children on employment with a probit model estimation. Other covariates in the participation equation include experience and its polynomial term, a set of regional dummies for France and Finland, linear, quadratic, and cubic time trends, health characteristics, marital status and education (tertiary level diploma). Standard errors in parentheses. *, ** and *** denotes statistical significance at 10, 5, and 1 percent levels.

Table 12: Descriptive statistics: Average for employed individuals

	Participate					
	France		**Finland**		**UK**	
	Males	Females	Males	Females	Males	Females
Couple	0.78	0.75	0.77	0.76	0.74	0.72
Tertiary education level	0.36	0.42	0.43	0.57	0.52	0.54
Age	42.26	42.91	41.26	42.81	40.48	41.12
Experience	20.62	19.02	19.48	20.11	17.33	16.41
Partner's income	1 9063.15	29 386.22	25 434.47	36 649.02	20 021.51	33 558.30
With young children (aged 3 or under)	0.14	0.11	0.14	0.06	0.14	0.11
Family benefits (as a share of disposable household income)	0.04	0.04	0.05	0.03	0.03	0.04
Observations	67471		50363		82402	

Note: The reported numbers are the weighted average. Family benefits correspond to the family/children related allowance collected at the household level as a share of disposable household income.

Table 13: Descriptive statistics: Average for unemployed individuals

	Non-participate					
	France		Finland		UK	
	Males	Females	Males	Females	Males	Females
Couple	0.51	0.75	0.46	0.75	0.48	0.67
Tertiary education level	0.21	0.21	0.19	0.38	0.39	0.38
Age	42.46	43.26	44.44	40.66	41.57	40.66
Experience	17.01	13.31	20.80	17.03	12.68	11.76
Partner's income	13 173.79	25 552.89	19 899.80	31 010.94	11 605.30	31 468.91
With young children (3 or less)	0.08	0.20	0.06	0.39	0.09	0.25
Family benefits (as a share of disposable household income)	0.04	0.09	0.03	0.12	0.08	0.14
Observations	16949		13086		24531	

Notes: The reported numbers are the weighted average. Family benefits correspond to the family/children related allowance collected at the household level as a share of disposable household income.

Table 14: Descriptive statistics from OECD database

	Labour force participation rate						Employment rate					
	France		Finland		United-Kingdom		France		Finland		United-Kingdom	
	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females	Males	Females
2007-2010	75	65	77	73	83	70	69	60	71	68	77	66
2011-2013	75	66	77	73	83	71	68	60	70	68	76	66
2014-2018	75	68	78	75	83	73	68	61	71	68	79	70

Notes: The labour force participation rates are calculated as the labour force divided by the total working-age population. The working-age population refers to people aged 15 to 64. Employment rates are calculated as the ratio of the employed to the working-age population. Labour force participation rates and employment rates are computed using OECD data, available at the following link: OECD Labour force participation rate and OECD employment rate.

Table 15: Descriptive statistics of the propensity score of participation

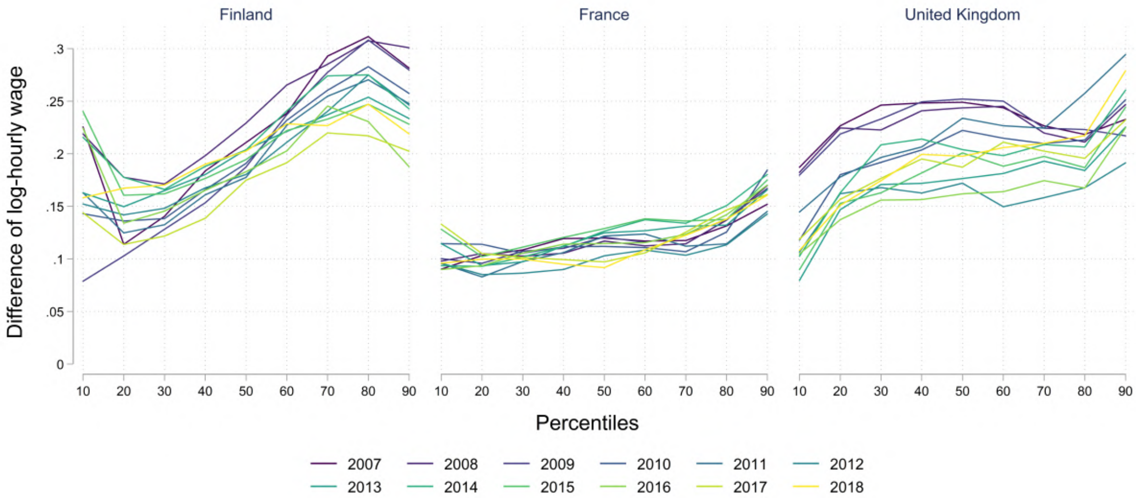
	Mean			**1st Decile**			**Median**			**9th Decile**			**Kolmogorov-Smirnov test**
	Males	Females	Gap	Males	Females	Gap	Males	Females	Gap	Males	Females	Gap	Difference
France	0.853	0.749	0.104	0.674	0.474	0.200	0.906	0.802	0.104	0.956	0.930	0.026	0.3375 ***
Finland	0.819	0.773	0.047	0.621	0.436	0.186	0.865	0.834	0.031	0.954	0.927	0.026	0.1851 ***
United-Kingdom	0.821	0.729	0.092	0.591	0.386	0.205	0.899	0.806	0.093	0.968	0.924	0.044	0.3357 ***

Notes: First-stage results of the propensity score of participation obtained with the probit model in table 2. The reported numbers in the gap row correspond to the propensity score difference between men and women. The Kolmogorov–Smirnov test determines the largest difference between the male and female distribution of propensity score and its significance.

Table 16: Selection parameter and its sign over the business cycle

	France		**Finland**		**United Kingdom**	
	Males	**Females**	**Males**	**Females**	**Males**	**Females**
			2007-2010			
ρ *(Frank copula)*	-0.937	-1.662	1.759	-0.467	0.604	1.169
CI	(-3.014 ; 1.140)	(-2.723 ; -0.600)	(-0.617 ; 4.134)	(-2.793 ; 1.858)	(-1.162 ; 2.370)	(-0.592 ; 2.930)
Spearman correlation	-0.1544	-0.2673	0.2817	-0.0777	0.1002	0.1914
			2011-2013			
ρ *(Frank copula)*	-1.213	-0.394	0.778	0.858	2.669	2.566
CI	(-3.532 ; 1.106)	(-1.736 ; 0.948)	(-1.447 ; 3.003)	(-1.046 ; 2.761)	(0.805 ; 4.534)	(0.983 ; 4.150)
Spearman correlation	-0.1983	-0.0655	0.1287	0.1416	0.4077	0.3943
			2014-2018			
ρ *(Frank copula)*	-2.196	-1.425	2.865	2.854	4.179	3.792
CI	(-4.083 ; -0.309)	(-3.002 ; 0.153)	(0.329 ; 5.400)	(1.326 ; 4.381)	(2.612 ; 5.746)	(2.326 ; 5.257)
Spearman correlation	-0.3444	-0.2313	0.4322	0.4309	0.5742	0.5365

Notes: Frank copula estimation. The dependence parameter, ρ, captures the dependence between U and V, the two error terms. A negative ρ indicates positive selection into employment and vice versa. Standard errors are computed based on subsampling. Sample size is chosen as a constant (1000) plus the square root of the sample size, following Arellano and Bonhomme (2017).



Notes: EU-SILC data for 2007-2018. Distribution of log-hourly wages, conditional on employment.

Figure 11: Distribution of the uncorrected gender gap

Table 17: Exclusion restriction test of D'Haultfoeuille, X., Hoderlein, S & Sasaki, Y.

	France		**Finland**		**United Kingdom**	
	KS statistic	**P-value**	**KS statistic**	**P-value**	**KS statistic**	**P-value**
Males	2.932	0.000	2.156	0.000	2.060	0.000
Females	4.460	0.000	1.533	0.000	1.090	0.000

Notes: Results of the exclusion restriction test of D'Haultfœuille et al. (2021) of the traditional instrumental variable, the presence of young children. Null hypothesis: Exclusion restriction is satisfied.

Sample construction and description of variables

Sample construction The sample is restricted to individuals aged 23-59 at the survey date, excluding individuals in full-time education or military service, family workers, in retirement, permanently disabled and self-employed.

Hourly wage The wage variable refers to gross cash income paid from the employer to the employee, in euro. It includes wages and salaries paid for time worked in main and any secondary job, holiday payments, usual paid overtime, commissions, tips, gratuities, supplementary payments (e.g. thirteenth-month payment), profit share bonuses, etc.

It excludes non-cash benefits from the employer and the employer's social insurance contributions, reimbursements for work-related expenses, income from investments, assets, savings, stocks and shares.

Except for data collection in the UK, the SILC survey asks about the total income of household members during the calendar year before the survey interview. However, as it's difficult for survey respondents to recall accurately all components of their work (time worked, type of contract, etc.) over an arbitrary historical period, the time frame for non-income information refers to the time of the interview (Iacovou et al., 2012). To correct for the reference period mismatch between income and non-income information in Finland and France, I follow the recommendations of Iacovou et al. (2012), using the longitudinal dataset for this cross-national analysis, matching the income variables recorded in year t with all the other variables for the same individual recorded in year $t-1$.

All monetary variables are deflated and expressed in Purchasing Power Parity (PPP) following Mack et al. (2020) guidelines. Inflation rates are constructed as the relative growth of inflation compared to the reference year, using Harmonised Indices of Consumer Prices (HICP) available from Eurostat.[20]

Hourly wages

All statistics and computations have been realized considering the log of the hourly wage. To calculate hourly wage, I follow the strategy of Engel and Schaffner (2012), with

$$\text{Hourly wage} = \frac{\text{Gross deflated annual income}}{\text{Number of months worked} \times \text{Number of hours worked by week} \times 4,345}.$$

To compute the hourly wage considering that the workers can have different working-time or employment statuses within the same reference period, the set of rules described by Engel and Schaffner (2012) are used sequentially.

Variable description

[20]Purchasing power parities and Harmonised Indices of Consumer Prices can be found in Eurostat website at the following links: PPP, HICP.

Table 18: Description of the variables used in the study

Variable Name	Description
Working	Individuals who work as employees and earned an hourly wage of more than one euro. Individuals are considered as non-working if they are unemployed, fulfilling domestic tasks and care responsibilities and other inactive persons.
Experience	Number of years spent in paid work (as employee or self-employee). If not reported, difference between age and year when the individuals began they first regular job.
Education	Dummy variable indicating if the highest education level attained is post-secondary or tertiary education.
Regions	Dummies variables referring to the classification NUTS-01.
Health characteristics	Dummy variable indicating if the individuals are strongly limited in activities because of health problems.
Number of children split by age categories	Number of dependent children in the household split by age categories (age under or equal 3, between 4 and 6, between 7 and 10, between 11 and 15, and between 16 and 17)
Marital status	Dummy variable indicating if the individual is single. Individuals are considered as single if they are not in a consensual union (whether or not on a legal basis). A consensual union with a legal basis includes both married couples and registered partners. Consensual unions without a legal basis are partners living in the same household.
Trend	Time trend variable (time index in year 2007).
Presence of young children	Having at least one child aged 3 or under.

Mata and Machado (2005)'s method

The Mata and Machado (2005) method allows computing the counterfactual distribution of the outcome variable, corrected for selection.

The counterfactual distribution can be recovered as follows:

$$F_{Y_c}(y) = F_{Y\langle i|j\rangle}(y) = \int F_{Y_i|X_i}(y \mid x) dF_{X_j}(x).$$

It can be rewritten as follows:

$$\begin{aligned} F_{Y_c}(y) = F_{Y\langle i|j\rangle}(y) &= \int \left\{ \int_0^1 I\left[Q_\tau \left(Y_i \mid X_i \right) \leq y \right] d\tau \right\} dF_{X_j}(x) \\ &= \int \left\{ \int_0^1 I\left[X\beta_i \leq y \right] d\tau \right\} dF_{X_j}(x) \end{aligned}$$

Then, we can identify the counterfactual outcome distribution where men have women's characteristics but with male's returns, $F_{Y_{c2}}$.

$$
\begin{aligned}
F_{Y_{\mathrm{c1}}}(y) &= \int \left\{ \int_0^1 I\left[X\beta_{\mathrm{m}} \leq y\right] d\tau \right\} dF_{X_{\mathrm{f}}}(x) \\
&\qquad (\text{ counterfactual distribution 1}), \\
F_{Y_{\mathrm{c2}}}(y) &= \int \left\{ \int_0^1 I\left[X\beta_{\mathrm{f}} \leq y\right] d\tau \right\} dF_{X_{\mathrm{m}}}(x) \\
&\qquad (\text{counterfactual distribution 2})
\end{aligned}
\tag{2}
$$

$F_{Y_{c2}}$ represents the counterfactual distribution with men's characteristics and female's returns.

The differences in the distributions $F_1 - F_{c1}$ provide insights into structural effects while the difference in F_{c2} refers to the composition effect, due to differences in characteristics.