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Wage inequality in Uruguay: Technological change impact on occupational tasks

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Desigualdad salarial en Uruguay: Impacto del cambio tecnológico sobre las tareas ocupacionales

Sandra Rodríguez López*

Resumen

Basándonos en el "enfoque de tareas", el objetivo de esta investigación es analizar la contribución del contenido tecnológico de las tareas ocupacionales al cambio en la desigualdad salarial de los hombres en Uruguay entre la última década de los 90 y la primera de los 2000. Para ello, utilizamos regresiones cuantílicas no condicionales y un método de descomposición basado en regresiones sobre funciones de influencia recentrada (RIF). Nuestras estimaciones surgieren que el contenido tecnológico de las tareas ocupacionales contribuye a explicar los cambios en la distribución salarial de los hombres en Uruguay. Sin embargo, sus efectos son mayormente captados por el contenido de información de las ocupaciones en lugar de por su contenido de automatización, por lo cual no es posible confirmar la hipótesis de rutinización de Autor Levy y Murnane.

Palabras clave: desigualdad salarial, regresiones RIF, tecnología, tareas ocupacionales

Código JEL: J3, J5

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Wage inequality in Uruguay: Technological change impact on occupational tasks

Sandra Rodríguez López

Abstract

Based on the "task approach" to labor markets this research seeks to analyze the contribution of technology content of tasks as another explanation factor to the distribution of men wages in Uruguay during the nineties and the first decade of the 2000s. We use unconditional quantile regressions (UQR) and a decomposition method based on the recentered influence function (RIF) regression approach. Our estimates suggest that technological task content of occupations contributes to explain changes in the distribution of men wages in Uruguay, but these effects are better capture by the information content of task rather than the automation content, therefore we cannot confirm Autor, Levy and Murnane's routinization hypothesis.

Keywords: wage inequality, RIF regressions, technology, occupational tasks

JEL codes: J3, J5

Introducción

Labor markets, both in developed and developing economies had shown an increasing demand for highly educated workers and had paid increasing wages for skilled workers. Therefore, studies on inequality in labor markets had focus on changes in the returns to skills. For many decades along the 20th century, the employment perspectives as well as the wage level had had a direct increasing relationship with each additional year of education. From the theoretical point of view this evolution has been explained by what Acemoglu and Autor (2011) had called the “canonical model”, which assumes two distinct skill groups that perform two different and imperfectly substitutable tasks or produce two imperfectly substitutable goods. Technology is assumed to take a factor-augmenting form which, by complementing either high or low skill workers, can generate skill biased demand shifts (Autor and Dorn, 2013).

However, the canonical model cannot explain certain patterns observed during the nineties in labor markets of industrialized economies, which contradict the traditional hypothesis of a monotonic increasing demand for those more qualified together with a decreasing demand for the less skilled. Notably, the continuous rise in wage inequality at the top of the wage distribution and the stagnant or even decreasing wage dispersion at the bottom (which has been referred as “polarization”); the broad-based increases in employment in both extremes: high-education, high-wage occupations and low-education low-wage occupations relative to middle skilled occupation; the rapid diffusion of new technologies that directly substitute capital for labor in tasks previously performed by moderately-skilled workers (Acemoglu and Autor, 2011).

The main hypothesis of Autor, Levy and Murnane (2003) (from here on ALM) commonly known as the “routinization hypothesis” - later formalized by Acemoglu and Autor (2011) - is that the polarization in the labor market – that is the fall in the employment and wages in the middle of the skill distribution relative to those at the top and the bottom of the skilled distribution – is explained by the fact that technological change complement and enhance the productivity of analytical tasks performed mostly by highly educated workers, substitute the routine tasks often performed by middle educated workers and have a relatively minor effect in the cost of performing manual non-routine tasks related to personal services that demand low educated workers. Therefore, according to ALM´s hypothesis the returns to occupational tasks have a role to explain changes in wage distribution, increasing wages at the extremes of the distribution relative to those at the middle.

Although the polarization pattern is less evident in Latin-American countries, the evolution on wage distribution during the 2000s also contradicts the predictions of the canonical model. While the raise in returns to tertiary education during the nineties is in line with the ALM’s hypothesis that ICTs complement the productivity of task mostly associated to be performed by highly educated workers, after a decade of increasing inequality in labor earnings, Latin-American labor markets, including the Uruguayan one, have assisted to a sharp decline in inequality of wages during the 2000s mainly due to a reduction in the returns to skills and in particular the return to secondary education (World Bank, 2012).

As the increasing use of technology is a global phenomenon it is expected that its impacts also affect labor markets in emerging economies, such as Uruguay, although certain lag may exist. However, while in developed countries the task approach and the ALM routinization hypothesis have attracted a large amount of interest recently, mainly because of the polarization observed in the distribution of wages, there is no (at least we have not found) study considering the task content of job to analyze the distribution of wages in developing countries.

The goal of this paper is to consider the technology content of tasks as another explanation factor to the distribution of men wages in Uruguay and test ALM´s routinization hypothesis. We are particularly interested in addressing the following questions: To what extent did the technology task content of occupations contribute to changes in the distribution of wages in Uruguay in the last two decades? Did the change in wage distribution was due to changes in observed characteristics of individual or because the returns to these characteristics changed over time?

To answer these questions we follow Firpo, Fortin and Lemieux (2011). First, we measure the task content of occupations using O*NET data and construct two indexes of tasks content to capture the potential effect of technological change on wage distribution. This allowed us to rank each occupation according to the grade of automation and information required to perform the tasks associated to them, and then to incorporate this indexes into the decomposition analysis. An advantage of the task-based framework is that it can be use to investigate the implications of capital (embodied in machines) directly displacing workers from tasks that they previously performed. Although, in general, it is expected that task performed by workers with any level of skills are subject to machine displacement, the set of task most subject to machine displacement in the last decades are those that are routine or codifiable. That is, tasks which are primarily, though not exclusively, performed by medium skill (semiskilled) workers (Acemoglu and Autor, 2011). Second, we estimate unconditional quantile effects using the recentered influence function (RIF) regression approach of Firpo, Fortin and Lemieux (2007, 2010) and decompose them to quantify the contribution of occupations, as summarized by the task content of jobs, in overall changes in the unconditional distribution of wages over the last two decades.

Up to our knowledge, this is the first study to use UQR and the RIF-regression decomposition approach to analyze the distribution of wages in Uruguay. It is also the first attempt to introduce the “task approach” as an explanation to the evolution in the distribution of wages in Uruguay, a relatively new approach which, though still incipient, has been gaining growing attention.

The paper is organized as follows. Section II, summarizes the main results find in the literature. In Section III we present the decomposition methodology based on recentered influence function regressions and describe the data used as well as the construction of the task content measures. Section IV describes the wage data used and documents the changes in the level and dispersion of wages across the different periods of analysis. In section V, we show the empirical results of the decomposition analysis and we conclude in Section VI.

2. Literature Review

Since the nineties the wage structure in many developed countries, reflect a polarization pattern where employments that require middle educated people started to decline as a proportion of total employment, while the share in employment of low and high specialization levels increased.[1] Simultaneously, the evolution of the respective wages have followed a U shape, with bigger increases in the “upper tail” of the distribution of wages, moderate increases in the “lower tail” and relative lower increases in the median of the distribution (Autor and Dorn, 2013). This pattern contradicts the premise of skilled biased technology change which leads to a greater demand for skilled workers creating a permanent increase in inequality among skilled and unskilled workers.

According to Autor et al. (2003), a hypothesis to explain this “polarization” is related to the new information and communication technology (ICT), and to the non-neutrality of the technology progress. Critically, computers do not compete directly with abstract and/or analytical and coordination tasks that characterize tasks performed by highly skilled workers like professionals or managers, enhancing their productivity while performing the routine part of their work faster. However, this same technology directly compete with routine tasks, which although requiring middle qualified workers, can be reduced to a group of instructions that can be easily codified and followed by a machine and therefore can be automatized. On the other extreme, occupations that rely on “manual” tasks and flexible interpersonal communication may require very little specialization and may not require a lot of skill but may be difficult to be automated. Consequently, in these occupations (which are generally associated to personal services occupations[2]) the automation of routine tasks has no substitution or complementation effect. Therefore, information and communication technology raise the aggregated demand for skilled work and reduce the demand for routine work reducing its wages and moving unskilled workers to service occupations. So in this last sector the effect over wages is ambiguous because while it increases the demand for unskilled workers it also raises its offer, so it is not possible to determinate in advance what will happen with wages.

Autor et al. (2003) and Autor and Dorn (2013) find evidence to support ALM´s routinization hypothesis in the US labor market. Using information from the United State Labor Department regarding tasks involved in different occupations, they classify the different occupations into routine or non-routine and evaluate their vulnerability to automation. They find evidence that the polarization of the US labor market between 1980 and 2005 was more evident in those employments with tasks more vulnerable to automation.

Similar “polarization” patterns can also be seen in the nineties in different industrialized countries. Michaels et al. (2013) using industry level data for 11 industrial economies – 9 Europeans, US and Japan – test ALM’s ICT-based polarization hypothesis for the period 1980 -

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[1] See Autor, Levy and Murnane (2003), Autor, Katz and Kearney (2006), Goos and Manning (2007), Antonczyk, Fitzemberger and Leuschner (2009), Goos, Manning and Salomons (2009, 2011), Dorn (2009), Michaels, Natraj and Van Reenen (2010), Jung and Mercenier (2010), Antonczyk, DeLeire and Fitzenberger (2010), Firpo, Fortin and Lemieux (2011).

[2] According to Autor and Dorn (2012), the secular rise in employment and wages in service occupations with low qualification is caused by the interaction between consumer preferences, which favor variety instead of specialization, and non-neutral technology progress, that reduces the cost of performing routine tasks but has a relative minor effect on the cost of performing personal services tasks. If consumer preferences do not admit substitutes for tangible products of service occupations – such as meals in restaurants, house cleaning, security services and home health service – non neutral technology progress concentrated in the production of goods (that is non-service occupations) has the potential to increase aggregated demand for services and to rise the employment and wages of services occupations.

2004. They find that ICTs can explain up to a quarter of the raise in the demand for college educated since 1980. The industries with faster growth in ICT technologies (measured by their expenses on ICT and their expenses on R&D) also had a greater increase in their demand for high educated workers and greater reductions in their demand for middle educated workers.

Goos et al. (2009, 2011), describe labor market polarization for several OECD countries in the nineties similar to that found for the US and the UK, with an increase in the share in employment of managers, professionals and low educated service personnel relative to manufacturing workers and occupations with routine clerk tasks. Using a model to capture the effects of technology, globalization, institutions and the demand for goods in the demand of different occupations, they find evidence that the ALM routinization hypothesis is the main factor to explain the heaps observed in the employment structure.

More recently, Acemoglu and Autor (2011) developed a Ricardian model of the labor market based on the task content of jobs to explain the effect of technological change on wage inequality. They extend and adapt the canonical model to allow the endogenous allocation of skill groups across tasks and workers across skill groups. In the context of this model, technical change can affect both the productivity of different types of workers in all tasks, such as the canonical model predicts, but also in specific tasks, thus changing the comparative advantage of the different types of workers with low, medium or high skills. As the model distinguish between “tasks” and “skills”, it treats skills, technologies, and trade or offshoring as offering competing inputs for accomplishing various tasks, and the final use of each input to perform a certain task depends on its costs and comparative advantage. Therefore, the relative wages of low, medium and high skilled workers are determined by relative supplies and tasks allocations. Although, the canonical model fits as a especial case of this task-based model, while in the canonical model one factor-augmenting technical progress always increases all wages, in this more general model it can reduce the wage of certain groups. Thus, technological change could explain why wages in the middle of the distribution fell in relation to wages at the “upper” and the “bottom” tail.

Like industrialized economies Uruguay has also experienced a growing inequality process in wage distribution especially during the nineties and the first years of the 2000s. Most studies have attributed this rise in inequality to increasing returns to education.

Vigorito (1994) and Gradín and Rossi (2000, 2006) observe an increase in the first and last wage quantile relative to the middle of the distribution. In particular, Gradín and Rossi (2000, 2006) find that for the period 1989-1997 in the case of wages there was redistribution from the middle to the extremes that turned out in an increased polarization of wages, similarly to what is observed in the US since the second half of the eighties. In Montevideo, these authors explained polarization by education and age, which they consider to be consistent with increasing returns to education and experience. In the case of the rest of the country polarization is explained by public versus private sector and activity sector. Besides, for the period 2001-2009 Espino (2011) finds that regarding employment creation the most dynamic occupations were those that require skills at the extremes distribution; i.e primary school or tertiary level.

Contrary to Gradín and Rossi (2000, 2006), Alves, Arim et al. (2009), using data for a longer period that takes into account data since 1981 to 2007, find that the polarization pattern is less clear. Moreover, the evolution of inequality, as well as its determinants, is different in the upper and the lower end of the wage distribution. While for wages above the median of the distribution, the increase in inequality took place mainly during the nineties and was due to increasing returns to observed characteristics, especially to education. At the lower end, the increase in inequality occurred during the economic crises (1981 and 2002) and was explained by changes in unobserved characteristics.

Alves et al. (2013) and Sanguinetti (2007) using conditional quantile regressions find that wage differences among workers in Uruguay are not homogeneous along the wage distribution, highlighting the growing profile in the distribution of sex wage gap and the returns to education. Regarding this last issue, they observe a differentiated structure among education levels, and also that this differentials raise with wages, especially for the upper levels, which reflects a bigger wage dispersion not only between but also within the education levels, meaning that there are different returns to individuals that share the same formal level of education.

Therefore, there is evidence that the evolution of inequality in Uruguayan labor market has not followed a monotonic pattern in the upper and the lower ends of wage distribution. Until now, studies have attributed the increase in inequality in the upper tail of the distribution to changes in return to skill, supporting the skilled biased technology hypothesis. But this does not explain changes at the lower end of the distribution where, according to the routinization hypothesis, technology has a role to play and the task approach can shed light to explain changes in the distribution of wages.

3. Empirical Strategy

3.1 RIF-Regressions and Decomposition methodology

In this section we present the RIF-regression decomposition method introduce by Firpo, Fortin and Lemieux (2007, 2009, 2011 FFL from here on). A RIF-regression is a regression where the dependent variable, Y, has been replaced by the recentered influence function (RIF) of the statistic of interest *v(F)*. In general terms, a RIF-regression coefficient can be interpreted as the contribution of one observation to the individual statistic of interest.

$$(1) \qquad RIF(y;\, v) = v(F) + IF(y;\, v)$$

In the case of quantiles, the influence function IF $(Y;Q_\tau)$ is given by $(\tau - I\{Y \le Q_\tau\})/ f_Y(Q_\tau)$, where I {.} is an indicator function, f_Y (.) is the density of the marginal distribution of Y, and Q_τ is the population τ-quantile of the unconditional distribution of Y. As a result, $RIF(Y;Q_\tau)$ is equal to Q_τ + IF $(Y;Q_\tau)$, and can be rewritten as

$$(2) \qquad RIF(Y, Q_\tau) = Q_\tau + \frac{\tau - I\{Y \le Q_\tau\}}{f_Y(Q_\tau)} = c_{1,\tau}\,.\,I\{Y > Q_\tau\} + c_{2,\tau},$$

where $c_{1,\tau} = 1/f_Y(Q_\tau)$ and $c_{2,\tau} = Q_\tau - c_{1,\tau}(1-\tau)$. Except for the constants $c_{1,\tau}$ and $c_{2,\tau}$, the RIF for a quantile is simply an indicator variable $I\{Y \le Q_\tau\}$ for whether the outcome variable is smaller or equal to the quantile Q_τ .

In the particular case of quantiles the RIF-regression is known as unconditional quantile regression (UQR), as its coefficients reflect the partial effect over the unconditional quantile (UQPE). It estimates the impact of changes in the independent variables over the unconditional quantile of the explained variable. It seeks to answer questions such as: which is the impact of increasing one year of education over the quantile τ (for example, the median) of wages, keeping everything else constant?

Unlike the traditional (conditional) quantile regressions which focus on the determinants of the conditional distribution, the UQR allows to directly obtain the effects of small changes in the covariates over the unconditional quantile of the variable of interest. Another advantage of UQR, in particular, and RIF-regressions in general, is that they allow identifying non-monotonic effects. That is to say, they capture both, between and within (conditional distribution) effects of covariates. Specifically, they can capture the effect of a covariate not only because of changes in the conditional mean but also because of its changes along the whole distribution. Firpo, Pinto and Sanroman (2014), show that the OLS estimator of the UQPE is unbiased and consistent. Besides, RIF-Regressions could be extended to other statistics of interest such as the variance or the Gini index.

The goal of this paper is to explain changes on wage inequality and especially to measure the effect of technological change, as measured by the task content of occupations, on the distribution of wages. As has been mentioned, explanations regarding changes on wage inequality affect specific points of the distribution. For instance, the computerization of routine jobs proposed by ALM (2003) tends to affect the middle and lower-middle of the distribution. Therefore, it is important to go beyond the mean and summary measures such as the variance to better understand changes in wages inequality.

The RIF-Regression decomposition method proposed by FFL (2009, 2010) involves performing Oaxaca-Blinder type decomposition on the RIF estimates of the statistic of interest. This method presents several advantages, such as being easy to interpret and to be less computational intensive than other decomposition methods like Chernozhukov et al. (2013) or Machado and Mata (2005).[3] Another important advantage of this methodology is that it is path independent, because it is possible to isolate the effect of each covariate introducing all in only one step. Besides unlike other decomposition methods, this one allows us to perform detailed decompositions for any distributional statistic for which an influence function can be computed.

As in the case of the standard Oaxaca-Blinder decomposition, performing a decomposition based only on the RIF-regression may have a bias problem because the linear specification used in the regression is only a local approximation that does not generally hold for larger changes in the covariates (FFL, 2007). To solve this problem, FFL (2007, 2010) recommend a two-step procedure to estimate the different elements of the decomposition. In the first stage, distributional changes are divided into a wage structure effect and a composition effect. This stage is based on a reweighing procedure to cope with potential non-linearities in the true conditional expectation. The second stage further divides the wage structure and the composition effects into the contribution of each covariate, and is based on the estimation of RIF-regressions.

The aggregate decomposition (Δ_O^v) consists of dividing the overall change in a given distributional parameter into the effect of changes in coefficients (structure effect, (Δ_S^v)) and in characteristics (composition effect, (Δ_X^v)). The structure effect reflects the change on the conditional distribution (F(Y/X)) of the variable of interest and the composition effect reflects the effect of changing the distribution of the covariates (X).[4] The detailed decomposition permits a partition of the overall components into the contribution of each individual covariate (or group of covariates) to the differences in the distributional statistic, which let us compare the contribution of changes in the returns to occupational tasks to other explanations such as changes in the labor market returns to general skills (experience and education), which have been the most common explanations to changes in wage distribution.

The overall change over time of the distributional statistic *v* would be:

$$(3) \qquad \Delta_O^v = v\left(F_{Y1/T=1}\right) - v\left(F_{Y0/T=0}\right) = v_1 - v_0,$$

which can be decompose into:

$$(4) \qquad \Delta_O^v = (v_1 - v_c) + (v_c - v_0)$$

where the first term is the wage structure effect and the last one represents the composition effect. $v_c = v\left(F_{Y0/T=1}\right)$ is the counterfactual distributional statistic, that represents the distributional statistic that would have prevailed if individuals observed in T=0 had been paid under the wage structure of T=1. Then we have,

[3] Firpo, Fortin and Lemieux (2007, 2009 and 2010) explain in more detail how to perform this decomposition and illustrate how the different elements of the decomposition can be computed in the case of specific distributional statistics. Here, we simply present a short summary of the methodology based on those papers.

[4] In the literature the composition effects are usually referred to as the *explained effects* while the structure effects are named the *unexplained effects*.

(5) $\Delta_O^v = \Delta_S^v + \Delta_X^v$

By analogy to a standard Oaxaca-Blinder decomposition, we could write the wage structure and the composition effect as:

(6) $\Delta_S^v = E[X \mid T = 1]^T . (\gamma_1^v - \gamma_0^v)$

(7) $\Delta_X^v = [E(X \mid T = 1) - E(X \mid T = 0)^T] . \gamma_0^v$

where γ_1, γ_0 are the estimated coefficients of the RIF regression.

Following Dinardo et al. (1996), the first step of the estimation procedure consist of estimating the weighing function $\omega_C(T, X)$ and then to compute the distributional statistics directly from the appropriately reweighted samples. Without this reweighing procedure the decomposition would only yield consistent results if the true conditional expectation is in fact linear, which imposes a strong assumption on the data (FFL, 2007). The reweighing procedure generates a counterfactual observation that results if individuals of group 0 had the same distribution of observable characteristics as individuals in group 1. So that the weighing function $\omega_C(T, X)$ can be estimated as

(8) $\widehat{\omega_C}(X) = \frac{\Pr(T=1|X)}{\Pr(T=1)} . \frac{\Pr(T=0)}{\Pr(T=0|X)}$

The reweighing procedure is based on estimating a logit (or probit) model on the probability of being observed in group 1.[5]

In the second step, the decomposition analysis is performed on the reweighted data by estimating OLS regressions of the RIF on X for the T=0, 1 samples and the T=0 sample reweighted to have the same distribution of X as in T=1.

Following FFL (2011) the estimated composition effect $\hat{\Delta}_{X,R}^v$ can be divided into a pure composition effect $\hat{\Delta}_{X,p}^v$ using the wage structure of period 0 and a component measuring the specification error, $\hat{\Delta}_{X,e}^v$

(9) $$\hat{\Delta}_{X,R}^v = (\bar{X}_0^C - \bar{X}_0) . \hat{\gamma}_0^v + \bar{X}_0^C (\hat{\gamma}_C^v - \hat{\gamma}_0^v) = \hat{\Delta}_{X,p}^v + \hat{\Delta}_{X,e}^v$$

where γ_1, γ_0 and γ_C are the RIF estimated coefficients for the T=0, 1 samples and the T=0 sample reweighted to have the same distribution of X as in T=1, $\bar{X}_0 = E[RIF(y_{0;}v_0)|X, T = 0]$ and $\bar{X}_0^C = E[RIF(y_{0;}v_0)|X, T = 1]$

The second term in equation (9) is the approximation (specification) error, linked to the fact that a potentially incorrect specification may be used for the RIF-regression. The approximation error is large when the linearity of the RIF-regression is inappropriate and should be small when it provides an accurate approximation of the composition effect. Therefore, looking at the magnitude of the error provides a specification test of FFL's regression model-based procedure (FFL, 2007). In practice the total approximation error corresponds to the difference between the "Total wage structure" across the standard Oaxaca Blinder and the reweighted-regression decomposition.

[5] In this research, the reweighting function is computed as the ratio of the predicted probabilities obtained from a logit specification model that considers the explanatory variables of the decomposition analysis and their interaction.

The wage structure effect can be written as

$$(10)\qquad \hat{\Delta}^{v}_{S,R} = \bar{X}_1(\hat{\gamma}^{v}_1 - \hat{\gamma}^{v}_c) + (\bar{X}_1 - \bar{X}^{C}_0).\hat{\gamma}^{v}_c, \\ = \hat{\Delta}^{v}_{S,p} + \hat{\Delta}^{v}_{S,e}$$

where $\hat{\Delta}^{v}_{S,e}$ is the reweighting error, which tends to disappear in large samples if the reweighting matrix is consistently estimated and $plim(\overline{X^{C}_0}) = plim\,(\bar{X}_1)$. The difference between the wage structure effect in a standard Oaxaca-Blinder decomposition and that in equation (10) is that, instead of using the unadjusted regression coefficient for group 0 (γ^{v}_0), the FFL(2007) decomposition method use the regression coefficient when the group 0 data is reweighted to have the same distribution of X as group 1 (γ^{v}_c). Unlike the Oaxaca-Blinder decomposition, using the counterfactual coefficient avoids to contaminate the difference in the wage structure with differences in the distribution of the covariates between the two groups and therefore allows to reflect solely the differences between the structures in T=1 and T=0. That is, using γ^{v}_c instead of γ^{v}_0allows dealing with one of the two limitations of Oaxaca-Blinder decomposition.[6] However, the method does not allow solving the omitted group problem of standard decompositions: that is the sensitivity of the contribution of each covariate to the wage structure effect to the choice of a base group (FFL, 2007).

Then the size of the reweighting error provides another specification test of the FFL's approach. In practice the reweighting error can be estimated as the difference between the "Total Composition" across the classic Oaxaca-Blinder and the reweighted regression decomposition.

To sum up, the RIF-regression decomposition method is performed in practice as two standard Oaxaca-Blinder decompositions over the recentered influence functions. The composition effect is obtained by comparing time period 0 and the reweighted time period 0 that mimics time period 1, while the wage structure effect is obtained by comparing time period 1 and the reweighted time period 0.

3.2 Data

The empirical analysis is based on data from the Current Household Survey (Encuesta Continua de Hogares, ECH), collected by the National Statistics Institute (Instituto Nacional de Estadística, INE). The ECH provides information about socio-demographic variables, labor characteristics and income. For every year of analysis we pool two years of data together to improve the precision of the estimates. We consider two different periods 1991 to 1999 and 2001 to 2010. In the first case, we use 1991-92 as the base year and 1998-99 as the end year[7], and in the second case we use 2001-02 as the base year and 2009-10 as the end year. The reason for choosing these different periods is that there was a methodological change in the classification of occupations, so by choosing these two periods we avoid distortions in the analysis due to

[6] The standard Oaxaca-Blinder decomposition has two limitations, apart from not being suitable to examine changes in the entire distribution of the variable of interest for functional statistics other than the mean. One limitation is that the contribution of each covariate to the wage structure effect is sensitive to the choice of the base group. The other one is that the Oaxaca –Blinder decomposition provides consistent estimates of the wage structure and composition effect only under the assumption that the conditional expectation is linear, since when linearity does not hold, the decomposition based on linear regression will be biased (FFL, 2007).

[7] Alves, Arim et al. (2009) analyze the wage distribution inequality between 1981 and 2007. They find that the greater increase in wage distribution inequality during the period of analysis occurred between 1991 and 1999.

changes in coding of occupations. Besides, to avoid problems with the changes in the sample we only consider the observations corresponding to locations of 5,000 or more inhabitants.[8]

Like all reference studies regarding the "task approach", to carry out this research we focus on men to avoid self selection issues. The study considers active men workers under a dependence relationship – i.e. workers that receive a salary whether they work for the private or public sector – between the ages of 25 to 64. As wage measure we used the real log hourly wage, obtained by dividing earnings[9] deflated by Consumer Price Index and divided by hours of work. The ECH inquires the hours worked the week before the interview but the wage received the previous month. Thus, we assumed that hours worked during the week previous to the interview are the same for the whole month before the interview, and divide the wages by 4.3, before calculating the hourly wage.[10] We consider only wages and hours worked at the main occupation.

To compute measures of technological change we classify occupations according to their task content. As for Uruguay there are no studies nor a systematic database of task content of occupations, we use for this purpose the O*NET 15.0 data available from the National Center for O*NET Development[11] and construct a crosswalk between the Classification of Occupation for the Americas (COTA-70) occupation coding, used for the nineties period, and the Standard Occupational Classification Code used in the O*NET classification of occupations (O*NET – SOC), with currently 974 occupations data. For the period 2001-2010 we repeat the same procedure with the International Uniform Classification of Occupation (CIUO-88)[12], which was used by the INE to classify occupations since the 2001 ECH. In particular, we consider information and automation content using O*NET data. We construct indexes for 285 of 3-digit occupations available in the COTA-70 and used in the ECH (1991-1999) and 115 indexes for 3-digit occupations available in the CIUO-88. As there is no exact correspondence between the SOC codes and those of the COTA-70 or CIUO-88, when more than one SOC code corresponds to only one COTA-70 or CIUO-88 codes, its task content index is the simple average of the correspondent SOC task content indexes.

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[8] During the different periods of analysis there were some changes in the ECH´s samples that could cause some incompatibility problems. In 1991, 1992 and 1998 the ECH´s sample considered locations from 900 and more inhabitants. In 1999, based on the General Census of Population and Housing from 1996, the sample started considering locations from 5,000 and more inhabitants. In 2006 the sample changed again based on the information of the 2004 Census Phase 1. The samples for 2009 and 2010 include the whole country: all the locations and rural zones.

[9] To avoid differences due to changes on data available to compute monthly earnings we only consider salaries without other benefits such as earnings in species, holiday salaries, tips, commissions, etc.

[10] To avoid getting hourly wages atypically high, due to wrong declarations of hours of work, we eliminate the observations with less than six hours of work during the week.

[11] Available at www.onetonline.org The O*Net is the successor of the Dictionary of Occupational Titles (DOT), the database mostly used in research related to the ALM routinization hypothesis. The O*NET program constructs a database (now of 974 occupations), containing information on standardized and occupation-specific descriptors, which is continually updated by surveying a broad range of workers from each occupation. The O*NET database was initially elaborated by a group of occupation analysts; this information is augmented by ongoing surveys of each occupation's worker population and occupation experts. These statistical results are incorporated into new versions of the database on an annual schedule, to provide up-to-date information on occupations as they evolve over time.

[12] Actually, what is used is a national adaptation of the CIUO-88 (CNUO-95). The CIUO-88 presents a pyramidal hierarchical structure formed by 10 mayor groups at the mayor level of aggregation, subdivided in 28 main subgroups, 116 subgroups and 390 primary groups. According to the Guide to Codify Occupations published by INE (1996), the statistic unit for the CIUO-88 is the job, defined as the group of tasks performed or that should be performed by a person to accomplish it. A group of jobs with very similar tasks is defined as an occupation. The ability to perform the tasks inherent to a specific job defines the competency. The important thing to define an occupation are the competences needed to perform the tasks inherent to it, and not to know if the worker that performs certain occupation acquired its skills through formal or informal education and experience; it does not matter either if the worker is better or worse qualified that another one in the same occupation.

Although, the mapping might be imperfect, and the way of performing tasks in the US might not be exactly the same as in Uruguay, therefore the characteristics of occupations between one country and the other being different, we believe - as it is shown below - that the main characteristics regarding the possible influence of technology change on occupations remain similar especially when we consider the classification at a more aggregated level.

3.2.1 Task content measures

We construct the task content measures using the O*NET 15.0 database. The O*NET content model organizes the key features of an occupation into a standardized, measurable set of variables called "descriptors". The job information is classified into a structured system of six major categories describing the day – to – day aspects of the job and the qualifications and interests of the typical worker: Worker Characteristics (Abilities; Occupational Interests and Work Values; Work Styles), Worker Requirements (Skills; Knowledge; Education), Experience Requirements (Experience and Training; Skills and Entry Requirements; Licensing), Occupational requirements (Generalized and Detailed Work Activities; Organizational Context; Work Context), Occupation-Specific Information (Task; Tools and Technology) and Workforce Characteristics (Labor Market Information; Occupational Outlook).

Following Firpo et al. (2011) and Jensen and Kletzer (2010) we focus on the "Occupational Requirements" of occupations designed to provide *"a comprehensive set of variables or detailed elements that describe what various occupations require"* (National Center for O*NET Development 2006, 20, cited in Jensen and Kletzer, 2010). In the spirit of Autor et al. (2003) to measure routine versus non routine and cognitive versus non cognitive aspects of occupation, we consider two categories thought to be positively related to technology: "Information content" and "automation/routinization".

The first one intends to identify occupations with high information content that are likely to be affected by ICTs, and within the Generalized and Detailed Work Activities subdomain we consider the following work activities: "Getting information", "Processing information", "Analyzing data or information", "Interacting with computers" and "Documenting/Recording information".

The second one is constructed using the Work Context subdomain, to reflect the degree of potential automation: "degree of automation", "importance of repeating same tasks", "structured versus unstructured work (reverse)", "pace determined by speed of equipment", and "spend time making repetitive motions".

We compute two different measures of task content: i) the information content of jobs and, ii) the degree of automation of the job and whether it represents routine tasks. For the construction of these indexes we follow Firpo (2011). For each occupation, the O*NET provides information on the "importance" and "level" of required work activity and on the frequency of five categorical level of work context.[13] "Importance" is the rating of answers to the question:

[13]. We consider the following work activities: "Getting information" (4.A.1.a.1), "Processing information" (4.A.2.a.2), "Analyzing data or information" (4.A.2.a.4), "Interacting with computers" (4.A.3.b.1), "Documenting/Recording information" (4.A.3.b.6) and the following work context categories: "degree of automation" (4.C.3.b.2), "importance of repeating same tasks" (4.C.3.b.7), "structured versus unstructured work (reverse)" (4.C.3.b.8), "pace determined by speed of equipment" (4.C.3.d.3) and "spend time making repetitive motions" (4.C.2.d.1.i).

"How important is this skill to performance of the job?" Answers vary from "not important" to "extremely important", on a scale of 1 to 5. "Level" is the response to "What level of this skill is needed to perform this job?" ranging from low to high in a scale from 1 to 7 (Jensen and Kletzer, 2010), while the categorical levels of the frequency element of the work context range from never to every day in a scale from 1 to 5.

We assign a Cobb-Douglas weight of two thirds to "importance" (I) and one third to "level" (L) in using a weighted sum for work activities. While for work contexts, we multiply the frequency (F) by the value of the categorical level (V). Thereby, for each occupation *j* we compute two composite task content indexes (*TC*), so that:

$$(11) \quad Information\ Content_j = IC_j = \sum_{k=1}^{5} I_{jk}^{2/3} * L_{jk}^{1/3}$$

$$(12) \quad Automation\ Content_j = AC_j = \sum_{l=1}^{5} F_{jl} * V_{jl}$$

Where *k* is the number of work activity elements, and *l* the number of work context elements considered in the construction of the task content index. We normalize the task measures by dividing them by their maximum value observed over all occupations, so that they range between zero and one. That gives us a ranking of occupations for each of the two dimensions. We use these indexes to assess the impact of technological change on changes in wages.[14]

In Table 1 we report the average value and standard deviations of the measures of task content for five major occupational groups. As it is observed in Figure 1, alike the results reported by Firpo et al. (2011) using US data, Professional, managerial and technical occupations have the highest score in terms of their use of information, and a relative low score for automation. On the other hand, Production workers and operators have a low score in terms of their use of information and the highest score for automation. Therefore, technological change is expected to have an adverse impact on wages in this last group of occupations while benefiting those with a more intense use of information technology.

The distribution of both indexes among occupational categories is similar for both decades. The small changes in the overall mean of information and automation content from the 90s to the 2000s could be interpreted as changes in the share of occupations with a bigger information index and a smaller automation index, as the indexes used are the same for both decades. However, some change may also be attributed to the use of a different classification code for occupations.

We expect ICTs to enhance tasks involving the processing of information performed by high skilled workers while substituting those tasks that can be automated and generally performed by middle skilled workers. In this sense, we expect a direct relationship between the "information content" of task and wages and an inverted U-shaped relation between the "automation content" of task and wages. In Appendix Figure A.1 we show the relationship between our task measures and wages for both periods of analysis. We confirm that while information task content tend to be monotonically related to wages, automation task content follows an inverted U-shaped curve consistent with ALM's routinization hypothesis.

[14] In our case the occupation with the higher information content index is Financial Analyst and the one with the lowest one is models, followed by farmworkers and laborers. On the other hand, the occupation with the higher automation index is tire builders, plastic and rubber operators and the ones with the lowest one are models and tour guides.

4. Wage dispersion in Uruguay – Descriptive evidence

Appendix Table A.1 reports the mean and standard deviation values of several variables for the 90s and the 2000s. The most notable changes along the period of analysis are a raise in the participation of middle (between 10 and 16 years of schooling) and high educated (more than 16 years of schooling) in detriment of those less educated (less than 10 years of schooling). Regarding potential experience, the behavior is different between the two decades: while in the 90s there is an increase of those with little or middle experience in detriment of more experimented workers (more than 30 years), in the 2000s less experimented workers also increase its share but those with middle experience (between 10 to 30 years of experience) decrease.

With regard to hourly wages there is a relatively small increment during the whole period of analysis (0.024 in log terms). However, while in the 90s mean men hourly wages increased 0.103, between 2001/02 and 2009/10 the increase was barely 0.029. This difference is due to the great economic crisis that Uruguay suffered between 2001 and 2003 with the obviously negative impact on labor markets and especially on wages.[15] Actually, it took until 2010 for mean real wages to recover its pre-crisis levels.[16]

Regarding inequality, during the 90s global inequality raised mostly due to an increase at the top end of the distribution together with a smaller increase in the bottom half. However, during the first decade of the 2000s, global wage inequality decreased explained by a reduction both at the bottom and the upper half the distribution (See Appendix Table A.2). Nonetheless, inequality increased during the first half of the 2000s and started to decrease after 2007 (Perazzo, 2012).

Figure 2 confirms the previous analysis. It shows changes in log real wages ($ Dec. 2010) at each percentile of the wage distribution, for the different periods of analysis. During the nineties men wages at the top raised much more than wages in the middle, resulting in increased top-end inequality, while changes in the lower half of the distribution have been more modest. By contrast, from 2001/02 to 2009/10 changes in men real wages at each percentile of the wage distribution show a decrease in wages at the top end of the distribution and an increase in wages at the lower end, which results in a decrease in global inequality. Wage changes in Uruguay during the nineties are better explained by the canonical model but also in line with the ALM hypothesis that ICTs complements tasks performed by high educated workers. During the 2000s, however, changes in the lower half of the distribution seems to follow a pattern in line with ALM´s routinization hypothesis. Nevertheless, the evolution of inequality at the top end of the distribution seems to contradict the complementation hypothesis.

However, changes in wage distribution in the second half of the 2000s should be analyzed with caution as, together with a rapid economic growth, they were affected by important institutional changes: increase of minimum wage, restoration of wage councils, income tax inception and a Health Reform. After July 2007, Uruguay implemented a tax reform that introduced income taxes, which had a direct impact on wages actually received by those belonging to the upper tail of the distribution, while at the same time it increased or had no

[15] In 2001 Uruguay´s GDP dropped 3.8% while in 2002 GDP shrank 7.7%. Meanwhile, unemployment increased up to 20.4% in September 2002 and real wages declined 10.7% in 2002 and 12.4% in 2003.

[16] Measured by the Mean Real Wages Index (IMSR for its initials in Spanish).

impact on lower wages.[17] Besides in 2008 a Health Reform was implemented according to which each worker has to destine a mandatory percentage[18] of its wage to the National Health System.

At the same time, other institutional changes that affected the lower end of the distribution occurred since 2005. The national minimum wage introduced in 1969 in order to establish a wage floor for private workers over 18 years old, had had a declining tendency until almost having a marginal role to determine wages due to its constant loss of purchasing power.[19] Therefore, it became more a policy instrument to control government expenditure – since it was the reference measure to index social security variables – than an effective regulatory mechanism of labor markets. However, since 2005 the real minimum wage increased sharply. Indeed, between 2004 and 2010 the real minimum wage raised 157%. Besides, in 2005 collective negotiation of wages was reinstituted[20] and since the 2008 round minimum wages by category had had a bigger increase than medium wages (Cabrera and Cárpena, 2012) which, may have also impacted on the lower end of the wage distribution.

As a consequence of the above mentioned changes, it is not immediately to associate the reduction in inequality at the bottom end of the distribution between 2001 and 2010 with ALM's routinization hypothesis. To have a clearer idea of what happened to wage distribution before the tax reform and other institutional changes were implemented, we repeat the exercise for the change in wages between 2001/02 and 2005/06. For this last period data present a slight inverted U-shape,[21] suggesting that contrary to what could be expected, workers at the middle of the distribution were the less affected by the 2002 economic crisis. Besides, Alves et al. (2012) suggest that the decrease in inequality in the lasts years is related to institutional changes such as the ones mentioned above.

[17] Before the tax reform was implemented, wages had to pay a tax called IRP (Tax to personal remunerations) which was a fixed percentage over salaries with a rate between 0% and 6%. Several studies prove that the tax reform had had a positive impact to reduce inequality, increasing the income actually perceived by those at the bottom half of the distribution and reducing the income of those at the top end (See Amarante, Arim and Salas (2010), Perazzo and Rodríguez (2007)).

[18] 4,5% or 3% depending on having children or not.

[19] In 2004, the minimum national wage had a 24% power purchase of that of 1969. Besides Buchelli (1998) and Furtado (2006) state that minimum wage lost its effectiveness as a regulatory mechanism. Indeed, according to Buchelli (1998), while in 1986 between 18% to 40% of private wage-earner worker earned a minimum wage or less, in 1997 this group only represented between 2% and 6% of private wage-earners workers and in 2006 this percentage increase to 10,2% (PNUD, 2008).

[20] It must be said, however, that agreements became effective only since 2006.

[21] Although, what is actually observed are decreases in wages due to the fact that during 1998-2003 the Uruguayan economy experiment the worst crisis in the Uruguayan economic history, and wages did not fully recovered until 2010.

5. Decomposition results: Occupational Characteristics vs. Other Factors

5.1 RIF – regressions

Before showing the decomposition results, we first present some estimates from the RIF-regressions for the different wage quantiles, the variance of wages and its Gini coefficient. The RIF-regression coefficients for the 10th, 50th, and 90th quantiles in 1991/92, 1998/99, 2001/02 and 2009/10, along with their bootstrapped standard errors[22] are reported in Tables 2 and 4. The RIF-regression coefficients for the variance and the Gini index are reported in Tables 3 and 5. Detailed estimates for the 5th to the 95th quantiles are also reported in Figures 3 and 4.

We compute the influence function, IF($y_i;Q_\tau$), for each observation using the sample estimate of quantile, $Q_{\tau,}$ and the kernel density estimate of $f(Q_{\tau,})$ using a bandwidth of 0.06. In addition to the reweighting factors, we also use the ECH sample weights ("pesoan") throughout the empirical analysis, which in practice means that we multiply the relevant reweighting factor by the ECH sample weight. Apart from our two measures of occupational tasks, in the regressions we include covariates suggested by the literature as the major sources of changes in the distribution of wages: education (five groups) and potential experience[23] (nine groups) (Autor et al., 2006). We also include controls for geographic localization (capital city vs. rest of the country) public vs. private sector and marital status.[24]

The base group used in the RIF–regression models consists of married men living at Montevideo working at the private sector with six or less years of education, 10 to 15 years of potential experience, and following Firpo (2011) we normalize the occupational task measures variable at half a standard deviation below their sample averages.[25][26] So the wage structure effect for the task measure can be interpreted as the change over time in the wage impact of a half a standard deviation increase in the measure.[27] However, regarding composition effects of

[22] The analytical standard errors have to take account of the fact that the logit model used to construct the reweighting factor is estimated. That is why using bootstrapped standard errors is recommended. In practice, FFL (2011) recommend to bootstrap the whole estimation procedure (both the estimation of the logit/probit to construct the weights and the computation of the various elements of the decomposition), and that is how we proceeded.

[23] Measured as age minus years of education minus six.

[24] Concubinary unions are considered as married couples.

[25] The base education and experience categories were chosen based on the modal of each category.

[26] We also run the RIF-regressions and decomposition results considering sector of activity. As expected, this variable turns out to be significant. Regarding results, the main change is that compositions effects become more relevant, especially during the nineties, regarding our task content results the only significant change is that during the 2000s task content measures became not significant at the lower end of the distribution, while the covariate related to industries is significant. However, due to the fact that the coding occupation criterion, especially in the nineties, is closely related to the sector of activity and because we are using a task-content approach, where the "job task" – which are transversal to activity sectors - is the central unit of production which is then combined with capital and labor to produce output, we consider that it is better to concentrate the analysis on task content measures. In fact, other reference studies that consider the task content of occupations as an explanatory variable, does not include sector of activity in the regression.

[27] The choice of half of a standard deviation is based on the same criteria used by Firpo (2011) following that the difference between the mean value of task measures for all occupations and the mean for the major group with lowest mean ranges from 38 to 70 per cent of a standard deviation. For example, for 1991/92 to 1998/99 the mean for automation is 0.75 which is 0.0372 (or 0.60 standard deviation) above the mean for professional, managerial and technical occupations. This suggest that occupations at half a standard deviation below the mean are reasonably representative of a large group of occupations with relatively low values of the task measures. Thus, we use this criterion as a uniform way of choosing the base group for each task measure.

task measures, as we use the same task measure for every year – i.e they remain invariant over time –, if they exist they only reflect changes in shares of occupations over time.

To compute the reweighing factor we estimate a logit model with additional interaction terms.[28] As can be seen in Appendix Figure A.2, the reweighting approach performs well in the sense that the reweighting error tends to be zero and is not significant.[29] That is, the reweighted means of the covariates for the base period are very close to those for the end period.

An important feature of RIF-regressions is that they allow identifying non-monotonic effects. In the case of quantiles, this means that they capture the effect of covariates on both between and within group components of wage dispersion (FFL, 2011). Regarding our task measures, like FFL (2011) we find for both periods an inverse impact between the information and automation content of task on the distribution of wages (Figure 3).

In the case of *"information task content",* unlike Firpo (2011) we find that it increases inequality along the whole range of the wage distribution. Indeed, the UQR coefficient of the information task content increases across the different percentiles of wage distribution instead of reflecting an inverted U- shape, as the one found by FFL (2011) for the US during the nineties. Besides, changes over time show an increasing effect especially in the upper middle of the distribution.

On the other hand, the *"automation task content"* measure has a decreasing impact, with very little difference among its impact on the 10th through the 50th decile. Therefore, contrary to expected, automation content of task has almost no impact on inequality at the lower end of the distribution and *decreases* inequality at the higher end of the distribution. However, workers at the lower middle of the distribution have the biggest coefficient.

Consequently, in the case of Uruguay during the period of analysis, workers in the upper side of the distribution instead of workers in the middle of the distribution were more likely to experience negative wage changes as the "routine" tasks they used to perform could be executed by computer technologies, while workers at the lower middle of the distribution were the most positively affected by automation, indicating a non-substitution effect of their task by technology. Therefore, for the Uruguayan case the effect of automation and the consequences predicted by the "routinization hypothesis" seems to be displaced toward the right of the wage distribution. These may occur due to the different share of occupations in Uruguay compared to developed countries´ labor markets, as well as to a difference in the degree of automation of task in those markets compare to Uruguay´s.[30]

Besides, contrary to FFL (2011) the information content of tasks tends to increase inequality along the whole range of the distribution during both decades while, the automation content of task has a positive impact in reducing inequality, mainly due to its negative impact on the upper middle of the distribution rather than at the lower end. Looking at the Gini index, as a

[28] The logit specification also includes a full set of interaction between experience and education, and education and occupation task measures. We also tried with some interaction between localization and education and localization and experience, but they turned out to be not significant.

[29] The reweighting error presented in Appendix Figure A.2 is the difference between the total composition effect obtained by using the RIF-regression with reweighing and the RIF-regression without reweighing. It is found to be small and not significant. Nonetheless, when including controls for public sector the reweighing and specifications errors for the variance and the Gini index become significant in the 2000s, although for the quantiles remain not significant.

[30] Remember that as we are using O*NET data to classify the degree of automation of occupations we are classifying them according to their potential degree of automation in the US, which in practice might be different in Uruguay where this task may remain manual, due to relative prices between labor and technology.

summary measure of inequality, we find that technology contributes to reduce inequality due to the impact of the automation content of tasks.

As expected, in the case of education we find that it has a positive effect on inequality in the whole range of wage distribution, but its premium varies along the wage distribution and the years of education. That is, wage differentials among workers are not homogeneous: while the premium for years of education at tertiary level (13 and more years) is increasing over the wage distribution in every year of the analysis, the premium for high school drop outs (7 to 9 years) starts with a U-shape form in 1991, but becomes decreasing in 2010, meaning that the differentiation between workers with primary school (our base group) and those with some years of high school became less significant for occupations that are paid with higher wages. This reflects a within group effect, consistent with the results found by Alves et al. (2009) and Sanguinetti (2007). Besides, these results are in line with the hypothesis of increasing returns to education and the results of other studies for the Uruguayan case (Arim and Zoppolo, 2000; Sanguinetti, 2007; Alves et al., 2009). Nevertheless, premiums to years of education at the top end of the distribution in the 2000s diminished relative to the nineties (See Figure 4).

In the case of localization, like Alves et al. (2009) we find that the wage gap between Montevideo and the rest of the country has reduced between the nineties and 2009/2010 until having almost no impact, at least for the first half of the distribution.

5.2 Decomposition results

5.2.1 Overall Decomposition Results

The results of the decomposition are presented in Figure 5 and reported in Table 6 which summarizes the results of standard measures of top-end (90-50 gap) and low-end (50-10 gap) wage inequality together with the variance and Gini index of wages.

Figure 5 shows the overall change in (real log) wages at percentile τ, (Δ_O^τ), and decomposes the overall change into a composition (Δ_X^τ) and a wage structure effect (Δ_S^τ).[31] Figure 5a shows that along the nineties the overall change in real wages shows a positively sloped curve for all quantiles as wage dispersion increases at all points of the distribution, but with higher dispersion at the top end and much more stability at the lower end. While during the first decade of the 2000s the overall change in real wages show a negatively sloped curve with a decline of wages at the top end of the distribution (Figure 5b).

Table 6 summarizes the changes shown in Figure 5 by showing the results of the decomposition for the standard measures of top-end (90-50 gap) and low-end (50-10 gap) wage inequality, as well as for the variance of log wages and the Gini coefficient. For the nineties it shows a relatively large increase in inequality measures, such as the variance and the 90-10 gap, which captures wage changes over the entire distribution during the period of analysis. It can also be seen, that this increase in inequality is basically due to an increase in inequality at the top end of the distribution (the 90-50 gap), which more than doubles the inequality at the lower

[31] The composition effect reported in Figure 5 only captures the component, $\hat{\Delta}_{X,p}^{v}$, from equation (9). The specification error, $\hat{\Delta}_{X,e}^{v}$, corresponds to the difference between the total composition effect obtained by reweighting and the RIF-Regression methods without reweighing shown in Appendix Figure A2. As it can be seen the RIF-regressions capture quite accurately the overall trend in composition effects, although there are a number of small discrepancies particularly at the top end of the distribution.

end of the distribution (the 50-10 gap). For the 2000s the case is exactly the opposite as inequality diminish basically due to a reduction in inequality at the top end of the distribution.

It can also be seen that for the nineties composition effect accounts for a significant increase in inequality: 54 percent of the growth in the 90-50 gap and 41 percent of the growth in the 50-10 gap was due to composition effects which, together with the wage structure effect, also helps to explain the positive slope in overall inequality.[32]

On the other hand, during the first decade of the 2000s composition effect also contributes to an increase in inequality, but these effects were more than offset by changes in the wage structure that contribute to a decrease in inequality, which was mostly explained by a reduction on inequality at the top end of the distribution and to a less extent at the lower end.[33]

Consequently, composition effects account for a sizable part of growth on overall inequality but wage structures effects capture a major part of changes in the distribution of wages. Moreover, in both periods changes in the distribution of wages have been led by changes at the top end of the distribution explaining the increase of inequality during the nineties and its decrease during the 2000s.

5.2.2 Detailed Decomposition Results

The next step is to analyze the decomposition using RIF-regressions to compute the contribution of each set of covariates to the composition and the wage structure effects. Figure 6 reports the composition effect of the covariates that were grouped into five categories: technological content of tasks: information and automation content, education (5 dummy variables – 6 years or less omitted), experience (9 dummy variables – 5 to 10 years of experience omitted) and the control variable group others that includes, localization, marital status and working at the public sector.[34]

For 1991/92 to 1998/99 period, regarding composition effects all covariates result significant with the exception of information content of tasks.[35] Apart from experience, they all contribute positively to an increase in inequality along the distribution of wages which is larger on the 90-50 than on the 50-10 gap, consistently with the fact that the increase in inequality during that period was led by changes at the top end. What is more, composition effects related to education are the ones that account for most of the rise in inequality during the nineties, as changes in the composition effect of education represents almost 90% of the total composition effect for the 90-50 gap and 59% for the 50-10 gap (Table 7).

Contrary to the nineties in the 2001/02 to 2009/10 period overall inequality decreases. However, the composition effect of education and “others” have a positive contribution to

[32] The total change in the 90-50 and the 50-10 gap between 1991/92 and 1998/99 is 0.126 and 0.054, respectively. The corresponding composition effect is 0.068 and 0.022, respectively.

[33] Between 2001/02 and 2009/10 the total change in the 90-50 and the 50-10 gap is -0.093 and -0.018 respectively, while the corresponding composition effect is 0.045 and 0.019.

[34] The effect of each set of factors is obtained by summing up the contribution of the relevant covariates.

[35] As it was mentioned earlier, composition effects of task content measures only reflect changes in shares of occupations with one or other characteristics between the initial and end period, since we use the same index for every year.

increase inequality, meaning that the changes in the composition of education does not account for the large decrease in inequality observed during that period (Table 8).[36]

The contribution of each set of covariates to the wage structure effect is reported in Figure 7 and in Panel B of Tables 7 and 8. It also reports the change in the intercept in the RIF–regressions. The change in the intercepts captures the part of the wage structure effect that cannot be explained by the covariates.[37] It represents the change in the wage distribution for the base group used in the RIF-regression and can be interpreted as the residual change for that base group (Firpo, 2011).

In both periods the total change of wages was led by changes in the aggregate wage structure effect, which is clearly seen in Figure 5. For the nineties, changes in the return to covariates accounts for all or even more of the change in the 50-10 and 90-50 gap wage structure effect. However, -0.076 of the 0.059 change in the 90-50 gap and -0.052 of the 0.033 change in the 50-10 gap remains unexplained (the effect of the "constant" in Table 7). Besides contrary to composition effects, changes in return to potential experience turns out to be more important than changes in return to education, although, by construction, both factors reflect skill premiums.

On the other hand, for the 2000s the change in inequality at the top end is explained mainly by a reduction in the coefficients of experience and other factors, while technology, information task content in particular, contributes to an increase in inequality at the top end. However, at the lower end the reduction in inequality is explained by changes in almost all factors, with the exception of automation, which is not significant. What is more, as seen in Figure 7 and Appendix Figures A.3 and A.4, factors in the wage structure show a clear polarization pattern similar to that seen in the US during the nineties, led by education and experience but also technology.

Regarding the contribution of each covariate, Tables 7 and 8 show that changes in the wage structure linked to education and experience changed over time and have a different role at the bottom than at the higher end of the distribution. While during the nineties education and experience increased inequality over the whole range of the distribution of wages, during the 2000s changes in the wage structure linked to education had a positive role to increase inequality at the higher end of the distribution but reduce inequality at the lower end, while returns to experience reduce inequality at the whole range of the distribution.

The results show that, contrary to FFL's findings, changes in the wage structure linked to the technology task content measures made a very small and negative contribution to the increase in the inequality during the nineties, both at the top and the lower end. However, in the first decade of the 2000s, technology task content measures contribute to an increase in inequality at the upper end while reduce inequality at the lower end of the distribution, which is in line with the ALM´s routinization hypothesis.

Changes in the wage structure linked to technology, as capture by the occupation task measures included in the RIF–regressions had contributed to explain the changes in the distribution of men wages observed during the nineties and the 2000s. This indicates that during the period of analysis technology might have had a positive effect in reducing inequality

[36] Note that, as in an Oaxaca-Blinder decomposition, composition effects on the 50-10 and the 90-50 gap can be obtained directly by multiplying the difference in mean of the corresponding factor between the beginning and the end of each period by the respective RIF – regression coefficient for that factor on the base year.

[37] More formally, the total wage structure effect, $\hat{\Delta}^{\tau}_{S,p}$, is the sum of the component explained by the RIF-regression models, $\sum_{K=2}^{M} \overline{X_1} \, (\hat{\gamma}^{v}_{1} - \hat{\gamma}^{v}_{C})$, and the residual component $\hat{\gamma}^{v}_{1,1} - \hat{\gamma}^{v}_{C,1}$ captured by the change in the intercepts.

at the lower end of the distribution while having a small inequality enhancing effect at the top end of the distribution during the 2000s. So as predicted by ALM´s routinization hypothesis, a complementation effect of technology might prevail at the upper end, while a substitution effect would prevail in the middle of the distribution. However, this last effect is better capture by information content of task rather than automation content as expected.

To test the robustness of these results, we also applied the decomposition method excluding education and including technology and vice versa. We observe that when excluding education, the information and/or the automation content of tasks become significant when they were not in the model that includes both covariates. While in some cases the constant also becomes significant. On the other hand, when excluding technology the main change is that education becomes significant to explain the wage structure effect at the lower end of the distribution in the nineties and in the 90-10 gap in the 2000s. As expected, these results confirm that there is a correlation between education and technology, which reinforce the need of controlling by both covariates to differentiate their impact in changes in the distribution of wages.

6. Concluding remarks

In this paper we looked at the contribution of technology, as measured by the task content of occupations, to changes in the distribution of wages. We quantify the contribution of this factor to changes in wage inequality relative to other explanations such as changes in returns to skills (education and experience) and localization. We do so by using a decomposition method proposed by Firpo, Fortin, Lemieux (2009) based on the influence function regression approach. We have applied this methodology to Uruguay data for the periods 1991-1999 and 2001-2010, two periods where wage inequality presented two very different trends. Indeed, during the nineties there was an increase in wage inequality while during the first decade of the 2000s Uruguay presented a declining wage inequality.

During the nineties as well as the 2000s changes in the distribution of wages have been led by changes at the top end of the distribution explaining the increase in inequality during the first period and its decrease in the second one. These movements have been mainly captured by wage structure effects although composition effects had had an important role especially in the nineties. Indeed, our results suggest that during the nineties the total increase in men wage inequality was explained almost equally by both the composition effect and the wage structure effect. Meanwhile wage structure effects, which more than offset the impacts of compositions effects to increase inequality, account for the decrease in wage inequality during the first decade of the 2000s.

Regarding technology, our estimates suggest that its importance to explain the observed changes in the distribution of wages became more relevant in the last decade, which is consistent with the extended adoption of technology by economic sectors. During the nineties the composition effect of automation task content increased the inequality of wages at the top end of the distribution reflecting a change in the share of occupations with automated tasks. Meanwhile, contrary to expected, wage structure effects related to automation task content tended to reduce inequality at the top end. On the other hand, also contrary to expected, information task content had a significant impact to reduce inequality at the lower end of the distribution through its wage structure effect. Therefore, the net effect of technology – that is summing up the effects of information and automation content of task – over the distribution of wages increased wage inequality during the nineties through its composition effect which was partially offset by a negative impact of the wage structure effect.

In the first decade of the 2000s, technology task content composition effects were not significant, while wage structure effects contributed to an increase in inequality at the top while reducing inequality at the lower end of the distribution, creating a polarization effect which is in line with the ALM´s routinization hypothesis. That is, technology helped to decrease inequality at the lower end of the distribution by a substitution effect of routine task (placed at the middle of the distribution) and increases inequality at the upper end where a complementation effect prevailed. However, our estimates suggests that contrary to expected the predicted effect of technology at the lower end of the distribution is better captured by the information content of task rather than the automation content.

This might be explained, on the one hand, because the standard deviation of information doubles the one of automation so changes in returns to task content may be better captured in the first one. On the other hand, differences in the relative cost of labor and technology in the US relative to Uruguay could explain a shift to the right of the negative impact of automation over wages at the middle of the distribution. That is, in the case of Uruguay labor task subject to substitution by technology would be placed at an upper level of the distribution of wages rather than at the middle, since wages at the middle are still very low and therefore there are fewer incentives to substitute labor by technology.

With regards to skills dimensions, in both decades education played an important role to increase inequality mainly due to changes in the observed characteristics of individuals rather than to changes in the return to them.

Summing up, introducing tasks and occupations into the analysis helps to understand changes in wage distribution in Uruguay. In fact, in the 2000s technology has a polarizing effect over wages although it is not the only factor. However, this polarizing effect is better explained through the information task content of occupations rather than automation tasks content. Therefore, we could not confirm ALM´s routinization hypothesis

Despite these findings, a great deal of the distribution of wages remains unexplained. During the 2000s this could be attributed to institutional changes that were not included in the model (tax and health reform, increases in minimum wages, Collective Negotiation of Wages) which, for different reasons, had had an impact both at the top and the bottom of the wage distribution and generated a reduction in inequality. Trying to incorporate this variable into the analysis could be an interesting extension of this work.

7. References

Acemoglu, D. and Autor, D. (2011) “Skills, Tasks and Technologies: Implications for Employment and Earnings”. in O.Ashenfelter and D.Cards, eds., *Handbook of Labor Economics*, Amsterdam: North Holland, Vol. IV.B: 1043-1171.

Alves, G., Brum, M. and Yapor, M. (2013) “Wage inequality on the rise: the role of workers’ characteristics”. In second revision for the *Journal of Income Distribution.* Versión anterior “Cambios en la estructura salarial en Uruguay, 1986-2007: Un análisis mediante regresiones cuantílicas”. Instituto de Economía. Documentos basados en monografías de grado 01/09, Facultad de Ciencias Económicas y Administración, Universidad de la República. Available at: http://www.iecon.ccee.edu.uy/dtm-01-09-cambios-en-la-estructura-salarial-en-uruguay-1986-2007-un-analisis-mediante-regresiones-cuantilicas/publicacion/262/es/

Alves, G., Arim, R., Salas, G. and Vigorito, A. (2009) “Desigualdad salarial en Uruguay, 1981-2007. Una descomposición de su evolución en efecto precio y composición.” DT 05/09. Instituto de Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República. Available at: http://www.iecon.ccee.edu.uy/dt-05-09-desigualdad-salarial-en-uruguay-1981-2007-una-descomposicion-de-su-evolucion-en-efecto-precio-y-composicion/publicacion/161/es/

Alves, G., Amarante, V., Salas, G. and Vigorito, A. (2012) “La desigualdad de ingresos en Uruguay entre 1986 y 2009”. DT 03/12. Instituto de Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República. Available at: http://www.iecon.ccee.edu.uy/dt-03-12-la-desigualdad-del-ingreso-en-uruguay-entre-1986-y-2009/publicacion/286/es/

Amarante, V., Arim, R. and Salas, G. (2010) “La reforma tributaria y su impacto distributivo” in Narbondo, P.-Mancebo, Ma.E (Eds.). *Reforma del Estado y políticas públicas de la Administración Vázquez: acumulaciones, conflictos y desafíos,* Montevideo, Editorial Fin de Siglo: 80-97.

Amarante, V., Colafrancheschi, M and Vigorito, A. (2011) “Uruguay’s income inequality and political regimes during 1981–2010”. Working Paper No. 2011/94. UNU-WIDER. Available at: http://www.wider.unu.edu/publications/working-papers/2011/en_GB/wp2011-094/

Antonczyk, D., DeLeire, T. and Fitzenberger, B. (2010) “Polarization and rising wage inequality: comparing the US and Germany”. IZA Discussion Paper No. 4842. Forschungsinstitut zur Zukunft der Arbeit Institute for the Study of Labor (IZA), March. Available at: http://ftp.iza.org/dp4842.pdf

Antonczyk, D., Fitzenberger, B. and Leuschner, U. (2009) “Can a task-based approach explain the recent changes in the German wage structure?” Jahrbucher fur Nationalokonomie und Statistik (*Journal of Economics and Statistics*) 229 (2–3), 214–238.

Arim, R. and Zoppolo, G. (2000) "Remuneraciones relativas y desigualdad del mercado de trabajo. Uruguay: 1986-1999". Trabajo monográfico para obtener el título de Licenciado en Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República.

Autor, D.H. (2013) "The "Task Approach" to labor markets: An Overview". NBER Working Paper No. 18711. National Bureau of Economic Research. Cambridge, MA 02138. Available at: http://www.nber.org/papers/w18711

Autor, D.H. and Dorn, D.D (2013) "The growth of low skill service jobs and the polarization of the U.S. labor market." American Economic Review 103, 1553-1597.

Autor, D.H., Katz, L.F. and Kearney M. S. (2006) "The Polarization of the U.S. Labor Market", *American Economic Review* 96(2):189-194.

Autor, D.H., Levy, F. and Murnane, R. J. (2003) "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics*, 118(4): 1279-1333.

Borraz, F. and Gonzalez Pampillón N. (2011) "Assessing the Distributive Impact of More than Doubling the Minimum Wage: The Case of Uruguay". Documento de Trabajo No 17/11. Departamento de Economía, Facultad de Ciencias Sociales, Universidad de la República.

Bucheli, M. (1998) "Flexibilidad del mercado de trabajo en Uruguay", CEPAL. Montevideo: lc/mvd/r166.Rev.1

Cabrera, V. and Cárpena, M. (2012) "Consejo de Salarios en Uruguay 2007-2011: Construcción de una plataforma para su evaluación". Trabajo monográfico para obtener el título de Licenciado en Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República.

Chernozhukov, V., Fernández-Val, I., Melly, B. (2013) "Inference on Counterfactual Distributions", *Econometrica*, 81(6), 2205–2268.

Dinardo, J., Fortin, N. and Lemieux, T. (1996) "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, Econometric Society, vol. 64(5), pages 1001-44, September.

Dorn, D. (2009) "Essays on Inequality, Spatial Interaction, and the Demand for Skills", Dissertation of the University of St. Gallen no 3613, Graduate School of Business Administration, Economics, Law and Social Sciences (HSG) to obtain the title of Doctor Oeconomiae (1999): 907-940.

Espino, A. (2011) "Evaluación de los desajustes entre oferta y demanda laboral por calificaciones en el mercado laboral de Uruguay", Revista de Economía del Rosario. Vol. 14. No. 2. Julio - Dic 2011: 99 – 133.

EUROFOUND (2013) "Employment polarization and job quality in the crisis: European Jobs Monitor 2013, Eurofound, Dublin.

Firpo, S., Fortin, N. and Lemieux, T. (2007) "Decomposing Wage Distributions using Recentered Influence Function Regressions", Working Paper, Department of Economics, University of British Columbia.

Firpo, S., Fortin, N. and Lemieux, T. (2009) “Unconditional Quantile Regressions”, *Econometrica* 77(3): 953-973.

Firpo, S., Fortin, N. and Lemieux, T. (2010) “Decomposition Methods in Economics” In: Ashenfelter,O, Card, D (eds.): *Handbook of Economics*, Amsterdam: North-Holland, Vol IV.A: 1-102.

Firpo, S., Fortin, N. and Lemieux, T. (2011) “Occupational Tasks and Changes in the Wage Structure”, IZA Discussion Paper No. 5542. Forschungsinstitut zur Zukunft der Arbeit. Institute for the Study of Labor (IZA), February.

Firpo, S.; Pinto, C.; Sanroman, G. (2014), “Assessing functional form specifications for the Unconditional Quantile Partial Effects in the GMM framework", mimeo.

Furtado, M. (2006): “Uruguay: Impacto social y económico del salario mínimo”, en A. Marinakis y J. Jacobo Velasco (eds.): *¿Para qué sirve el salario mínimo? Elementos para su determinación en los países de Cono Sur*, Santiago de Chile: OIT.

Gonzales, X. and Miles, D. (1999) “Wage Inequality in a Developing Country: Decrease of Minimum Wages or Increase in Education Returns”.

Goos, M. and Manning, A. (2007) “Lousy and Lovely Jobs: The Rising Polarization of Work in Britain”, *Review of Economics and Statistics*, 89(1): 118-133.

Goos, M., Manning, A. and Salomons, A. (2009) “Job Polarization in Europe”, *American Economic Review,* 99(2):58-63.

Goos, M., Manning, A. and Salomons, A. (2011) "Explaining job polarization: the roles of technology, offshoring and institutions," Center for Economic Studies - Discussion papers N0. 1026, Katholieke Universiteit Leuven, Centrum voor Economische Studiën (LSE).

Gradín, C. and Rossi, M. (2000) “Polarización y Desigualdad Salarial en Uruguay, 1986-1997”, *El Trimestre Económico*, 267, Vol. LXVII (3): 421-443.

Gradín, C. and Rossi, M. (2001) “Income Distribution in Uruguay: The Effects of Economic and Institutional Reforms”. SSRN Scholarly Paper No. ID 282954. Social Sciences Research Network, Rochester, NY.

Gradin, C. and Rossi, M. (2006) “Income Distribution and income sources in Uruguay” *Journal of Applied Economics*, May, 2006/vol.IX, número 001, Universidad del CEMA, Buenos Aires, Argentina. Pp.49-69

Instituto Nacional de Estadística (1996) “Manual guía para la codificación de ocupaciones de actividad. Clasificación Internacional Uniforme de Ocupaciones (CIUO-88). Adaptada a Uruguay (CNUO-95)”. Available at: www.ine.gub.uy.

Instituto Nacional de Estadística, “Clasificador internacional de ocupaciones (COTA-70, CIUO-88)”. Available at: www.ine.gub.uy.

Jensen, J. B. and. Kletzer, L.G (2010) “Measuring the Task Content of Offshorable Services Jobs, Tradable Services and Job Loss,” In *Labor in the New Economy*, Katharine Abraham, Mike Harper, and James Spletzer, eds., Chicago: University of Chicago Press. 309-335.

Jung, J. and Mercenier, J. (2010) "Routinization-Biased Technical Change, Globalization and Labor Market Polarization: A Simple Model with Heterogeneous Agents". Available at: http://congres.afse.fr/docs/2010/658466mercenier.pdf

Machado, J. and Mata, J. (2005) "Counterfactual decomposition of changes in wage distributions using quantile regression", *Journal of Applied Econometrics*, Vol. 20 (4): 445–465, May/June 2005.

Michaels, G., Natraj, A. and Van Reenen, J. (2013) "Has ICT polarized skill demand? Evidence from eleven countries over 25 years", *Review of Economics and Statistics* 96:60-77.

National Center for O*NET Development (2010). "Data Dictionary O*NET 15.0 Database". Available at: http://www.onetcenter.org

Perazzo, I. (2012) "El mercado laboral uruguayo en la última década" DT 01/12. *Instituto de Economía*, Facultad de Ciencias Económicas y Administración, Universidad de la República. Available at: http://www.iecon.ccee.edu.uy/dt-01-12-el-mercado-laboral-uruguayo-en-la-ultima-decada/publicacion/281/es/

Perazzo, I. and Rodríguez, S. (2007) "Impactos de la Reforma Tributaria sobre el ingreso de los hogares" in QUANTUM • Volumen II Nº 1 / Octubre 2007, Montevideo: 62-78.

Programa Naciones Unidas para el Desarrollo (2008): "Desarrollo Humano en Uruguay: Política, Políticas y Desarrollo Humano", Montevideo: PNUD.

Sanguinetti, C. (2007), "Educación y dispersión salarial en Uruguay: Un análisis de regresión por cuantiles" Documents de Recerca del Programa de Doctorado en Economía Aplicada Universitat Autònoma de Barcelona, Noviembre 2007

Vigorito, A. (1994), "Una descomposición de la desigualdad de ingresos por trabajo en Uruguay. 1986-1996". En IX Jornadas Anuales BCU.

World Bank (2012), "The Labor Market Story Behind Latin America's Transformation". World Bank – LAC Tables.

8. Tables

Table 1. Average O*Net Indexes by Major Occupation Group

O*NET Indexes	**Information**	**Automation**
PANEL A: using 1991/92 -1998/99 data and COTA-70 Occupation codes		
Overall Mean	0,5921	0,7500
Standard Deviation	0,1095	0,0624
Professional, Managerial, Technichal	0,7126	0,7128
Clerical, Sales	0,6622	0,7489
Production, Operators	0,5750	0,7975
Primary, Construction, Transport	0,5503	0,7310
Service	0,5537	0,7364
PANEL B: using 2001/02 -2009/10 data and CIOU-88 Occupation codes		
Overall Mean	0,6222	0,7354
Standard Deviation	0,1223	0,0627
Professional, Managerial, Technichal	0,7822	0,6915
Clerical, Sales	0,6897	0,7557
Production, Operators	0,5600	0,7701
Primary, Construction, Transport	0,5452	0,7396
Service	0,5645	0,7148

Note: Task content indexes constructed as follow based on O*NET data.

$$(1) \quad Information\ Content_j = IC_j = \sum_{k=1}^{5} I_{jk}^{2/3} * L_{jk}^{1/3}$$

$$(2) \quad Automation\ Content_j = AC_j = \sum_{l=1}^{5} F_{jl} * V_{jl}$$

Where k is the number of work activity elements, and l the number of work context elements considered in the construction of the task of work content index.Task measures are normalized to range between zero and one.

Table 2. Unconditional Quantile Partial Effect on Men Log Wages (1991/92 - 1998/99) - RIF Regression

Year	1991/92			1998/99		
Explanatory Variables/ Quantile	**10**	**50**	**90**	**10**	**50**	**90**
Information content	0,048 ***	0,062 ***	0,163 ***	0,031 **	0,074 ***	0,177 ***
	(0,009)	(0,005)	(0,012)	(0,012)	(0,007)	(0,018)
Automation content	0,036 ***	0,036 ***	-0,041 ***	0,004	0,002	-0,022
	(0,008)	(0,005)	(0,013)	(0,010)	(0,008)	(0,014)
Education (6 years or less omitted)						
From 7 to 9 years	0,237 ***	0,213 ***	0,302 ***	0,244 ***	0,258 ***	0,240 ***
	(0,023)	(0,015)	(0,025)	(0,034)	(0,019)	(0,032)
From 10 to 12 years	0,338 ***	0,407 ***	0,781 ***	0,341 ***	0,449 ***	0,754 ***
	(0,029)	(0,022)	(0,055)	(0,036)	(0,023)	(0,062)
From 13 to 15 years	0,428 ***	0,639 ***	1,543 ***	0,435 ***	0,723 ***	1,549 ***
	(0,028)	(0,029)	(0,120)	(0,044)	(0,032)	(0,107)
16 and more years	0,470 ***	0,801 ***	2,483 ***	0,446 ***	0,929 ***	3,074 ***
	(0,031)	(0,028)	(0,140)	(0,039)	(0,032)	(0,185)
Experience (5<Experience<10 omitted)						
Experience<5	-0,021	-0,041	-0,615 **	-0,038	-0,136 **	-0,719 ***
	(0,065)	(0,062)	(0,239)	(0,081)	(0,080)	(0,233)
10<experience<15	-0,058	0,056 *	0,488 ***	-0,136 ***	-0,002 *	0,662 ***
	(0,041)	(0,029)	(0,094)	(0,044)	(0,040)	(0,096)
15<experience<20	0,006	0,149 ***	0,720 ***	-0,109 **	0,104 ***	0,941 ***
	(0,040)	(0,032)	(0,099)	(0,046)	(0,039)	(0,106)
20<experience<25	0,053	0,168 ***	0,763 ***	-0,003	0,201 ***	0,988 ***
	(0,041)	(0,034)	(0,098)	(0,036)	(0,043)	(0,101)
25<experience<30	0,088 **	0,225 ***	0,852 ***	-0,019	0,244 ***	1,078 ***
	(0,035)	(0,032)	(0,101)	(0,046)	(0,040)	(0,098)
30<experience<35	0,101 **	0,295 ***	1,054 ***	-0,060	0,229 ***	1,052 ***
	(0,040)	(0,030)	(0,109)	(0,049)	(0,043)	(0,119)
35<experience<40	0,121 **	0,313 ***	1,045 ***	0,029	0,327 ***	1,256 ***
	(0,050)	(0,036)	(0,114)	(0,047)	(0,044)	(0,109)
Experience>40	0,168 ***	0,343 ***	1,054 ***	-0,010	0,339 ***	1,285 ***
	(0,042)	(0,035)	(0,102)	(0,052)	(0,041)	(0,117)
Nonmarried	-0,142 ***	-0,152 ***	-0,181 ***	-0,216 ***	-0,174 ***	-0,184 ***
	(0,022)	(0,013)	(0,026)	(0,030)	(0,016)	(0,032)
Rest of the country	-0,255 ***	-0,248 ***	-0,306 ***	-0,323 ***	-0,283 ***	-0,313 ***
	(0,018)	(0,014)	(0,025)	(0,031)	(0,016)	(0,032)
Public sector	0,050 **	-0,122 ***	-0,367 ***	0,191 ***	0,049 ***	-0,144 ***
	(0,020)	(0,012)	(0,025)	(0,024)	(0,015)	(0,040)
Constant	3,246 ***	3,697 ***	3,630 ***	3,524 ***	3,876 ***	3,714 ***
	(0,046)	(0,035)	(0,109)	(0,052)	(0,042)	(0,123)

Notes: Bootstrapped standard errors are in parenthesis (100 replications of the entire procedure).

Number of observations 1991/92:13,917 ; 1998/99: 13,294.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author´s own calculations. Results based on ECH 1991,1992 and 1998,1999 data.

Table 3. RIF Regression Of Inequality Measures on Men Log Wages (1991/92 - 1998/99)

Year	1991/92	1998/99	1991/92	1998/99
Explanatory Variables / Inequality Measure	Variance		Gini	
Information content	0,045 ***	0,055 ***	0,003 ***	0,004 ***
	(0,007)	(0,008)	(0,001)	(0,001)
Automation content	-0,042 ***	-0,024 ***	-0,004 ***	-0,002 ***
	(0,008)	(0,008)	(0,001)	(0,001)
Education (6 years or less omitted)				
From 7 to 9 years	0,018	-0,025	-0,003 ***	-0,008 ***
	(0,014)	(0,018)	(0,001)	(0,002)
From 10 to 12 years	0,160 ***	0,133 ***	0,007 **	0,003
	(0,025)	(0,022)	(0,002)	(0,002)
From 13 to 15 years	0,415 ***	0,436 ***	0,029 ***	0,025 ***
	(0,037)	(0,041)	(0,003)	(0,003)
16 and more years	0,996 ***	1,241 ***	0,075 ***	0,083 ***
	(0,050)	(0,059)	(0,004)	(0,004)
Experience (5<Experience<10 omitted)				
Experience<5	-0,497 ***	-0,488 ***	-0,041 ***	-0,033 ***
	(0,068)	(0,084)	(0,008)	(0,007)
10<experience<15	0,281 ***	0,383 ***	0,025 ***	0,031 ***
	(0,043)	(0,045)	(0,004)	(0,004)
15<experience<20	0,348 ***	0,481 ***	0,030 ***	0,038 ***
	(0,045)	(0,049)	(0,004)	(0,004)
20<experience<25	0,379 ***	0,472 ***	0,030 ***	0,035 ***
	(0,053)	(0,051)	(0,004)	(0,003)
25<experience<30	0,385 ***	0,526 ***	0,030 ***	0,039 ***
	(0,048)	(0,053)	(0,005)	(0,003)
30<experience<35	0,449 ***	0,550 ***	0,036 ***	0,041 ***
	(0,051)	(0,054)	(0,004)	(0,004)
35<experience<40	0,430 ***	0,596 ***	0,033 ***	0,043 ***
	(0,053)	(0,056)	(0,005)	(0,004)
experience>40	0,408 ***	0,615 ***	0,030 ***	0,045 ***
	(0,047)	(0,055)	(0,004)	(0,004)
Nonmarried	0,016	0,029	0,004 **	0,007 ***
	(0,017)	(0,020)	(0,002)	(0,002)
Rest of the country	-0,014	0,026 *	0,004 ***	0,008 ***
	(0,011)	(0,015)	(0,001)	(0,002)
Public sector	-0,208 ***	-0,201 ***	-0,018 ***	-0,018 ***
	(0,012)	(0,017)	(0,001)	(0,002)
Constant	-0,160 ***	-0,242 ***	0,040 ***	0,036 ***
	(0,049)	(0,056)	(0,004)	(0,004)

Notes: Bootstrapped standard errors are in parenthesis (100 replications of the entire procedure).

Number of observations 1991/92: 13,917 ; 1998/99: 13,294.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author´s own calculations. Results based on ECH 1991,1992 and 1998,1999 data.

Table 4. Unconditional Quantile Partial Effect on Men Log Wages (2001/02 - 2009/10) - RIF Regression

Year	2001/02			2009/10		
Explanatory Variables/ Quantile	10	50	90	10	50	90
Information content	0,080 ***	0,104 ***	0,326 ***	0,053 ***	0,111 ***	0,264 ***
	(0,012)	(0,009)	(0,023)	(0,008)	(0,007)	(0,014)
Automation content	0,052 ***	0,050 ***	0,011	0,051 ***	0,053 ***	0,000
	(0,012)	(0,008)	(0,016)	(0,005)	(0,005)	(0,011)
Education (6 years or less omitted)						
From 7 to 9 years	0,212 ***	0,222 ***	0,140 ***	0,250 ***	0,174 ***	0,079 ***
	(0,037)	(0,022)	(0,025)	(0,020)	(0,014)	(0,012)
From 10 to 12 years	0,327 ***	0,456 ***	0,540 ***	0,374 ***	0,427 ***	0,392 ***
	(0,038)	(0,026)	(0,040)	(0,022)	(0,017)	(0,023)
From 13 to 15 years	0,389 ***	0,763 ***	1,206 ***	0,475 ***	0,762 ***	1,010 ***
	(0,050)	(0,039)	(0,104)	(0,025)	(0,025)	(0,054)
16 and more years	0,377 ***	0,921 ***	2,451 ***	0,487 ***	0,920 ***	2,322 ***
	(0,043)	(0,040)	(0,155)	(0,025)	(0,027)	(0,084)
Experience (5<Experience<10 omitted)						
Experience<5	0,026	0,104	-0,894 ***	0,023	-0,104 *	-0,849 ***
	(0,056)	(0,065)	(0,210)	(0,044)	(0,053)	(0,107)
10<experience<15	-0,121 **	0,093 ***	0,747 ***	-0,085 ***	0,017	0,575 ***
	(0,048)	(0,036)	(0,082)	(0,030)	(0,022)	(0,050)
15<experience<20	-0,090 *	0,195 ***	0,920 ***	-0,076 **	0,117 ***	0,785 ***
	(0,047)	(0,034)	(0,087)	(0,031)	(0,025)	(0,053)
20<experience<25	-0,023	0,315 ***	1,007 ***	0,016	0,207 ***	0,871 ***
	(0,045)	(0,035)	(0,089)	(0,029)	(0,024)	(0,055)
25<experience<30	0,040	0,365 ***	1,065 ***	0,021	0,305 ***	1,015 ***
	(0,044)	(0,036)	(0,094)	(0,030)	(0,023)	(0,066)
30<experience<35	-0,001	0,373 ***	1,123 ***	0,060 **	0,370 ***	1,105 ***
	(0,054)	(0,037)	(0,102)	(0,029)	(0,027)	(0,063)
35<experience<40	0,022	0,450 ***	1,248 ***	0,081 ***	0,401 ***	1,109 ***
	(0,049)	(0,041)	(0,099)	(0,029)	(0,028)	(0,063)
Experience>40	0,040	0,535 ***	1,249 ***	0,029	0,385 ***	1,071 ***
	(0,058)	(0,041)	(0,097)	(0,030)	(0,026)	(0,061)
Nonmarried	-0,154 ***	-0,116 ***	-0,176 ***	-0,161 ***	-0,132 ***	-0,078 ***
	(0,029)	(0,016)	(0,031)	(0,015)	(0,011)	(0,020)
Rest of the country	-0,237 ***	-0,260 ***	-0,197 ***	-0,033 ***	-0,036 ***	-0,092 ***
	(0,025)	(0,016)	(0,028)	(0,011)	(0,010)	(0,017)
Public sector	0,264 ***	0,148 ***	-0,270 ***	0,189 ***	0,201 ***	-0,067 ***
	(0,022)	(0,015)	(0,037)	(0,013)	(0,012)	(0,023)
Constant	3,381 ***	3,658 ***	3,579 ***	3,234 ***	3,725 ***	3,761 ***
	(0,060)	(0,040)	(0,102)	(0,032)	(0,028)	(0,066)

Notes: Bootstrapped standard errors are in parenthesis (100 replications of the entire procedure).

Number of observations 2001/02:13,033 ; 2009/10: 30,631.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author´s own calculations. Results based on ECH 2001, 2002 and 2009, 2010 data.

Table 5. RIF Regression Of Inequality Measures on Men Log Wages (2001/02 - 2009/10)

Year	2001/02	2009/10	2001/02	2009/10
Explanatory Variables / Inequality Measure	Variance		Gini	
Information content	0,098 ***	0,102 ***	0,006 ***	0,007 ***
	(0,010)	(0,007)	(0,001)	(0,001)
Automation content	-0,045 ***	-0,045 ***	-0,005 ***	-0,005 ***
	(0,009)	(0,006)	(0,001)	(0,000)
Education (6 years or less omitted)				
From 7 to 9 years	-0,058 ***	-0,093 ***	-0,010 ***	-0,013 ***
	(0,020)	(0,011)	(0,002)	(0,001)
From 10 to 12 years	0,058 ***	-0,044 ***	-0,002	-0,011 ***
	(0,021)	(0,012)	(0,002)	(0,001)
From 13 to 15 years	0,362 ***	0,176 ***	0,019 ***	0,004 *
	(0,040)	(0,018)	(0,003)	(0,002)
16 and more years	1,027 ***	0,832 ***	0,068 ***	0,055 ***
	(0,058)	(0,031)	(0,004)	(0,003)
Experience (5<Experience<10 omitted)				
Experience<5	-0,511 ***	-0,477 ***	-0,039 ***	-0,038 ***
	(0,071)	(0,041)	(0,005)	(0,004)
10<experience<15	0,426 ***	0,317 ***	0,034 ***	0,028 ***
	(0,034)	(0,022)	(0,003)	(0,002)
15<experience<20	0,515 ***	0,411 ***	0,040 ***	0,035 ***
	(0,040)	(0,025)	(0,003)	(0,002)
20<experience<25	0,521 ***	0,424 ***	0,039 ***	0,034 ***
	(0,034)	(0,026)	(0,003)	(0,002)
25<experience<30	0,528 ***	0,468 ***	0,038 ***	0,037 ***
	(0,036)	(0,028)	(0,003)	(0,002)
30<experience<35	0,559 ***	0,500 ***	0,040 ***	0,038 ***
	(0,040)	(0,027)	(0,003)	(0,002)
35<experience<40	0,624 ***	0,487 ***	0,044 ***	0,037 ***
	(0,047)	(0,031)	(0,004)	(0,002)
experience>40	0,596 ***	0,476 ***	0,042 ***	0,037 ***
	(0,041)	(0,028)	(0,003)	(0,002)
Nonmarried	0,027	0,039 ***	0,006 ***	0,007 ***
	(0,023)	(0,012)	(0,002)	(0,001)
Rest of the country	0,026 *	-0,030 ***	0,007 **	-0,002 **
	(0,014)	(0,011)	(0,001)	(0,001)
Public sector	-0,295 ***	-0,208 ***	-0,028 ***	-0,020 ***
	(0,019)	(0,013)	(0,001)	(0,001)
Constant	-0,262 ***	-0,108 ***	0,038 ***	0,049 ***
	(0,043)	(0,028)	(0,004)	(0,002)

Notes: Bootstrapped standard errors are in parenthesis (100 replications of the entire procedure).

Number of observations 2001/02:13,033 ; 2009/10: 30,631.

*** p<0.01, ** p<0.05, * p<0.1

Source: Author´s own calculations. Results based on ECH 2001, 2002 and 2009, 2010 data.

Table 6. Aggregate Decomposition Results

Inequality Measure:	90-10	90-50	50-10	Variance	Gini
1991/92 - 1998/99					
Total Change	0,1797 ***	0,1260 ***	0,0538 ***	0,1037 ***	0,0079 ***
	(0,023)	(0,016)	(0,015)	(0,010)	(0,001)
Wage Structure	0,0918 ***	0,0589 ***	0,0329 ***	0,0609 ***	0,0045 ***
	(0,023)	(0,020)	(0,014)	(0,010)	(0,001)
Composition	0,0897 ***	0,0676 ***	0,0221 ***	0,0421 ***	0,0034 ***
	(0,014)	(0,012)	(0,004)	(0,006)	(0,001)
Specification Error	0,0074	0,0068	0,0006	0,0050	0,0004
	(0,025)	(0,022)	(0,015)	(0,011)	(0,001)
Reweighing Error	-0,0092	-0,0073	-0,0019	-0,0043	-0,0003
	(0,008)	(0,007)	(0,002)	(0,004)	(0,000)
2001/02 - 2009/10					
Total Change	-0,1113 ***	-0,0932 ***	-0,0181 *	-0,0719 ***	-0,0072 ***
	(0,017)	(0,014)	(0,013)	(0,010)	(0,001)
Wage Structure	-0,1779 ***	-0,1384 ***	-0,0395 ***	-0,1046 ***	-0,0098 ***
	(0,022)	(0,019)	(0,014)	(0,011)	(0,001)
Composition	0,0634 ***	0,0448 ***	0,0186 ***	0,0301 ***	0,0025 ***
	(0,017)	(0,013)	(0,005)	(0,008)	(0,001)
Specification Error	0,0086	0,0050	0,0036	0,0172 *	0,0016 *
	(0,027)	(0,021)	(0,021)	(0,012)	(0,001)
Reweighing Error	-0,0054	-0,0045	-0,0009	-0,0146 ***	-0,0014 ***
	(0,011)	(0,009)	(0,003)	(0,006)	(0,000)

Notes: FFL (2010) decomposition method with F(X) 1991/92 reweighted to 1998/99 and F(X) 2001/02 reweighted to 2009/2010.
Bootstraped standard errors are in parenthesis (100 replications of the entire procedure).
The formulas for the different components are as following. The reweighting error is the difference between the total change and the sum of the wage structure and composition effects and the specificacion error .

Total change: $\hat{\Delta}_O^{v} = \widehat{RIF}(Y_1, v) - \widehat{RIF}(Y_0, v)$ *Wage structure:* $\hat{\Delta}_{S,p}^{v} = \overline{X_1}\,(\hat{\gamma}_1^{v} - \hat{\gamma}_C^{v})$

Composition: $\hat{\Delta}_{X,p}^{v} = (X_0^{C} - \overline{X_0})\hat{\gamma}_0^{v}$ *Specification error:* $\hat{\Delta}_{X,e}^{v} = \overline{X_0^{C}}(\hat{\gamma}_C^{v} - \hat{\gamma}_0^{v})$

Number of observations 1991/92: 13,917 ; 1998/99: 13,294; 2001/2002: 13,033; 2009/10: 30,631.
Source: Author´s own calculations. Results based on ECH 1991,1992,1998,1999,2001,2002 and 2009,2010 data.

Table 7. Detailed Decomposition Results 1991/92 - 1998/99

Inequality Measure:	90-10	90-50	50-10	Variance	Gini
A: Detailed Composition Effects:					
Information	-0,0008	-0,0007	-0,0001	-0,0003	0,0000
	(0,002)	(0,002)	(0,000)	(0,001)	(0,000)
Automation	0,0048 ***	0,0046 ***	0,0001	0,0025 ***	0,0003 ***
	(0,002)	(0,002)	(0,001)	(0,001)	(0,000)
Education	0,0735 ***	0,0604 ***	0,0130 ***	0,0311 ***	0,0021 ***
	(0,015)	(0,013)	(0,003)	(0,007)	(0,001)
Experience	-0,0158 ***	-0,0123 ***	-0,0035 **	-0,0062 **	-0,0004 **
	(0,006)	(0,005)	(0,002)	(0,003)	(0,000)
Others	0,0282 ***	0,0156 ***	0,0126 ***	0,0150 ***	0,0015 ***
	(0,005)	(0,003)	(0,003)	(0,002)	(0,000)
Total Composition Effect	0,0897 ***	0,0676 ***	0,0221 ***	0,0421 ***	0,0034 ***
	(0,014)	(0,012)	(0,004)	(0,006)	(0,001)
B: Detailed Wage Structure Effects:					
Information	-0,0006	0,0010	-0,0015 **	-0,0005	-0,0001
	(0,002)	(0,001)	(0,001)	(0,001)	(0,000)
Automation	-0,0019 **	-0,0019 **	0,0000	-0,0006 *	-0,0001 **
	(0,001)	(0,001)	(0,000)	(0,000)	(0,000)
Education	0,0473	0,0160	0,0313	0,0270 **	0,0009
	(0,057)	(0,048)	(0,029)	(0,016)	(0,002)
Experience	0,2501 *	0,1828	0,0673	0,1246 **	0,0085 **
	(0,159)	(0,147)	(0,064)	(0,061)	(0,005)
Others	-0,0752 *	-0,0629 *	-0,0123	-0,0068	0,0013
	(0,057)	(0,048)	(0,035)	(0,023)	(0,002)
Constant	-0,1279	-0,0760	-0,0519	-0,0826	-0,0060
	(0,203)	(0,192)	(0,088)	(0,073)	(0,006)
Total Wage Structure Effect	0,0918 ***	0,0589 ***	0,0329 ***	0,0609 ***	0,0045 ***
	(0,023)	(0,020)	(0,014)	(0,010)	(0,001)

Notes: FFL (2010) Decomposition method with F(X) 1991/92 reweighted to 1998/99.

Bootstrapped standard errors are in parenthesis (100 replications of the entire procedure).

Explanatory grouped variables include,automation and information content of tasks, 5 education classes (6 years or less ommited),

9 potential experience classes (5 to 10 years ommited), others (rest of the country, public sector and nonmarried).

*** p<0.01, ** p<0.05, * p<0.1

Number of observations 1991/92: 13,917 ; 1998/99: 13,294.

Source: Author´s own calculations. Results based on ECH 1991,1992 and 1998,1999 data.

Table 8. Detailed Decomposition Results 2001/02 - 2009/10

Inequality Measure:	90-10	90-50	50-10	Variance	Gini
A: Detailed Composition Effects:					
Information	-0,0042	-0,0037	-0,0005	-0,0019	-0,0001
	(0,005)	(0,005)	(0,001)	(0,002)	(0,000)
Automation	-0,0012	-0,0011	-0,0001	-0,0019 *	-0,0002 *
	(0,001)	(0,001)	(0,000)	(0,001)	(0,000)
Education	0,0452 ***	0,0290 ***	0,0162 ***	0,0166 ***	0,0007 *
	(0,015)	(0,011)	(0,005)	(0,006)	(0,000)
Experience	-0,0126 *	-0,0076 *	-0,0050 *	-0,0056 *	-0,0004 *
	(0,008)	(0,006)	(0,003)	(0,004)	(0,000)
Others	0,0363 ***	0,0283 ***	0,0080 ***	0,0229 ***	0,0024 ***
	(0,006)	(0,004)	(0,003)	(0,003)	(0,000)
Total Composition Effect	0,0634 ***	0,0448 ***	0,0186 ***	0,0301 ***	0,0025 ***
	(0,017)	(0,013)	(0,005)	(0,008)	(0,001)
B: Detailed Wage Structure Effects:					
Information	0,0092 ***	0,0115 ***	-0,0024 *	0,0013	-0,0001
	(0,004)	(0,004)	(0,002)	(0,001)	(0,000)
Automation	0,0021 *	0,0012	0,0009	0,0008	0,0000
	(0,001)	(0,001)	(0,001)	(0,001)	(0,000)
Education	-0,0091	0,0145	-0,0236	-0,0238 *	-0,0013
	(0,041)	(0,038)	(0,034)	(0,019)	(0,002)
Experience	-0,1252	-0,0285	-0,0967 **	-0,0980 **	-0,0035
	(0,120)	(0,113)	(0,054)	(0,046)	(0,004)
Others	-0,2729 ***	-0,1859 ***	-0,0869 ***	-0,1103 ***	-0,0122 ***
	(0,054)	(0,048)	(0,033)	(0,025)	(0,002)
Constant	0,2180 *	0,0487	0,1693 **	0,1254 **	0,0073 *
	(0,158)	(0,148)	(0,074)	(0,061)	(0,005)
Total Wage Structure Effect	-0,1779 ***	-0,1384 ***	-0,0395 ***	-0,1046 ***	-0,0098 ***
	(0,022)	(0,019)	(0,014)	(0,011)	(0,001)

Notes: FFL (2010) Decomposition method with F(X) 2001/02 reweighted to 2009/10.

Bootstrapped standard errors are in parenthesis (100 replications of the entire procedure).

Explanatory grouped variables include,automation and information content of tasks, 5 education classes (6 years or less ommited),

9 potential experience classes (5 to 10 years ommited), others (rest of the country, public sector and nonmarried).

*** p<0.01, ** p<0.05, * p<0.1

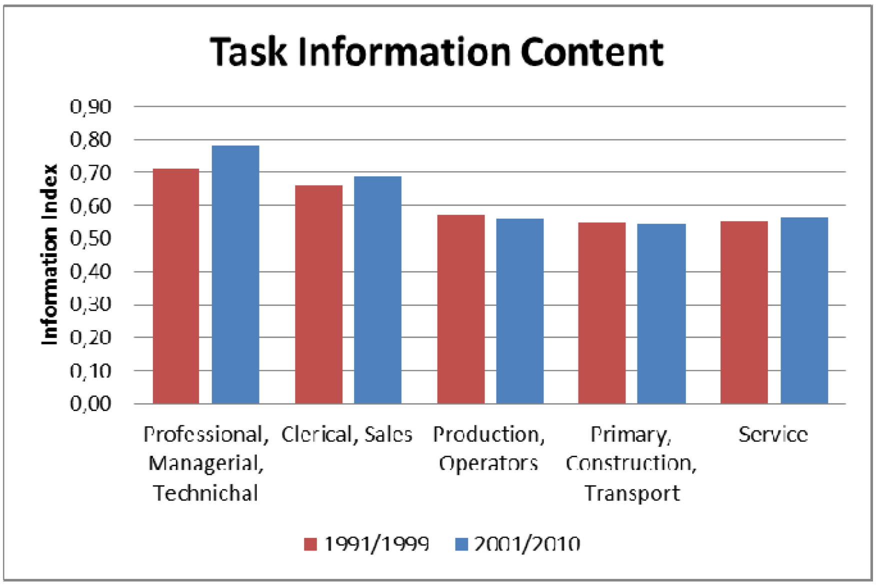
Number of observations 2001/2002: 13,033; 2009/10: 30,631.

Source: Author´s own calculations. Results based on ECH 2001,2002 and 2009,2010 data.

9. Figures

Figure 1. Task Content Measures by Occupational Category

Information Content measure by Occupational Category



Automation Content measure by Occupational Category

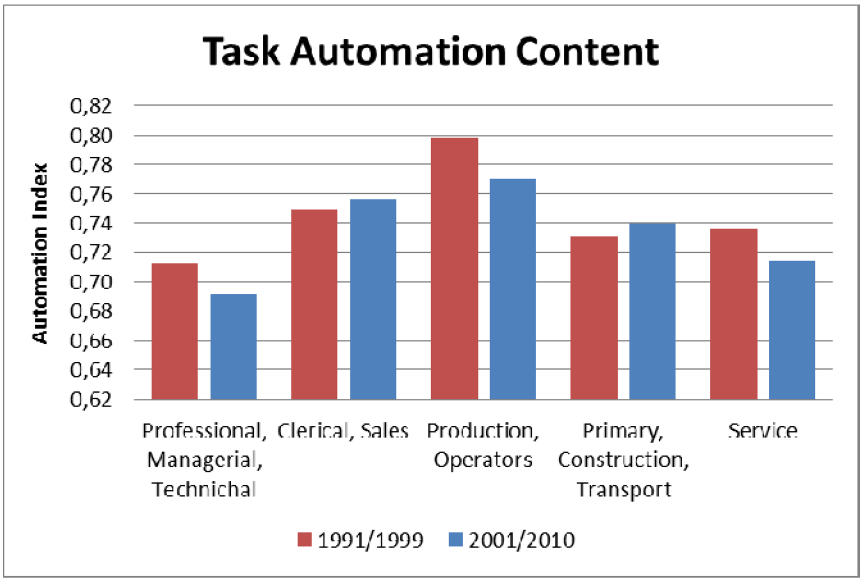
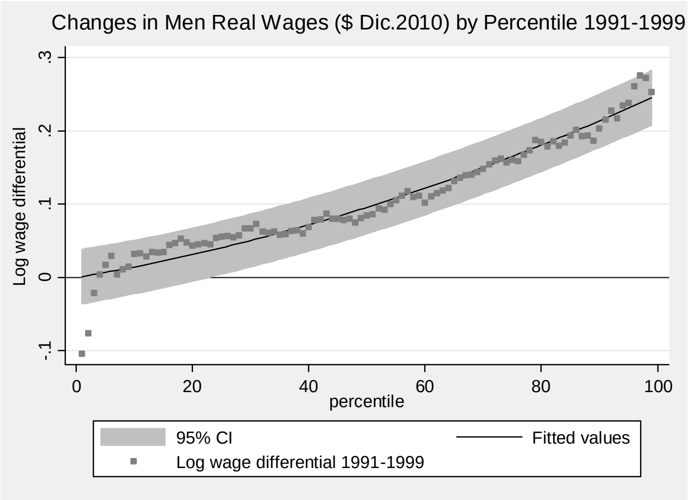
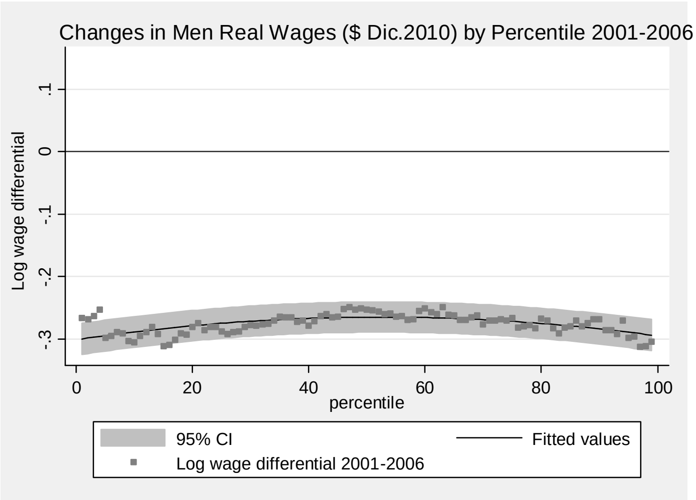


Figure 2. Changes in Real Wages ($ Dic. 2010) by Percentile, Men





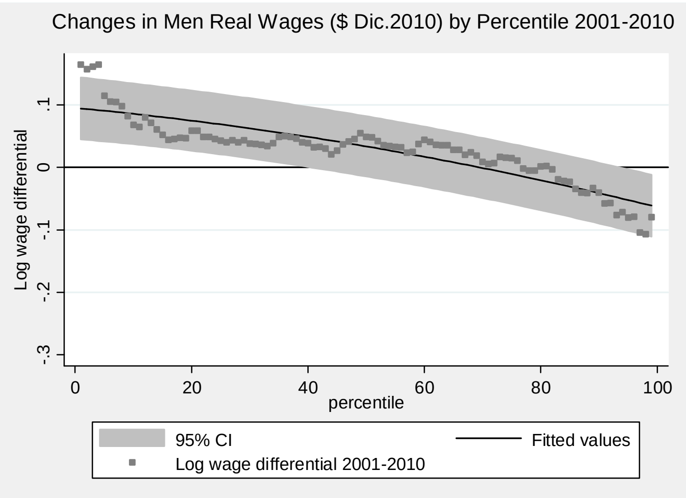
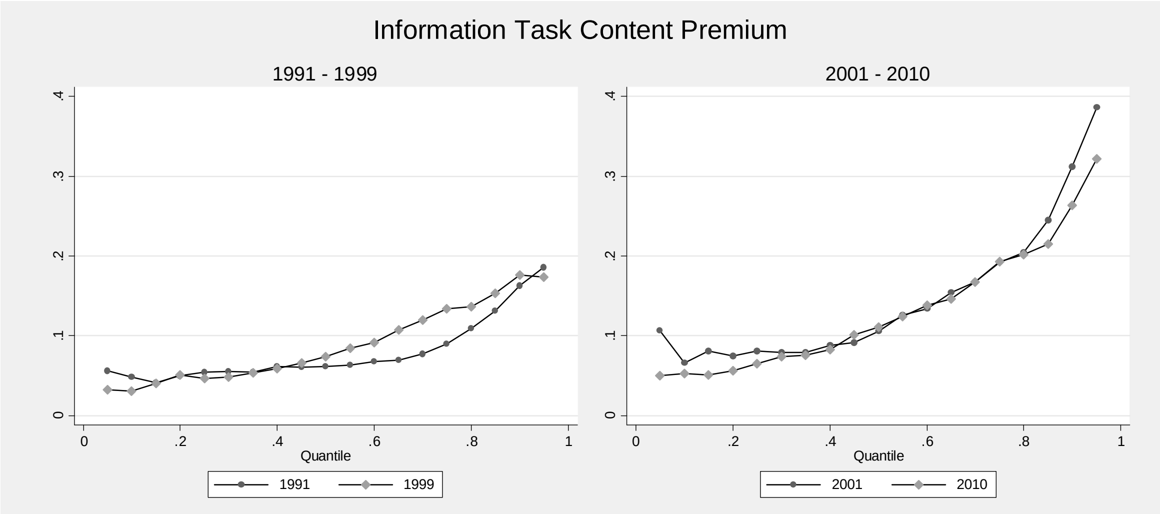
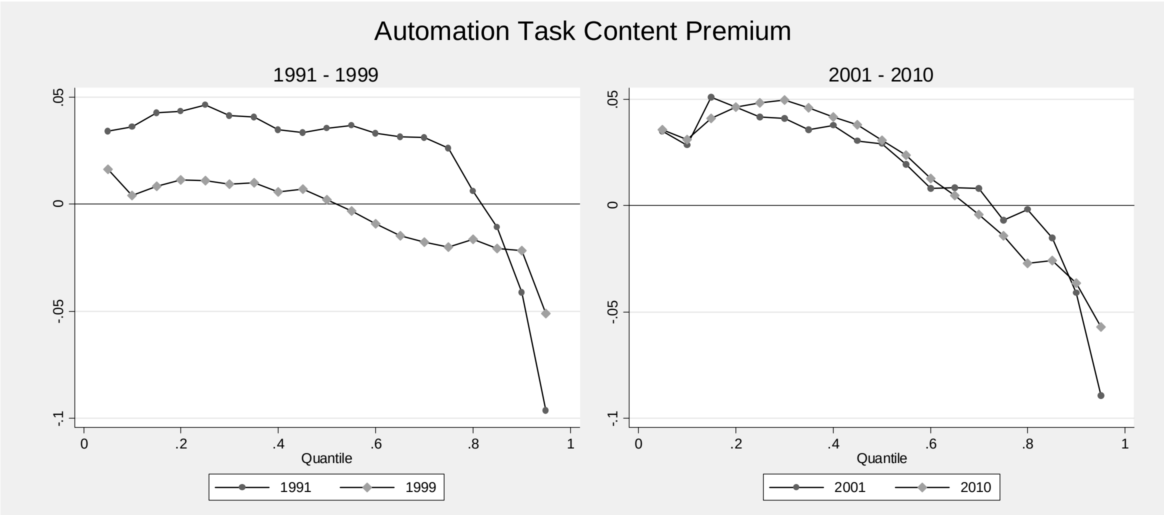


Figure 3. Unconditional Quantile Regression Coefficients:

Occupational Task 1991/92 – 1998/99 – 2001/02 – 2009/10



Source: Author's own estimations



Source: Author's own estimations

Figure 4. Unconditional Quantile Regression Coefficients:

Selected Demographic Variables 1991/92 – 1998/99 – 2001/02 – 2009/10

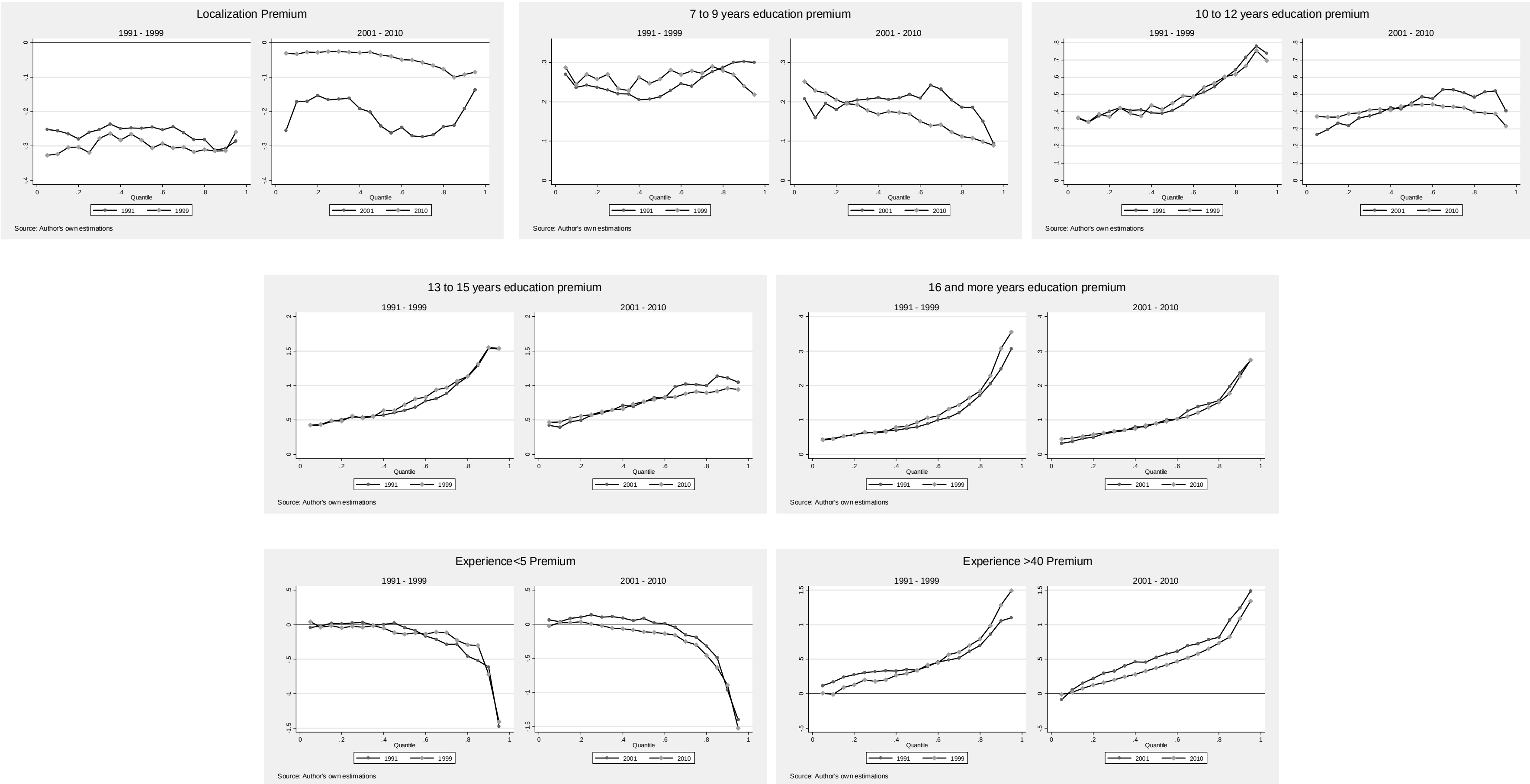
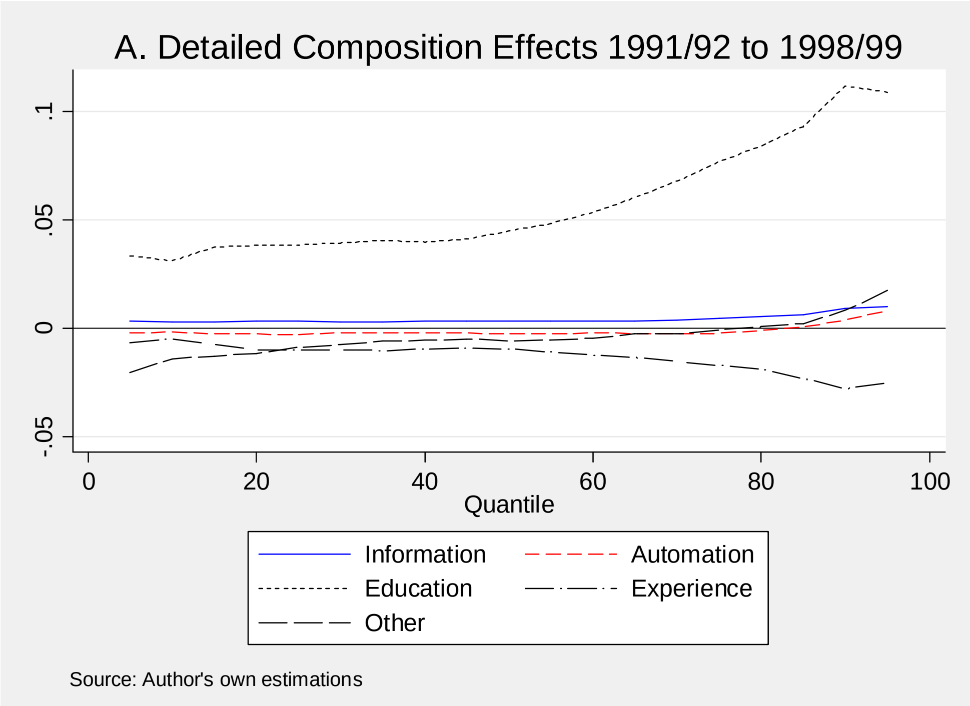


Figure 5. Decomposition of Total Change into Composition and Wage Structure Effects

Source: Author´s own estimations

Source: Author's own estimations

Figure 6. Detailed Decomposition of Composition Effects



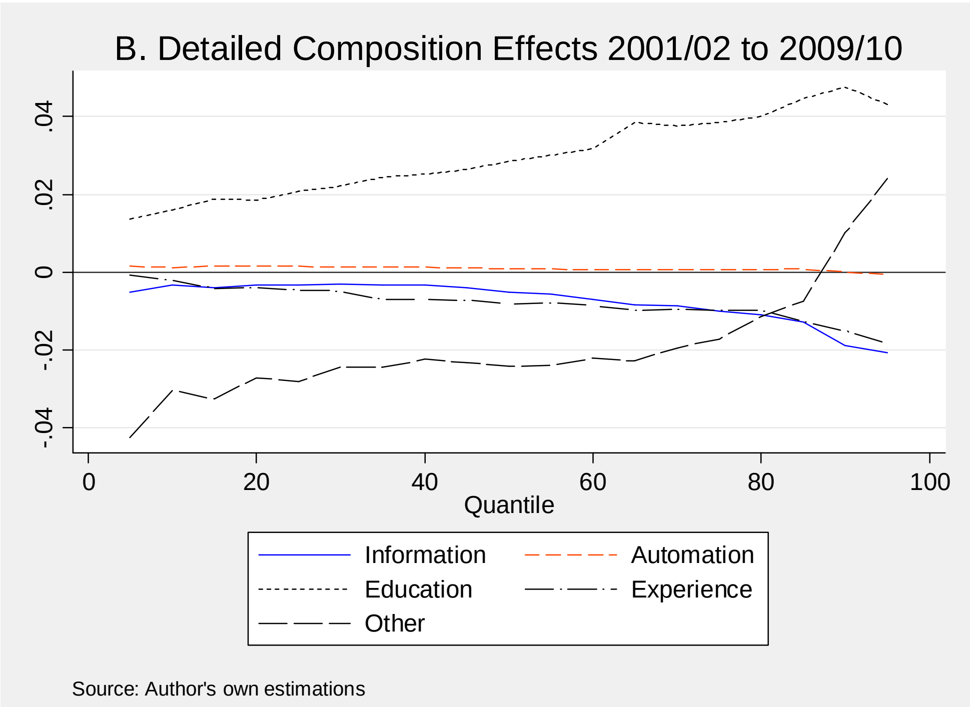
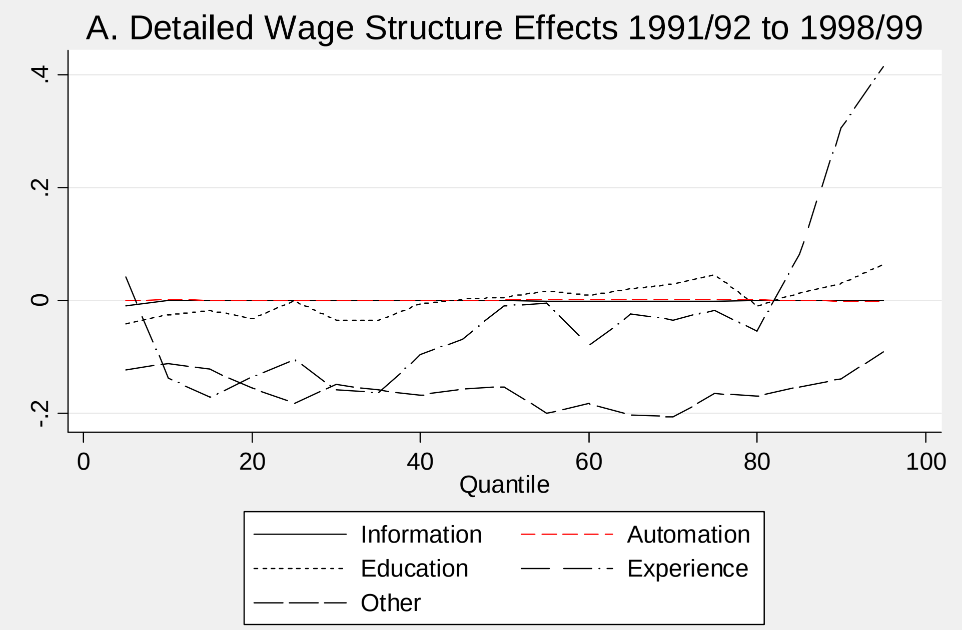
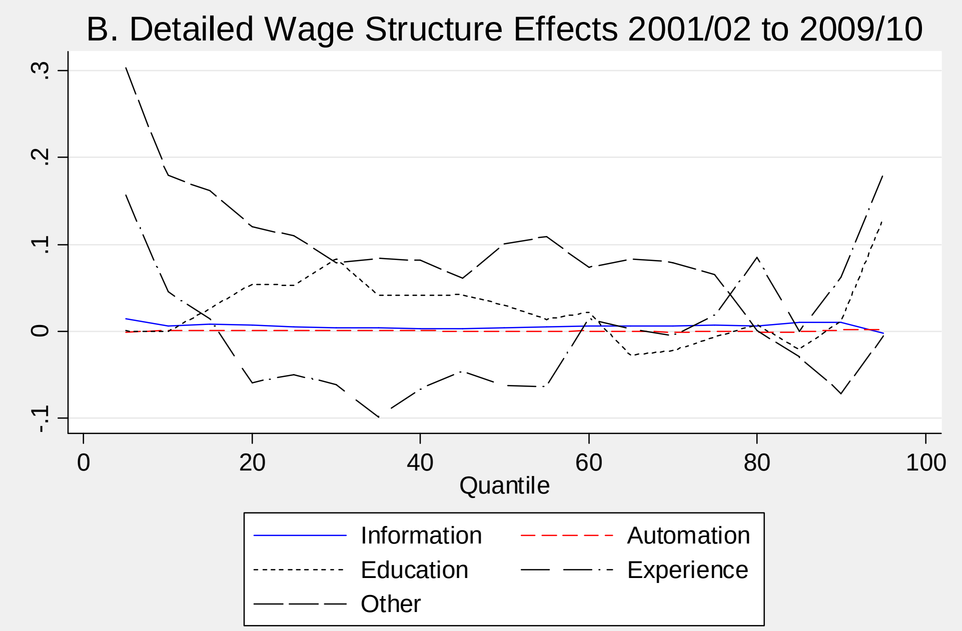


Figure 7. Detailed Decomposition of Wage Structure Effects



Source: Auhtor's own estimation



Source: Author's own estimations

9. Annex Tables and Figures

Appendix Table A.1. Descriptive Statistics

	1991/92		1998/99		Diff. in Means	2001/02		2009/10		Diff. in Means	Diff. in Means
Variable	Mean	Std.Dev	Mean	Std.Dev.	(98/99 - 91/92)	Mean	Std.Dev.	Mean	Std.Dev.	(09/10 - 01/02)	(09/10-91/92)
Log wages	4,094	0,666	4,198	0,739	0,104	4,100	0,764	4,118	0,70	0,018	0,023
Non-Married	0,189	0,392	0,216	0,412	0,027	0,241	0,428	0,252	0,43	0,011	0,063
Age	41,562	10,792	41,111	10,482	-0,451	41,502	10,684	41,747	10,71	0,245	0,184
Education											
6 years or less (ed1)	0,415	0,493	0,339	0,473	-0,076	0,274	0,446	0,251	0,43	-0,023	-0,164
From 7 to 9 years (ed2)	0,324	0,468	0,320	0,467	-0,004	0,284	0,451	0,280	0,45	-0,004	-0,044
From 10 to 12 years (ed3)	0,147	0,354	0,200	0,400	0,053	0,279	0,449	0,293	0,46	0,014	0,146
From 13 to 16 years (ed4)	0,052	0,222	0,064	0,245	0,012	0,067	0,250	0,076	0,26	0,008	0,024
16 and more years (ed5)	0,062	0,241	0,076	0,265	0,014	0,096	0,295	0,100	0,30	0,004	0,039
Experience											
Experience <5 (exp1)	0,007	0,081	0,008	0,087	0,001	0,008	0,088	0,008	0,09	0,000	0,001
5<Expereince>10 (exp2)	0,035	0,185	0,044	0,206	0,009	0,051	0,221	0,054	0,23	0,003	0,019
10<Experience<15 (exp3)	0,118	0,323	0,136	0,343	0,018	0,137	0,344	0,126	0,33	-0,011	0,008
15<Experience<20 (exp4)	0,163	0,369	0,147	0,354	-0,016	0,148	0,355	0,157	0,36	0,009	-0,006
20<Experience<25 (exp5)	0,137	0,344	0,147	0,354	0,010	0,143	0,350	0,142	0,35	-0,001	0,005
25<Experience<30 (exp6)	0,124	0,330	0,140	0,347	0,016	0,133	0,340	0,124	0,33	-0,009	0,000
30<Experience<35 (exp7)	0,115	0,319	0,114	0,317	-0,002	0,125	0,331	0,132	0,34	0,007	0,017
35<Experience<40 (exp8)	0,105	0,307	0,106	0,308	0,001	0,103	0,304	0,108	0,31	0,005	0,003
Experience>40 (exp9)	0,195	0,396	0,158	0,364	-0,038	0,152	0,359	0,149	0,36	-0,003	-0,047
Rest of the country	0,474	0,499	0,493	0,500	0,019	0,500	0,500	0,521	0,50	0,021	0,047

Results based on ECH data from 1991, 1992, 1998, 1999, 2001, 2002, 2009, 2010.

Number of observations 1991/92: 13,918; 1998/99: 13,294; 2001/02: 13,018; 2009/10: 30,609.

Source: Author´s own calculations.

Appendix Table A.2. Men hourly wage inequality measures

Year/Inequality Measure	90-10 gap	90-50 gap	50-10 gap	Variance	Gini
1991/92	1,635	0,891	0,745	0,444	0,089
1998/99	1,807	1,009	0,798	0,545	0,097
Change	0,171	0,118	0,053	0,102	0,008
2001/2002	1,850	1,055	0,795	0,582	0,105
2009/2010	1,728	0,959	0,768	0,491	0,095
Change	-0,122	-0,095	-0,027	-0,091	-0,011

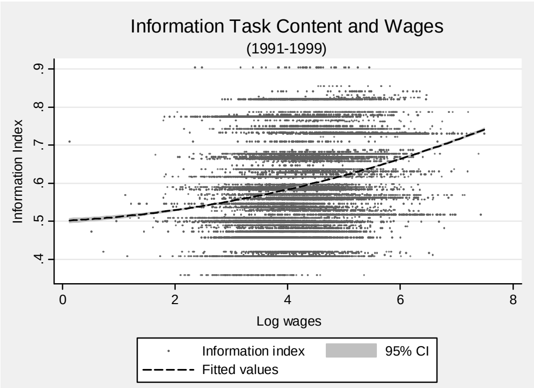
Results based on ECH data from 1991, 1992, 1998, 1999, 2001, 2002, 2009, 2010.

Number of observations 1991/92: 13,918; 1998/99: 13,294; 2001/02: 13,018; 2009/10: 30,609.

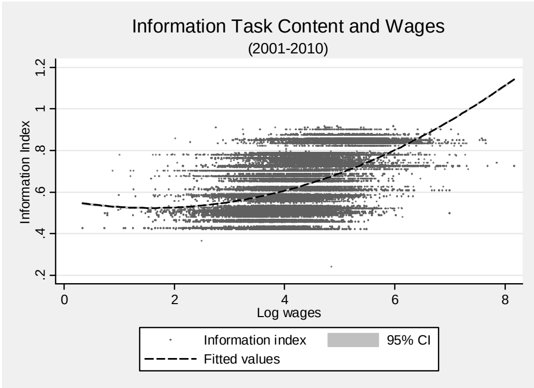
Source: Author´s own calculations.

Appendix Figure A.1

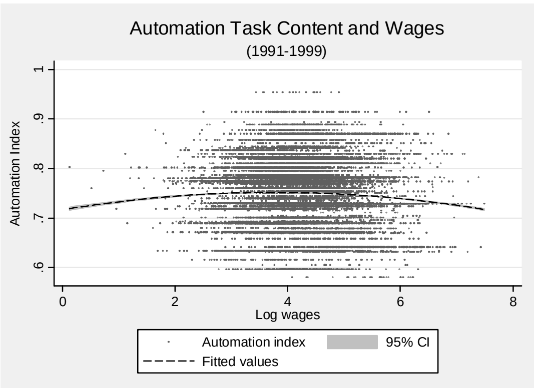
(i)



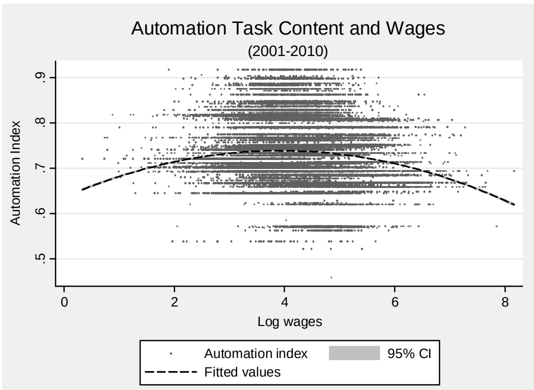
(ii)



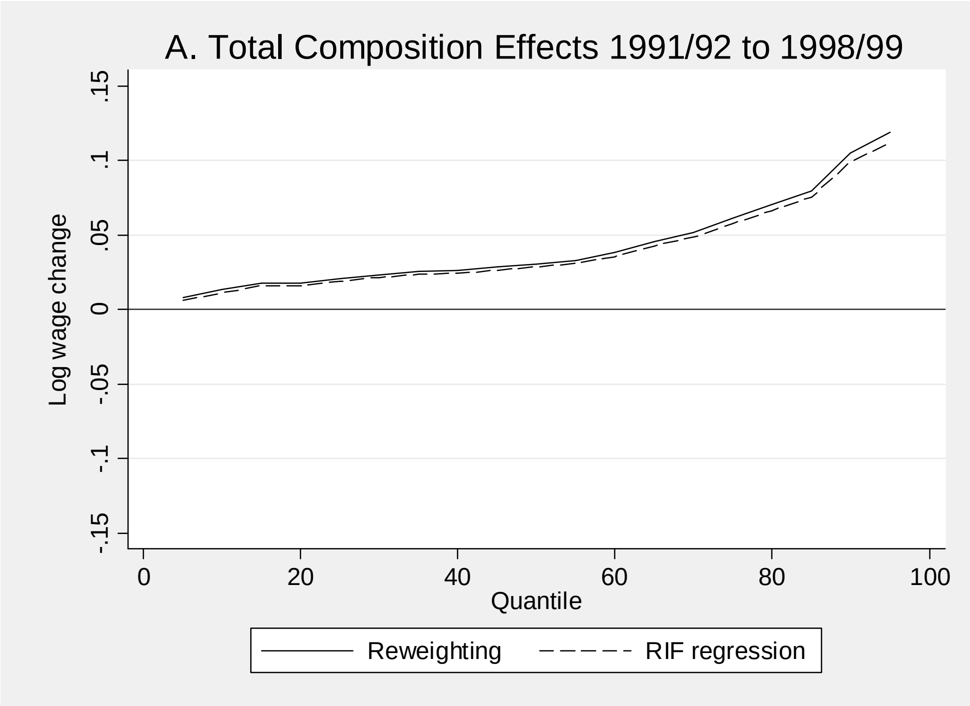
(iii)

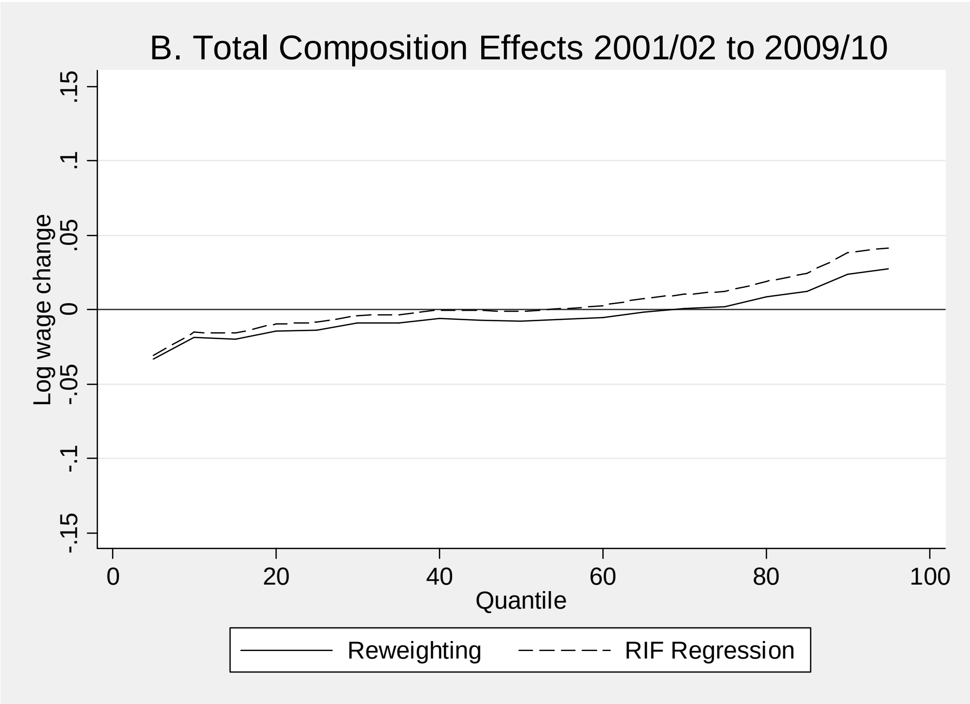


(iv)

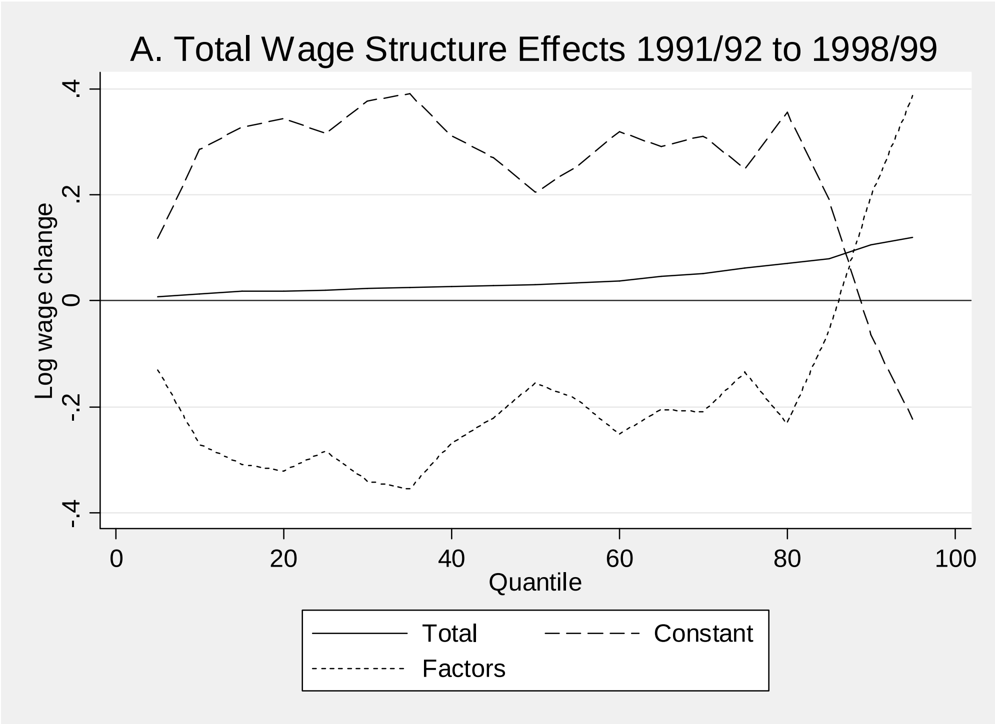


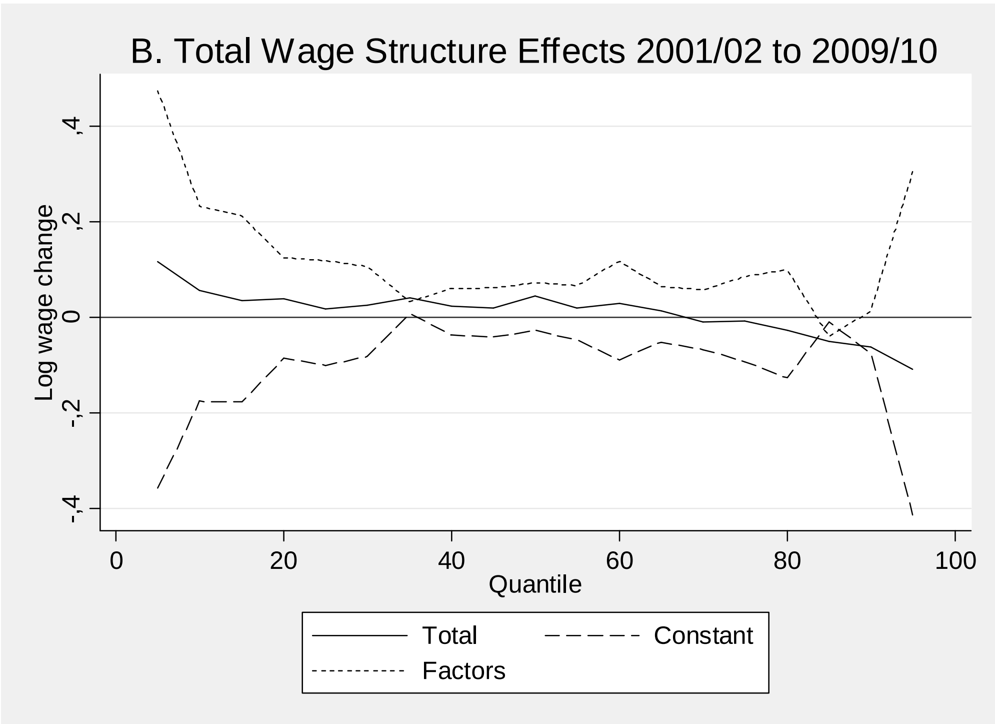
Appendix Figure A.2



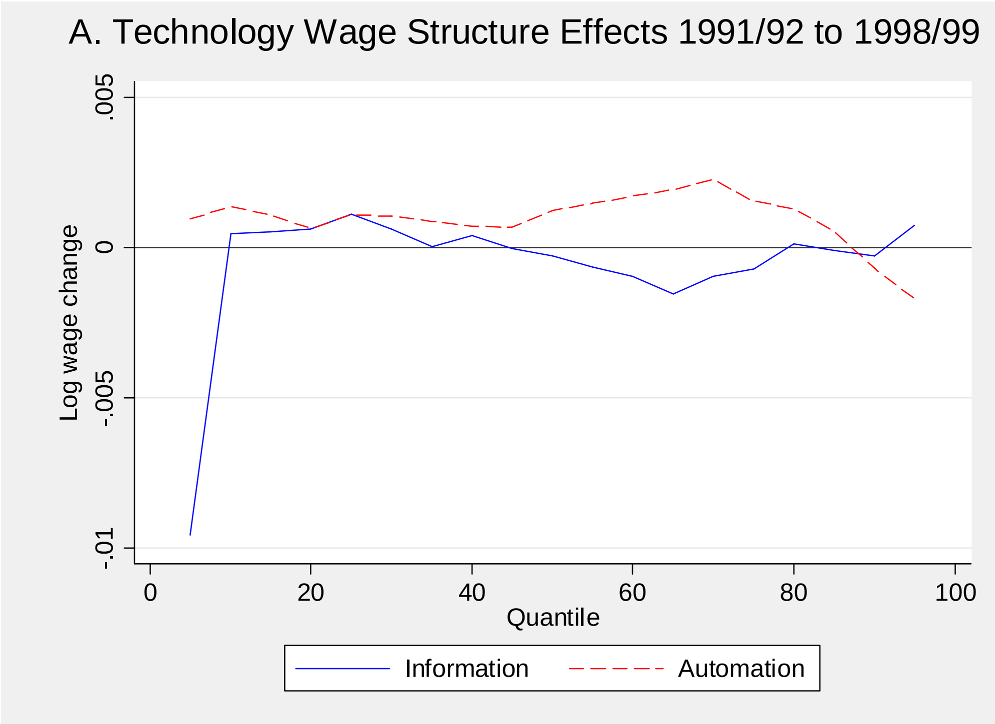


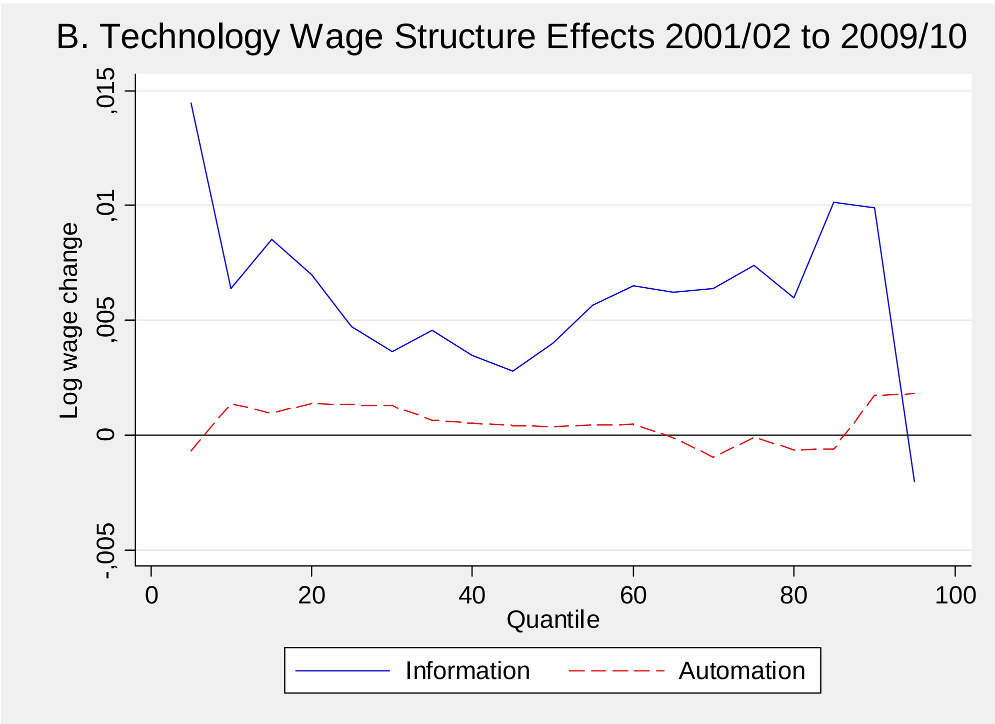
Appendix Figure A.3





Appendix Figure A.4





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