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Technology, routinization and wage inequality: Difference between men and women in the case of Uruguay

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INSTITUTO DE ECONOMÍA 06, 2019
Serie Documentos de Trabajo DT 14/2019

ISSN: 1510-9305 (en papel)
ISSN: 1688-5090 (en línea)

Este trabajo contó con el apoyo financiero del Programa CSIC I+D 2016 (Proyecto "Regresiones de Funciones de Influencia Recentrada: aplicaciones al estudio de la desigualdad de ingresos y salarios").

Forma de citación sugerida para este documento: Rodríguez López, S. Sanromán, G. (2019) "Technology, routinization and wage inequality: Difference between men and women in the case of Uruguay". Serie Documentos de Trabajo, DT 14/2019 Instituto de Economía, Facultad de Ciencias Económicas y Administración, Universidad de la República, Uruguay.

Tecnología, rutinización y desigualdad salarial: Diferencias entre hombres y mujeres en Uruguay

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Resumen

La tecnología ha ido cambiando las formas de trabajo, creando y destruyendo puestos de trabajo pero sobretodo modificando la forma tareas necesarias para llevar adelante los mismos. Este documento busca analizar la contribución del cambio tecnológico a los cambios en la distribución salarial en Uruguay y su diferencia en el impacto sobre salarios de hombres y mujeres. Para ello adoptamos el “enfoque de tareas” y estimamos regresiones cuantílicas no condicionales sobre los salarios para 2005 y 2015. Utilizando el método de descomposición basado en regresiones de influencia recentradas (RIF-Regressions), nuestras estimaciones sugieren que incorporar las tarea s ocupacionales vinculadas a la tecnología como una variable explicativa del análisis contribuye a explicar cambios en la distribución salarial durante dicho período. Encontramos, que el rol de la tecnología ha sido diferente en la explicación de la distribución salarial de hombres y mujeres. Mientras que en el caso de los hombres ha contribuido más a explicar el crecimiento de la desigualdad en el tramo superior de la distribución en el caso de las mujeres fue más relevante para explicar los cambios en el tramo inferior. Si bien el período de análisis no registra una polarización en la distribución salarial ni de hombres ni de mujeres, encontramos que la predicción de la hipótesis de rutinización de Autor, Levy y Murnane (2003) se refleja mejor en el impacto que la tecnología ha tenido en la evolución de la distribución salarial de los salarios de las mujeres.

Palabras clave: Regresiones RIF; tecnología; desigualdad salarial; desigualdad de género

Código JEL: J3, J5

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Technology, routinization and wage inequality: Difference between men and women in the case of Uruguay

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June 26, 2019

Abstract

Technology has changed the way we work, creating and destroying employment but especially modifying the occupational tasks we must perform. This paper seeks to analyze the contribution of technology to changes in the distribution of wages in Uruguay and its differences between genders. We address this question from the perspective of the task-based approach. We use the recentered influence function regression (RIF-Regression) decomposition method and apply it to men and women wage data for the period 2005-2015. Our estimates suggest that introducing occupational tasks linked to technology into the analysis contributes to explain changes in the distribution of wages in Uruguay during the period of analysis. However, technology played a different role in explaining the evolution of men and women wages. While it was relatively more important to explain the reduction in wage inequality at the top end of the distribution of men wages it was more relevant to explain changes at the lower end of the distribution of women wages. Although, nor men neither women wages did polarized during the period of analysis, we find that the predicted effect of the routinization hypothesis seems to be more in line with the impact of technology over the evolution of women wages.

JEL Classification: J3, J5

Keywords: Occupational Tasks; RIF-Regressions; Technology; Wage Inequality; Gender Inequality

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‡This research was funded by Comision Sectorial de Investigacion Cientifica (CSIC) Program I+D 2016 - grant ID 740

1 Introduction

The rapid development of new information and communication technologies and its increasing use on day to day occupational tasks has influenced labor market conditions and wages around the world. Until the nineties, there was a major consensus in the economic literature that technology was "skill-biased" and therefore contributed to increase inequality. However, in the nineties, labor markets of industrialized economies experienced polarization of wages and employment, which contradicted the traditional hypothesis of a permanent increase in inequality among skilled and unskilled workers due to technological progress (Autor and Dorn (2013)).[1] As an explanation to the observed U-shape distribution of wage changes Autor et al. (2003) (ALM henceforth) proposed the "routinization" hypothesis, relating this "polarization" to the non-neutrality of technological progress, which affects different occupational tasks in diverse ways.

According to ALM's hypothesis, technology directly competes 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, hence can be automated. However, this same technology, by performing routine tasks faster, complements and enhances the productivity of abstract and/or analytical and coordination tasks performed mostly by highly skilled workers. On the other extreme, occupations that rely on "manual" no routine tasks and flexible interpersonal communication may require very little specialization and although, not demanding a lot of skill, they may be difficult to be automated. Consequently, in these occupations (which are generally associated to personal services occupations) the automation of routine tasks has no substitution or complementation effect. Thus, information and communication technologies (ICTs) raise the relative demand for skilled and unskilled work and diminish the demand for routine work, reducing its wages and moving unskilled workers at "routine" jobs to service occupations. As a result, in this last sector the effect over wages is ambiguous, since while it increases the demand for unskilled workers it also raises its supply, leaving its net effect on wages undetermined.

The polarization pattern has been less evident in developing countries. However, the evolution of wage distribution in Latin-American countries during the 2000s also contradicts the prediction of increasing returns to skills along the whole range of the distribution derived from the "skilled biased" technological change hypothesis. During the nineties the raise in returns to tertiary education was in line with the hypothesis that information and communication technologies complement the productivity of task performed mostly by highly educated workers. However, 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 (de la Torre (2012)).

[1] See Autor et al. (2003, 2008); Goos and Manning (2007); Antonczyk and Leuschner (2009); Goos et al. (2009, 2011); Dorn (2009); Michaels et al. (2014); Jung and Mercenier (2010); Antonczyk et al. (2010); Firpo et al. (2011b)

In a recent paper Das and Hilgenstock (2018) find that the risk of displacement of labor by information technology – that is the exposure to routinization – is significantly less for developing economies than for developed ones, finding little evidence of polarization in developing countries. However, since there is a rising exposure to routinization in these last countries, there is a risk of labor market polarization in the future. Moreover, they show that among countries with high initial exposures to routinization, polarization dynamics have been strong and subsequent exposures have fallen; while among those with low initial exposure, the globalization of trade and structural transformation have prevailed and routine exposures have risen.

As argued by Hallward-Driemeier and Nayyar (2017), impacts may differ across developing economies, since the pace of change is uneven and opportunities remain in certain sub-sectors to pursue production with existing technologies and use of lower-skilled workers. However, rising routine exposures in these economies implies that currently labor-intensive industries may be getting increasingly exposed to technological disruptions, with potential for significant labor displacement.

Considering the differences documented on developed and developing countries, the goal of this paper is to quantify the contribution of the technology content of tasks to the distribution of male and female 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 between 2005 and 2015? Did the change in wage distribution is due to changes in observed characteristics of individual or because the returns to these characteristics changed over time? Given that men and women are not homogeneously distributed among occupations, does technology have different effects on the distribution of wages?

To answer these questions we follow Firpo et al. (2011b). First, using O*NET data we construct two indexes of tasks content of occupations to capture the potential effect of technological change on wage distribution. Then we incorporate these indexes into the analysis, and estimate unconditional quantile effects using the recentered influence function (RIF) regression approach of Firpo et al. (2011a, 2018). We decompose the RIF to quantify the contribution of technology in overall changes in the unconditional distribution of wages between 2005 and 2015.

The main contribution of this paper is to incorporate the task-based approach and to test the routinization hypothesis as an explanation to changes in the distribution of wages in a small emerging economy. Furthermore, as we compare the effects of technological change in male and female wages, we add new evidence to understand the evolution of gender pay gap. This is a relatively new approach which has been gaining increasing attention. Furthermore, as we follow an empirical strategy similar to the one applied for studies of the United States, this research allows comparing empirical results for different economies.

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. In section IV, we show the empirical results of the decomposition analysis and we conclude in Section V.

2 Literature Review

A general theoretical framework regarding the task-based model to explain certain empirical patterns observed in the last decades in most developed countries can be found in Acemoglu and Autor (2011). They developed a Ricardian model of the labor market based on the task content of jobs and ALM's "routinization" hypothesis to explain the effect of technological change on wage inequality. This model allows the endogenous allocation of skill groups across tasks and workers across skill groups. In this context, technical change can affect the productivity of different types of workers in all tasks, 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 and technologies 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 skill biased technological change hypothesis fits as a especial case of Acemoglu and Autor's task-based model, while in the first one a factor-augmenting technical progress always increases all wages, in the second one 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" end of the distribution.

Empirically, several studies have found evidence to support ALM's routinization hypothesis in developed countries. Using information regarding tasks involved in different occupations, Autor et al. (2003), Firpo et al. (2011a) and Autor and Dorn (2013) find evidence that technological change, and automation in particular, helps to explain the polarization of US labor market over the nineties. Similar patterns are also explained in Michaels et al. (2014) who test ALM's ICT-based polarization hypothesis for 11 industrial economies – 9 Europeans, US and Japan – for the period 1980 - 2004. Likewise Goos et al. (2009, 2011), describe labor market polarization for several OECD countries in the nineties, and find evidence that the "routinization" hypothesis is the main factor to explain the heaps observed in the employment structure. Also Oesch and Rodriguez Menes (2010), analyzing the pattern of occupational change over de last two decades in Britain, Germany, Spain and Switzerland, find a U-shaped outline of job creation which is consistent with the routinization hypothesis: massive occupational upgrading that matches with educational expansion in parallel with a decline of mid-range occupations relative to those at the bottom. Although it seems that technology is a better substitute for average-paid clerical and manufacturing jobs than for low-end service employment, they find that wage setting institutions play an important role in country differences in low-paid service job creation, channeling technological change into more or less polarized patterns.

Like industrialized economies Uruguay experienced a growing inequality process in wage distribution 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 Gradin and Rossi (2000, 2006)). Regarding employment creation, Espino (2011) finds that for the period 2001-2009 the most dynamic occupations were those requiring skills at the extremes of the distribution; i.e primary school or tertiary level, which is in line with the polarization observed in developed countries.

Contrary to Gradin and Rossi (2000, 2006), Alves et al. (2009), using data for a 1981 to 2007, find that there was no clear polarization pattern. Moreover, the evolution of inequality, as well as its determinants, was different at the upper and at the lower end of the wage distribution. For wages above the median of the distribution the increase in inequality took place mainly during the nineties and it was due to increasing returns to observed characteristics, especially to education. On the other hand, at the lower end the increase in inequality occurred during the economic crises (1981 and 2002) and was explained by changes in returns to unobserved characteristics.

Alves et al. (2009) 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 gender pay gap and the returns to education. Regarding this last issue, they observe a differentiated structure among education levels, and also that these differentials raise with wages, especially for the upper levels, which reflects 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.

Amarante et al. (2016) apply the Firpo et al. (2009, 2018) decomposition method to study the role of formalization in the labor market over the evolution of wages for 2001-2013. They found significant evidence that formalization together with a large impact of the returns to education contributed to reduce wage inequality. Using the same decomposition methodology, Yapor (2018) studies the effect of increases in minimum wages and the implementation of a progressive tax reform in wages inequality during 2005 and 2015. He finds a reduction in wage inequality and that these policies affected returns to schooling, although the most educated workers were able to, at least partially, mitigate the redistributive effect of the tax reform.

These studies show evidence that the evolution of inequality in Uruguayan labor market has not followed a monotonic pattern at the upper and at the lower ends of wage distribution. During the nineties, most studies have attributed the increase in inequality at the upper tail of the distribution to changes in returns to skill, supporting the skilled biased technology hypothesis. However, in the first decades of the 2000s we have assisted to a decrease in inequality, mostly explained by the reduction in returns to schooling and the implementation of certain policy reforms (such as the tax reform, the increase of minimum wages and the growing formalization of the labor market). But none considers changes due to technology, which according to the routinization hypothesis, may have a role to explain changes at the top as well as at the bottom of the wage distribution.

3 Empirical Strategy

3.1 RIF-Regressions and Decomposition methodology

In this section we present the RIF-regression decomposition method introduced by Firpo et al. (2009, 2011a, 2018) (FFL from here on). In what follows we present the main ideas and refer to this authors for further details. 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 the particular case of quantiles, the RIF-regression is known as unconditional quantile regression (UQR) since, unlike conditional quantile regressions, its coefficients reflect the partial effect of changes in the covariates over the unconditional quantile of the variable of interest (UQPE).

An advantage of RIF-regressions is that they allow identifying non-monotonic effects, like explanations regarding changes on wage inequality that affect specific points of the distribution. For instance, the automation of routine jobs proposed by ALM tends to affect the middle and lower-middle of the distribution. As RIF-regressions can be applied to quantiles and other distributional statistics, they represent a good methodological alternative to go beyond the mean to better understand changes in wages inequality.

Once the RIF-regressions are estimated it is straightforward to decompose the overall change of the statistic of interest (quantile, variance, Gini index, etc.) performing Oaxaca-Blinder. The idea is to use the RIF for the statistic of interest instead of the outcome variable as the left hand side variable in a regression. The estimated coefficients of the RIF-regression can be used to perform the detailed decomposition in the same way as a standard Oaxaca-Blinder decomposition (Firpo et al. (2011a)).

The proposed method presents several advantages, such as: being easy to interpret and less computational intensive than other decomposition methods like Chernozhukov et al. (2013) or Machado and Mata (2005). Another important advantage is that the detailed decomposition of wage structure and composition effects is path independent since it is possible to isolate the effect of each covariate introducing all covariates in one step.

As in the case of the standard Oaxaca-Blinder decomposition, performing a decomposition based only on the RIF-regression may have a bias problem if the linear specification used in the regression is inadequate (Firpo et al. (2018)). To solve this problem, Firpo et al. (2011a, 2018) recommend a two-step procedure to estimate the different elements of the decomposition. In the first stage, distributional changes are divided into a 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 structure and the composition effects into the contribution of each covariate, and is based on the estimation of RIF-regressions.

The aggregate decomposition consists of dividing the overall change (over time in our context) of a given distributional statistic (Δ_O^v) into the effect of changes in coefficients (structure effect, (Δ_S^v)) and in characteristics (composition effect, (Δ_X^v)).

$$\Delta_O^v = \Delta_S^v + \Delta_X^v \tag{1}$$

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).[2] 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. This lets 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.

Following Firpo et al. (2011a, 2018) we run a two-step estimation procedure, where the first step consists of estimating the weighting function $\omega_C(T, X)$ and then to compute the distributional statistics directly from the appropriately reweighted samples. The reweighting procedure, based on estimating a logit (or probit) model on the probability of being observed in period 1, generates a counterfactual observation that results if individuals of period 0 had the same distribution of observable characteristics as individuals in period 1.[3] So that, the weighing function $\omega_C(T, X)$ can be estimated as

$$\omega_C(T, X) = \frac{Pr(T=1|X)}{Pr(T=1)} \frac{Pr(T=0|X)}{Pr(T=0)} \tag{2}$$

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

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

[3]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.

$$\widehat{\Delta}_{X,R}^{v} = \left(\overline{X}_0^{C} - \overline{X}_0\right)\widehat{\gamma}_0^{v} + \overline{X}_0^{C}\left(\widehat{\gamma}_c^{v} - \widehat{\gamma}_0^{v}\right) = \underbrace{\widehat{\Delta}_{X,p}^{v}}_{\text{composition effect}} + \underbrace{\widehat{\Delta}_{X,e}^{v}}_{\text{specification error}} \tag{3}$$

where γ_0, γ_1 and γ_C are the RIF estimated coefficients for the T=0, 1 samples and the T=0 sample reweighed to have the same distribution of X as in T=1, $\overline{X}_0 = E[RIF(y_0; v_0)|X, T = 0]$ and $\overline{X}_0^{C} = E[RIF(y_0; v_0)|X, T = 1]$

The second term in equation (3) is the approximation (specification) error, linked to the fact that a potentially incorrect specification may be used for the RIF-regression. The specification 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 (Firpo et al. (2018)).

The wage structure effect can be written as

$$\widehat{\Delta}_{S,R}^{v} = \overline{X}_1\left(\widehat{\gamma}_1^{v} - \widehat{\gamma}_C^{v}\right) + \left(\overline{X}_1 - \overline{X}_0^{C}\right)\widehat{\gamma}_C^{v} = \underbrace{\widehat{\Delta}_{S,p}^{v}}_{\text{wage structure effect}} + \underbrace{\widehat{\Delta}_{S,e}^{v}}_{\text{reweighting error}} \tag{4}$$

where $\hat{\Delta}_{S,e}^{v}$ is the reweighing error, which tends to disappear in large samples if the reweighing matrix is consistently estimated and $plim(\overline{X}_0^{C}) = plim(\overline{X}_1)$. The difference between the wage structure effect in a standard Oaxaca-Blinder decomposition and that in equation (4) is that, instead of using the unadjusted regression coefficient for group 0 $\widehat{\gamma}_0^{v}$, the Firpo et al. (2018) decomposition method uses the regression coefficient when the group 0 data is reweighed to have the same distribution of X as group 1 $\widehat{\gamma}_C^{v}$. 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 hence allows to reflect solely the differences between the structures in T=1 and T=0. That is, using $\widehat{\gamma}_C^{v}$ instead of $\widehat{\gamma}_0^{v}$ allows dealing with one of the two limitations of a Oaxaca-Blinder decomposition.[4]

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 reweighed time period 0 that mimics time period 1, while the wage structure effect is obtained by comparing time period 1 and the reweighed time period 0.

[4]The standard Oaxaca-Blinder decomposition has two other 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 of its limitation is that it provides consistent estimates of the wage structure and composition effect only under the assumption that the conditional expectation is linear, then when linearity does not hold, the decomposition based on linear regression will be biased (Firpo et al. (2018)). The other one is the sensitivity of the contribution of each covariate to the wage structure effect to the choice of the base group (omitted group problem). This last limitation is not solved by the FFL method.

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 sociodemographic 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 use 2005-06 as the base year and 2014-15 as the end year.

As wage measure we use the real log hourly wage, obtained by dividing salaries deflated by Consumer Price Index and divided by hours of work.[5] We consider only wages and hours worked at the main occupation.

The study considers active men and women workers under a dependence relationship – i.e. workers that receive a salary - working at the private sector – between the ages of 25 to 64.

Table 1 reports the mean and standard deviation values of several variables for the period of analysis. For men as well as for women, the most notable changes along this period are a raise in the participation of middle (between 10 and 12 years of schooling) and high educated (more than 13 years of schooling) in detriment of those less educated (less than 10 years of schooling), together with a decrease of informal jobs and an increase of employment outside the capital city.

Figure 1 shows changes in log real wages at each percentile of the wage distribution for men and women. Between 2005-06 and 2014-15 changes in men and women real wages at each percentile of the wage distribution show an increase in wages at the lower end of the distribution higher than that at the middle, which in time is higher than that at the top end, resulting in a decrease in global inequality. So, we cannot see a polarized pattern on wage distribution. On the contrary, during the period of analysis we assist to a high equalizing phenomenon. However, it is interesting to notice that middle wages did increase less than low wages, as predicted by ALM's routinization hypothesis. In contrast, the evolution of inequality at the top end of the distribution seems to contradict the complementation hypothesis. Nevertheless, notice that while at the very top female wages registered a small increase, male wages remain almost equal. [6]

[5]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.

[6]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. 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 et al. (2010); Perazzo and Rodriguez (2007)). Besides, in 2005 collective negotiation of wages was reinstituted and since the 2008 round minimum wages by category have had a bigger increase than medium wages (Cabrera and Cárpena (2012)), which may have also impacted on the lower end of the wage distribution. Besides, Alves et al. (2012) suggest that the decrease in inequality during the lasts years is related to institutional changes such as the ones mentioned above. Yapor (2018) showed that the observed large increase in the minimum wage had an

We consider changes in men and women wage distributions separately due to the existing gender occupational segregation, which implies different task content by gender. Figure 2 shows, that women have overtaken men in their relative representation among professional and technicians, are strongly over represented among clerical, sales and service workers, but underrepresented among production, primary, construction and transportation workers. This is particularly challenging when estimating the impact of occupational task, since as seen in Table 2 an important part of the variation in the occupational task measures comes from the production operators, primary, construction and transport occupations (Firpo et al. (2011b)). Fifty eight percent of men but only 9 percent of women are in these occupations, which have very low scores for information and very high scores for automation.

3.2.1 Task content measures

To compute measures of the possible impact 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.[7] We construct a crosswalk between the national version of the International Uniform Classification of Occupation (CIUO-88), which was used by the INE to classify occupations since the 2001 ECH and the Standard Occupational Classification Code used in the O*NET classification of occupations (O*NET –SOC). For the years 2014-2015 we repeat the same procedure with the Revision 2008 of the International Uniform Classification of Occupation (CIOU-08) which was used by the INE to classify occupations since the 2012 ECH.

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.

We construct our task content measures following Firpo et al. (2011b) and Jensen and Kletzer (2010) who focus on the "Occupational Requirements" of occupations. 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 *Information Content Index* seeks to identify occupations with high information content that are likely

important effect at the low end of the wage distribution, affecting those workers with 6 or less years of education. On the other hand, the changes of tax structure reduced post-taxes wages of more educated workers, placed at the higher end of the distribution. However, the evolution of pre and post-tax wages show the same pattern.

[7] Available at www.onetonline.org. The mapping might be imperfect, and the way of performing tasks in the US might not be exactly the same as in Uruguay, thus the characteristics of occupations between one country and the other might be different. However, we believe that the main characteristics regarding the potential influence of technological change on occupations remain similar especially when we consider the classification at a more aggregated level.

to be positively 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 *Automation Content Index* is constructed using the Work Context subdomain, to reflect the degree of potential automation, including: "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 et al. (2011b). 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. 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 context 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:

$$Information\ Content_j = \sum_{k=1}^{5} I_{jk}^{\frac{2}{3}} * L_{jk}^{\frac{1}{3}} \tag{5}$$

$$Automation\ Content_j = \sum_{l=1}^{5} F_{jl} * V_{jl} \tag{6}$$

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. This gives us a ranking of occupations for each of the two dimensions.[8] We use these indexes to assess the impact of technological progress on changes in wages. Since the task content indexes are not readily interpretable, we compute quartiles of each of the two task content measures.

As it is observed in 3, alike the results reported by Firpo et al. (2011b) 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. According to the routinization hypothesis, technological change is expected to have an adverse impact on wages in this last group of occupations, which tends to be the most subject to machine displacement, while benefiting those with a more intense use of information technology.

[8]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

In Table 2 we report the average value and standard deviations of the measures of task content indexes for five major occupational groups. As it can be seen, the distribution of both indexes among occupational categories by gender shows significant differences. The average Information Index of male occupations is higher than that of female occupations, except for service and clerical workers. While, apart from professional workers, the average Automation Index is higher for female occupations.

In Table 3 we report the percentage of workers, by gender, in five major occupational groups that rank in the top quartile of each of our O*NET task content measures in 2014-2015. As expected, the higher percentage of workers in the top quartile of our information content measure is found among professional, managerial and technical occupations and among these occupations, men are more likely than women (92 percent vs. 81 percent) to be in the top quartile of our information content measure. On the other hand, more than half of production workers are in the top quartile of our automation/routine measure.

In the overall, the percentage of women in the top 25 percent of information is smaller than the percentage of men, while in the case of automation is the other way around. That is, among each occupational group women are more likely than men to perform tasks more likely to be automated, except for service occupations. However, an important part of the variation in the occupational task measures comes from the production operators, primary, construction and transport occupations and 58 percent of men but only 9 percent of women are in these occupations, which have very low scores for information and very high scores for automation.

In the group of professional, managerial and technical occupations, which is the group with the highest index of information, a smaller percentage of women than men are placed in the top quartile, although in both cases the percentage is quite large. On the other hand, in the case of automation, in the group of production and operators occupations, where only 6 percent of women are working, 70 percent of women work at occupations at the top 25 percent rank of the automation index. Besides, among clerical and sales workers, which gather 35 percent of women, more than half of them are at the top quartile degree of automation. However, women are still concentrated in the service sector (42 percent of women), which after professional and technical occupations is the group with the minor index of automation task content.

Given these dissimilarities between genders in the distribution of occupations and their degree of automation and information task content, technology is expected to impact men and women employments and salaries in a quite different way.

What is more, it is interesting to notice that in the period of analysis, while in the case of women employment increased mostly among professional and technicians and in clerical and sales occupations, in the case of men most new employments were created at the agricultural, construction and transport group. The first ones demand high and middle educated workers, and the last ones demand low educated workers. However, in the case of women, more than half percent of clerical and sales occupations are at the top quartile of our automation score. Therefore, are more vulnerable to being substitute by a machine in the future, since 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 line with ALM's routinization hypothesis we expect a monotonically increasing relationship between the "information content" of task and wages and an inverted U-shaped relation between the "automation content" of task and wages. Figure 11 confirms these patterns between our task measures and wages for the period of our analysis. Besides, we find a positive correlation of 40 and 50 percent between information task content and the level of wages of men and women respectively. However, in the case of the automation index, the correlation with wages is almost null in both cases, although is negative for men and positive for women.

4 Decomposition results: Occupational Characteristics vs. Other Factors

4.1 RIF – regressions

We first estimate the RIF-regressions for different wage quantiles. We compute the quantiles influence function, $IF(y_i; Q_\tau)$, for each observation using the sample estimate of quantile, Q_τ, and the kernel density estimate of $f(Q_\tau)$. Apart from the quartile dummies for our two measures of occupational tasks, in the regressions we include covariates suggested by the literature as the major sources of impact in the distribution of wages: education (five groups) and potential experience (nine groups)[9] (Autor et al. (2006)). We also include controls for region (capital city vs. rest of the country), marital status and being registered in the social security system (formal vs. informal workers).

We estimate RIF-regressions separately for each gender. The base group used in the RIF–regression models consists of married formal workers living in Montevideo working at the private sector with six or less years of education, 10 to 15 years of potential experience, and at the bottom quartile of each of the task content measures.[10] So, the wage structure effect for the task measure can be interpreted as the change over time in the wage impact of working at an occupation at the top quartile of our task measures content relative to working at one at the bottom quartile. In the case of composition effects of task measures, since 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.[11] In addition to the reweighing

[9]Potential experience is measured as age minus years of education minus six.

[10]The omitted group education and experience categories were chosen based on the modal of each category.

[11]The logit specification also includes a full set of interaction between experience and education, and between education, formality, location and occupation task measures.

factors, we also use the ECH sample weights throughout the empirical analysis, which in practice means that we multiply the relevant reweighing factor by the ECH sample weight.

Tables 4 and 5 report the RIF-regression coefficients at 10^{th}, 50^{th}, and 90^{th} quantiles of male and female wage distribution for the period 2005/06 to 2014/15, along with their bootstrapped standard errors.[12] Detailed estimates for the 5^{th} to the 95^{th} quantiles are also reported in Figures 4, 5 and 6.

Regarding our task measures, we find non-monotonic coefficients across the percentiles of the wage distribution that are different for men and women. In both cases we find an inverse impact between the information and automation content of task on the distribution of wages (Figure 4). In the case of men *"information task content"* 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. However, in the case of women the premium for information task content, although is increasing until the 80^{th} decile, it shows an inverted U-shape at the end of the distribution, which is in line with the results presented by Firpo et al. (2011b) for the US during the nineties. Besides, changes over time show a decreasing effect over inequality for both genders.

On the other hand, the premium to the *"automation task content"* has a positive impact in reducing inequality, mainly due to its negative impact on the upper middle of the distribution rather than a positive impact at the lower end. For both genders it exhibits a monotone decreasing impact across the wage distribution, with almost no difference among its impact through the 10^{th} to the 60^{th} decile. Nevertheless, it is interesting to notice the difference between genders: while for men the premium is almost zero until the 60^{th} decile, for women it is positive and significant until the 80^{th} 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. This would not be consistent with ALM's routinization hypothesis, that postulates that workers at the middle of the distribution are more likely to experience negative wage changes as the "routine" task they perform are more likely to be executed by machines. Rather workers at the top of the distribution seem to be the ones more negatively affected by automation.

Consequently, in the case of Uruguay during the period of analysis the effect of automation and the consequences predicted by the *"routinization hypothesis"* seem to be displaced towards the right of the wage distribution. Workers with wages over the 60^{th} percentile instead of those at 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. On the contrary, workers at the lower middle of

[12] Firpo et al. (2011b) recommend using bootstrapped standard errors for 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), to take account of the fact that the model used to construct the reweighing factor is estimated.

the distribution were the most positively affected by automation in the case of women or not affected at all in the case of men, indicating a non-substitution effect of their task by technology, which is similar to the results presented by Firpo et al. (2013) for the nineties. The heterogeneous impact of automation by genders could be explained by the prevalent presence of women at the service sector. In that sector wages tend to be placed at the lower middle of the distribution and due to the characteristics of the tasks involved are less subject to automation (see Table 2). Thus, these tasks are less subject to displacement effects.

The shift to the right of the negative impact of automation may be linked to diverse reasons: different share of occupations in Uruguay compare to labor markets in developed countries, differences in the degree of automation of task in Uruguay in relation to those markets,[13] differences in the relative cost of labor and technology in the US relative to Uruguay. That is, like in other developing countries, 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. Moreover, this seems to be consistent with the shift of the negative impact towards the middle observed at the coefficients of the automation content of tasks in the results presented by Firpo et al. (2013) for the last three decades.

As expected, in the case of education we find that 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 strongly increasing over the wage distribution in every year of the analysis, the premium for highschool dropouts (7 to 9 years) is decreasing, meaning that the differentiation between workers with primary school (our base group) and those with some years of high school is less significant for occupations that are paid with higher wages. These results are in line with the hypothesis of increasing returns to education during the nineties and the results of other studies for the Uruguayan case (Arim and Zoppolo (2000); Sanguinetti (2007); Alves et al. (2013)). Nevertheless, premiums to years of education at the top end of the distribution in 2015 diminished relative to the first years of the decade, which is also in line with the evidence of other studies regarding skill premiums in Latin American and Uruguay (de la Torre (2012); Yapor (2018)) (See Figure 5).

For 10 to 12 years of education, it is worth noticing the difference between men and women, since for men premiums are increasing along quantiles while for women these premiums decrease at the top middle of the distribution. That is, for men, to have a high school degree it is more worthy at employments with wages at the top of the distribution than for employments with wages at the bottom of the distribution. But, for women, these extra years of education have a better reward at employments which pay lower wages. A possible explanation for this might be the later entrance of women into the labor market, so

[13] 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.

men compensate with experience their fewer years of education.

It is also interesting to see the difference in the pattern displayed by the premiums to education among men and women in the case of tertiary level (13 to 15 years and 16 and more years of education). Although premiums are increasing along the wage distribution for both, women premiums at the top are under men premiums. On the other hand, the reduction in premiums at the top between 2015 and 2005 has been bigger in the case of men than in the case of women. Therefore, despite women being on average more educated than men, skill premiums received by women at the top were significantly less than those perceived by men.

In the case of region, for men as well as for women, we find that the wage gap between the capital city and the rest of the country has reduced significantly during the period of analysis. However, for women the reduction in the wage gap has been bigger for wages at the lower end of the distribution, with the negative premium becoming almost equal along the whole range of the distribution. Even though differences in male premiums between Montevideo and the rest of the country have almost disappeared, women not working at the capital city still receive a minor wage at the whole range of the distribution (see Figure 6).

4.2 Decomposition results

4.2.1 Overall Decomposition Results

The results of the decomposition are presented in Figure 7 which 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).[14] Figure 7.A and Figure 7.B illustrate the overall change in men and women real wages along the period of analysis. They show a negatively sloped curve, indicating an increase of wages at the bottom of the distribution higher than that at the top.

Table 6 summarizes the changes shown in Figure 7 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. We also report the specification errors computed as the difference between composition effects estimated using the RIF-regression and those estimated non-parametrically using a reweighed procedure. The relative small specification errors indicate that the linear RIF-regressions provide a good approximation relative to non-parametric estimates.

It is shown that overall inequality (90-10 gap) decreased along the period (50 log point for men and 42 for women). For men and women, composition as well as wage structure effects contribute to a decrease in

[14] The composition effect reported in Figure 7 only captures the component,($\hat{\Delta}_{X,p}^v$), from equation 4. 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 in the case of men and at the middle of the distribution in the case of women.

inequality. Overall, composition effects account for a small part of the decrease on inequality, since wage structure effects capture a major part of changes in the distribution of wages (94 to 88 percent). For men, changes in the distribution of wages have been led by changes at the top end of the distribution (90-50) (28 log points) complemented by a 22 log points of reduction at the lower end, explaining the decrease in inequality during 2005 to 2015. For women, on the other hand, the reduction in wage inequality was almost equality distributed between the higher and the lower end (50-10) of the distribution, due to the fact that the reduction of inequality for women at the top end have been smoother than for men (21 log point vs. 28 log points). However, composition effects only contribute to explain the reduction in inequality at the lower end of the distribution of female wages.

4.2.2 Detailed Decomposition Results

The next step is to obtain the detailed decomposition using RIF-regressions to compute the contribution of each set of covariates to the composition and the wage structure effects. Figure 8 reports the composition effect of the covariates that were grouped into five categories: technological content of tasks: information and automation content (first quartile omitted), education (5 dummy variables – 6 years or less omitted), experience (9 dummy variables – 15 to 20 years of experience omitted) and the control variable group others that includes, region, marital status and being registered in the social security system.[15]

In the 2005/06 to 2014/15 period overall inequality decreases. However, the composition effect related to education, has a positive contribution to increase inequality for men as well as for women. Although, composition effects linked to education are more important for women than for men at the bottom end of the distribution, where they account for 1.3 log point growth in the 50-10 gap. Regarding the other covariates, it is significant the role played by formality, which contributes to the reduction of inequality but, with some difference between men and women. While it is more important to reduce top end inequality in the case of men it is more relevant to decrease low end inequality in the case of women. These results are consistent with the sharp increase of workers registered at the social security system during the period of analysis, and specially of domestic workers.

The contribution of each set of covariates to the wage structure effect is reported in Figure 9 and in Panel B of Table 7 . It also reports the change in the intercept in the RIF–regressions which captures the part of the wage structure effect that cannot be explained by returns to covariates. 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 et al. (2011b)).

The total change of wages is mostly led by changes in the aggregate wage structure effect, which is clearly seen in Figure 7 . The change in inequality of male wages at the top end as well as at the low end

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

is explained mainly by a reduction in the returns to education and of those related to the information content of task (54 percent of the decline in the 90-50 gap and 19 percent of the decline at the 50-10 gap). What is more, as seen in Figure 9, the sum of factors in the wage structure shows a certain polarization pattern similar to that seen in the US during the nineties, led by education and technology, but that affects mostly the top end of the distribution.

The estimated wage structure effect of -5.61 log points of our technological task measures (the sum of automation and information content tasks) accounts for 20 percent of the decline in the 90-50 gap of men, while the effect at the bottom end (-1.3 log points) accounts for 6 percent in the decrease in the 50-10 (See Table 7). The information content of task has an equalizing effect at the top as well as at the low end of the distribution, while the automation content of task operates the other way around, but in a smaller magnitude (Figure 10) Therefore, the wage structure effects linked to technological change does not have the polarizing effect predicted by the ALM routinization hypothesis in the case of male wages.

Regarding female wages, there are some differences in the factors that explain the reduction in inequality, particularly with regard to our task content measures. Technological change accounts for 14 percent of the decline in the 50-10 gap and only 1 percent of the decline of inequality at the top of the distribution. While, as expected, at the higher end of the distribution, information has an enhancing effect over inequality, it has a reducing effect at the lower end. Meanwhile, automation task content has an equalizing effect at the top as well as at the bottom of the distribution of wages. However, a large part of the reduction in the top end inequality is mostly seen by a reduction in the constant, leaving an important part of the reduction unexplained. On the other hand, at the bottom end, the reduction in inequality is mostly explained by changes in returns to observable characteristics considered.

To sum up, changes in the return to occupational task measures linked to technology, as captured by the occupation task measures included in the RIF–regressions, have a significant contribution to explain the changes in the distribution of wages observed during the period of analysis. Considering both task contents together, technology has a positive effect in reducing inequality at the higher end of the distribution as well as at the lower end. However, while its contribution to changes of men wages was more important at the top end, in the case of women it was more relevant to explain changes at the lower end.

As predicted by ALM's routinization hypothesis, a substitution effect would have prevailed at the lower middle of the distribution, particularly in the case of women where the effect of automation overcomes that of information. On the contrary, in the case of men, contrary to expected, the impact of information was more important than that of automation to explain the reduction of inequality between the 50^{th} and the 10^{th} decile.

Regarding the top end of the distribution we find a complementation effect of the information content of task in the case of women which is offset by a substitution effect of the automation content of task, resulting in a small inequality reducing effect. In the case of men however, the expected complementation effect is better captured by automation content of task which is more than compensated by a significant reduction in the premium to the information content of tasks. Then, contrary to expected a substitution rather than a complementation effect might have prevailed at the upper end of the distribution of men wages.

Consequently, during the period of analysis, the predicted polarization of wages of ALM's routinization hypothesis seems to be more appropriate to explain the behavior of female rather than male wages.

5 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), region and formality. We do so by using a decomposition method proposed by Firpo et al. (2009) based on the influence function regression approach. We have applied this methodology to Uruguay data for the period 2005-2015 where wage inequality presented a clearly decreasing pattern. Although these evolution does not appear to be in line with the polarization predicted by ALM's routinization hypothesis middle wages did increase less than low wages, as predicted by ALM's routinization hypothesis.

As well as other studies (Amarante et al. (2016); Yapor (2018); among others) we find evidence that the decrease of wage inequality was mostly due to the reduction in returns to education. These studies also attributes this decrease to institutional factors occurred during this period, like the reduction of informality, the large increase in minimum wages and the implementation of a tax reform that affected wages of most educated workers.

Nonetheless, our estimates suggest that technology is also relevant to explain the observed changes in the distribution of wages in the period of analysis, which is consistent with the extended adoption of technology by economic sectors. What is more, as expected, considering the dissimilar distribution of employments among sectors between men and women, we find that the impact of technology over wage distribution is also different between genders.

A number of interesting conclusions emerge from the analysis. First, women are strongly overrepresented among clerical, sales and service workers, but underrepresented among production, primary, construction and transportation workers, sectors which are more prone to automation. Although, on average the mean degree of automation among task performed by men and women is similar, like Brussevich and Kochhar (2018) we find that in all sectors women are over represented in tasks with the higher degree of automation and underrepresented in task with higher degree of information – that is that requires more analytical or abstract thinking-. Second, the change in inequality of wages of men was led by the top end of the distribution while for women this change was equally distributed along the whole range of the distribution. Third, the wage structure effects linked to technology, as captured by the occupation task measures, help to explain the reduction in wage inequality between 2005 and 2015. However, its contribution is different for men and women. While technology is relatively more important to explain the reduction in wage inequality at the top end of the distribution of men wages, it is more relevant to explain changes at the lower end of the distribution of women wages. Fourth, the predicted effect of routinization hypothesis seems to be more in line with the evolution of women wages in the period of analysis rather than the evolution of men wages. Finally, the predicted effects of automation over wage distribution, is displaced towards the right end of the distribution compared to what is observed in developed countries like the US. That is, in the case of Uruguay, like other developing countries, 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 low and therefore, there would be fewer incentives to substitute labor by technology.

Summing up, introducing tasks and occupations into the analysis helps to understand changes in wage distribution in Uruguay. In fact, during 2005 - 2015 technology had a polarizing effect over women wages. However, this polarizing effect is not present in the case of men wages where the reduction in the premium to the information task content has a major role. On the contrary in this case technology has an equalizing effect.

Despite these findings, a great deal of the distribution of wages remains unexplained. During this period it 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, as shown by other studies.

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Table 1: Descriptive statistics

Variable:	2005/06		2014/15		Diff. in means
	Mean	s.d	Mean	s.d	2015 - 2015
A: Men					
Log wages	3.760	0.76	4.278	0.59	0.518
Non-married	0.261	0.44	0.281	0.45	0.020
Age	40,506	10.68	40.532	10.59	0.026
Education					
6 years or less	0.286	0.45	0.261	0.44	-0.025
7 to 9 years	0.325	0.47	0.281	0.45	-0.044
10 to 12 years	0.246	0.43	0.305	0.46	0.059
13 to 16 years	0.067	0.25	0.078	0.27	0.011
16 and more years	0.076	0.27	0.075	0.26	-0.001
Rest of the country	0.491	0.50	0.558	0.50	0.068
Not registered	0.207	0.41	0.093	0.29	-0.114
B: Women					
Log wages	3.600	0.77	4.110	0.61	0.509
Non-married	0.437	0.50	0.379	0.49	-0.058
Age	41,240	10.53	41.090	10.45	-0.151
Education					
6 years or less	0.247	0.43	0.197	0.40	-0.051
7 to 9 years	0.261	0.44	0.228	0.42	-0.034
10 to 12 years	0.277	0.45	0.347	0.48	0.070
13 to 16 years	0.102	0.30	0.105	0.31	0.003
16 and more years	0.113	0.32	0.124	0.33	0.011
Rest of the country	0.438	0.50	0.525	0.50	0.087
Not registered	0.276	0.45	0.119	0.32	-0.157

Number of observations: 2005/2006 38,145 2014/2015 47,992

Source: Compiled by authors based on ECH 2005, 2006 and 2014, 2015 data.

Table 2: Average O*NET Indexes by Major Occupation Group 2005-2015

	Men		Women		Diff. in means	
O*Net Indexes	Information	Automation	Information	Automation	Information	Automation
Overall Mean	0.595	0.739	0.612	0.732	- 0.017 ***	0.007 ***
Standard Deviation	0.116	0.062	0.113	0.061		
Manager , Professionals, Technicians	0.794	0.704	0.774	0.682	0.021 ***	0.022 ***
Clerical support and sale workers	0.668	0.741	0.671	0.747	- 0.003 **	- 0.006 ***
Plant and machines operators and assemblers	0.549	0.773	0.518	0.804	0.031 ***	- 0.031 ***
Agricultural, construction and transport workers	0.546	0.740	0.541	0.746	0.005 **	- 0.006 ***
Service workers	0.534	0.712	0.538	0.725	- 0.004 ***	- 0.013 ***

Source: Compiled by authors based on ECH 2005, 2006 and 2014, 2015 data and O*NET.

Note: The information content index is computed as $IC_j = \sum_{k=1}^{5} I_{jk}^{\frac{2}{3}} * L_{jk}^{\frac{1}{3}}$ where where $k =$ *"work activities"*: Getting information, Processing information, Analyzing data or information, Interacting with computers, Documenting/Recording information. The automation content is defined as $AC_j = \sum_{l=1}^{5} F_{jl} * V_{jl}$ where $l =$ *"work context"*: Degree of automation, Importance of repeating same tasks, Structured versus unstructured work (reverse), Pace determined by speed of equipment, Spend time making repetitive motions. Task measures are normalized to range between zero and one.

Table 3: Percentage of Workers in the Top Quartile of Task Content Indexes by Major Occupation Group in 2014/2015

	Percentage of workers		Technology			
Task Content Indexes			Information		Automation	
	Men	Women	Men	Women	Men	Women
Overall	100	100	25	22	23	25
Manager, Professionals, Technicians	12	15	92	81	1	5
Clerical support and sale workers	18	35	52	30	22	56
Plant and machines operators and assemblers	19	6	3	0	51	70
Agricultural, construction and transport workers	38	3	11	0	23	31
Service workers	13	42	0	0	1	0

Source: Compiled by authors based on ECH 2005, 2006 and 2014, 2015 data and O'Net.

Note: The numbes in each of the task content incexes columns indicate the percentage of workers in each major occupation by gender, which fall in the top 75 percent of their category.

Table 4: Unconditional Quantile Partial Effects on Men Log Hourly Wages (2005 - 2015) - RIF Regression

Covariates	2005/06			2014/15		
Quantile	10	50	90	10	50	90
Information content	0.109***	0.256***	0.799***	0.099***	0.193***	0.424***
	(0,029)	(0,022)	(0,052)	(0,016)	(0,013)	(0,027)
Automation content	0.020	-0.039*	-0.313***	0.045***	0.007	-0.218***
	(0,027)	(0,019)	(0,047)	(0,014)	(0,011)	(0,024)
Education (6 years or less omitted)						
From 7 to 9 years	0.190***	0.177***	0.148***	0.156***	0.130***	0.102***
	(0,028)	(0,018)	(0,024)	(0,016)	(0,011)	(0,012)
From 10 to 12 years	0.283***	0.369***	0.573***	0.238***	0.302***	0.344***
	(0,030)	(0,023)	(0,041)	(0,017)	(0,013)	(0,017)
From 13 to 15 years	0.354***	0.634***	1.453***	0.299***	0.504***	0.951***
	(0,035)	(0,036)	(0,104)	(0,020)	(0,021)	(0,050)
16 and more years	0.367***	0.797***	2.988***	0.353***	0.700***	2.066***
	(0,037)	(0,035)	(0,168)	(0,020)	(0,020)	(0,084)
Experience (15<Experience<20 omitted)						
Experience<5	-0.019	-0.074	-2.074***	0.034	-0.084**	-1.325***
	(0,056)	(0,050)	(0,213)	(0,026)	(0,036)	(0,118)
5<experience<10	-0.007	-0.145***	-0.929***	0.000	-0.132***	-0.559***
	(0,030)	(0,036)	(0,088)	(0,020)	(0,019)	(0,039)
10<experience<15	-0.103***	-0.149***	-0.184***	-0.032	-0.060***	-0.158***
	(0,035)	(0,023)	(0,041)	(0,020)	(0,016)	(0,022)
20<experience<25	0.037	0.106***	0.144***	0.053***	0.060***	0.074***
	(0,034)	(0,024)	(0,046)	(0,020)	(0,015)	(0,023)
25<experience<30	0.075**	0.138***	0.276***	0.056***	0.095***	0.151***
	(0,032)	(0,025)	(0,048)	(0,020)	(0,014)	(0,021)
30<experience<35	0.079**	0.158***	0.216***	0.068***	0.117***	0.188***
	(0,033)	(0,026)	(0,047)	(0,019)	(0,016)	(0,025)
35<experience<40	0.087**	0.147***	0.248***	0.074***	0.137***	0.230***
	(0,037)	(0,025)	(0,046)	(0,021)	(0,016)	(0,026)
Experience>40	0.037	0.160***	0.277***	0.078***	0.107***	0.173***
	(0,039)	(0,024)	(0,041)	(0,020)	(0,015)	(0,023)
Nonmarried	-0.094***	-0.174***	-0.188***	-0.071***	-0.111***	-0.132***
	(0,023)	(0,017)	(0,025)	(0,012)	(0,009)	(0,016)
Region	-0.099***	-0.101***	-0.173***	-0.052***	-0.020**	-0.042***
	(0,018)	(0,013)	(0,028)	(0,010)	(0,008)	(0,014)
Informal	-0.518***	-0.347***	-0.063**	-0.554***	-0.239***	-0.001
	(0,034)	(0,018)	(0,025)	(0,031)	(0,012)	(0,014)
Constant	2.837***	3.471***	4.406***	3.443***	3.942***	4.705***
	(0,048)	(0,030)	(0,056)	(0,023)	(0,018)	(0,028)

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

Source: Compiled by authors based on ECH 2005, 2006 and 2014, 2015 data and O*NET.

Number of observations 2005/2006: 20,264 ;2014/15: 24,847.

Table 5: Unconditional Quantile Partial Effects on Women Log Hourly Wages (2005 - 2015) - RIF Regression

Covariates	2005/06			2014/15		
Quantile	10	50	90	10	50	90
Information content	0.212***	0.536***	0.713***	0.031**	0.349***	0.563***
	(0,031)	(0,029)	(0,064)	(0,015)	(0,018)	(0,038)
Automation content	0.199***	0.248***	-0.103**	0.201***	0.185***	-0.186***
	(0,026)	(0,022)	(0,048)	(0,017)	(0,013)	(0,029)
Education (6 years or less omitted)						
From 7 to 9 years	0.206***	0.124***	0.054***	0.150***	0.079***	0.029***
	(0,038)	(0,021)	(0,019)	(0,022)	(0,013)	(0,010)
From 10 to 12 years	0.296***	0.272***	0.223***	0.328***	0.322***	0.167***
	(0,039)	(0,023)	(0,027)	(0,025)	(0,013)	(0,015)
From 13 to 15 years	0.347***	0.562***	0.815***	0.422***	0.588***	0.610***
	(0,043)	(0,033)	(0,067)	(0,027)	(0,020)	(0,037)
16 and more years	0.367***	0.770***	2.016***	0.465***	0.738***	1.782***
	(0,044)	(0,036)	(0,106)	(0,028)	(0,022)	(0,069)
Experience (15<Experience<20 omitted)						
Experience<5	0.084*	-0.082*	-1.420***	0.020	-0.108***	-0.973***
	(0,050)	(0,047)	(0,165)	(0,022)	(0,029)	(0,107)
5<experience<10	0.050	-0.124***	-0.510***	0.006	-0.088***	-0.372***
	(0,035)	(0,028)	(0,067)	(0,019)	(0,017)	(0,039)
10<experience<15	-0.011	-0.082***	-0.149***	-0.029	-0.092***	-0.097***
	(0,037)	(0,022)	(0,043)	(0,022)	(0,014)	(0,026)
20<experience<25	0.027	0.090***	0.103**	0.049**	0.023	0.056**
	(0,040)	(0,027)	(0,043)	(0,019)	(0,014)	(0,026)
25<experience<30	0.103***	0.135***	0.132***	0.042**	0.054***	0.096***
	(0,038)	(0,027)	(0,042)	(0,021)	(0,015)	(0,027)
30<experience<35	0.090**	0.144***	0.180***	0.065***	0.064***	0.176***
	(0,042)	(0,025)	(0,048)	(0,022)	(0,014)	(0,028)
35<experience<40	0.146***	0.171***	0.163***	0.077***	0.061***	0.143***
	(0,044)	(0,028)	(0,048)	(0,021)	(0,017)	(0,030)
Experience>40	0.067	0.234***	0.181***	0.041*	0.060***	0.106***
	(0,045)	(0,027)	(0,039)	(0,025)	(0,015)	(0,024)
Nonmarried	-0.098***	-0.092***	-0.115***	-0.048***	-0.072***	-0.084***
	(0,021)	(0,015)	(0,025)	(0,011)	(0,007)	(0,015)
Region	-0.310***	-0.252***	-0.196***	-0.108***	-0.113***	-0.095***
	(0,026)	(0,016)	(0,024)	(0,011)	(0,010)	(0,016)
Informal	-0.506***	-0.147***	-0.074***	-0.613***	-0.154***	-0.030**
	(0,042)	(0,016)	(0,020)	(0,034)	(0,012)	(0,013)
Constant	2.501***	3.022***	4.159***	3.176***	3.633***	4.520***
	(0,054)	(0,036)	(0,054)	(0,032)	(0,023)	(0,045)

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

Source: Compiled by authors based on ECH 2005, 2006 and 2014, 2015 data and O*NET.

Number of observations 2005/2006: 17,875 ;2014/15: 23,144.

Table 6: Aggregate Decomposition Results

Inequality Measure: 2005/06 - 2014/15	90-10	90-50	50-10
A: Men			
Total Change	-0.4976 ***	-0.2819 ***	-0.2157 ***
	(0.0015)	(0.0013)	(0.0009)
Composition	-0.0310 ***	-0.0160 ***	-0.0150 ***
	(0.0012)	(0.0010)	(0.0004)
Wage Structure	-0.4678 ***	-0.2735 ***	-0.1942 ***
	(0.0014)	(0.0011)	(0.0009)
Specification Error	-0.0028	0.0018	-0.0046 ***
	(0.0019)	(0.0016)	(0.0011)
Reweighing Error	0.0040 ***	0.0058 ***	-0.0018 ***
	(0.0007)	(0.0005)	(0.0001)
B: Women			
Total Change	-0.4204 ***	-0.2181 ***	-0.2022 ***
	(0.0014)	(0.0010)	(0.0010)
Composition	-0.0417 ***	0.0029	-0.0446 ***
	(0.0032)	(0.0026)	(0.0010)
Wage Structure	-0.3692 ***	-0.2235 ***	-0.1457 ***
	(0.0017)	(0.0014)	(0.0012)
Specification Error	0.0037	0.0095 ***	-0.0058 ***
	(0.0030)	(0.0025)	(0.0006)
Reweighing Error	-0.0131 ***	-0.0070 ***	-0.0061 ***
	(0.0019)	(0.0017)	(0.0014)

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

Source: Compiled by authors based on ECH 2005, 2006 and 2014, 2015 data.

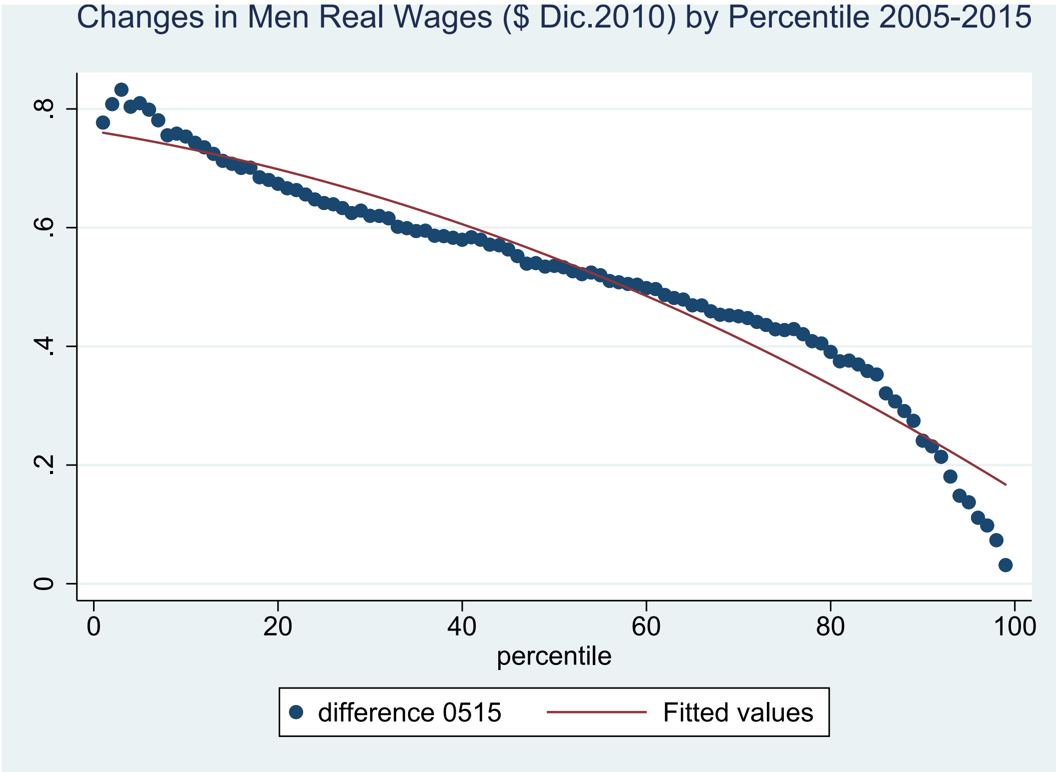
Table 7: Detailed Decomposition Results based on Unconditional Quantile Partial Coefficients

	Men			Women		
Inequality Measure:	90-10	90-50	50-10	90-10	90-50	50-10
A: Detailed Composition Effects:						
Information	-0.0004	-0.0003	-0.0001	-0.0049***	-0.0015***	-0.0034***
	(0,0004)	(0,0003)	(9,7221)	(0,0004)	(0,0001)	(0,0003)
Automation	-0.0056***	-0.0047***	-0.0009***	-0.0306***	-0.0374***	0.0069***
	(0,0002)	(0,0001)	(5,7353)	(0,0006)	(0,0007)	(0,0002)
Education	0.0281***	0.0194***	0.0087***	0.0334***	0.0204***	0.0130***
	(0,0009)	(0,0008)	(0,0002)	(0,0030)	(0,0023)	(0,0008)
Experience	-0.0121***	-0.0101***	-0.0020***	-0.0105***	-0.0067***	-0.0038***
	(0,0004)	(0,0003)	(0,0001)	(0,0005)	(0,0004)	(0,0002)
Others	-0.0511***	-0.0336***	-0.0176***	-0.0542***	-0.0049***	-0.0493***
	(0,0004)	(0,0003)	(0,0002)	(0,0005)	(0,0003)	(0,0004)
Total Composition Effect	-0.0310***	-0.0160***	-0.0150***	-0.0417***	0.0029	-0.0446***
	(0,0012)	(0,0010)	(0,0004)	(0,0032)	(0,0026)	(0,0010)
B: Detailed Wage Structure Effects:						
Information	-0.0815***	-0.0664***	-0.0151***	0.0034	0.0124***	-0.0089***
	(0,0012)	(0,0011)	(0,0007)	(0,0024)	(0,0020)	(0,0012)
Automation	0.0121***	0.0103***	0.0018***	-0.0266***	-0.0149***	-0.0117***
	(0,0010)	(0,0009)	(0,0005)	(0,0022)	(0,0015)	(0,0012)
Education	-0.1034***	-0.0824***	-0.0210***	-0.0502***	-0.0495***	-0.0007
	(0,0025)	(0,0023)	(0,0017)	(0,0044)	(0,0031)	(0,0035)
Experience	-0.0110***	-0.0093***	-0.0018	0.0178**	0.0780***	-0.0602***
	(0,0031)	(0,0024)	(0,0018)	(0,0088)	(0,0043)	(0,0061)
Others	0.0717***	0.0286***	0.0430***	0.0057***	0.0191***	-0.0135***
	(0,0018)	(0,0015)	(0,0012)	(0,0021)	(0,0019)	(0,0019)
Constant	-0.3827***	-0.2400***	-0.1427***	-0.3148***	-0.2712***	-0.0436***
	(0,0060)	(0,0050)	(0,0040)	(0,0109)	(0,0094)	(0,0074)
Total Wage Structure Effect	-0.4678***	-0.2735***	-0.1942***	-0.3692***	-0.2235***	-0.1457***
	(0,0014)	(0,0011)	(0,0009)	(0,0017)	(0,0014)	(0,0012)

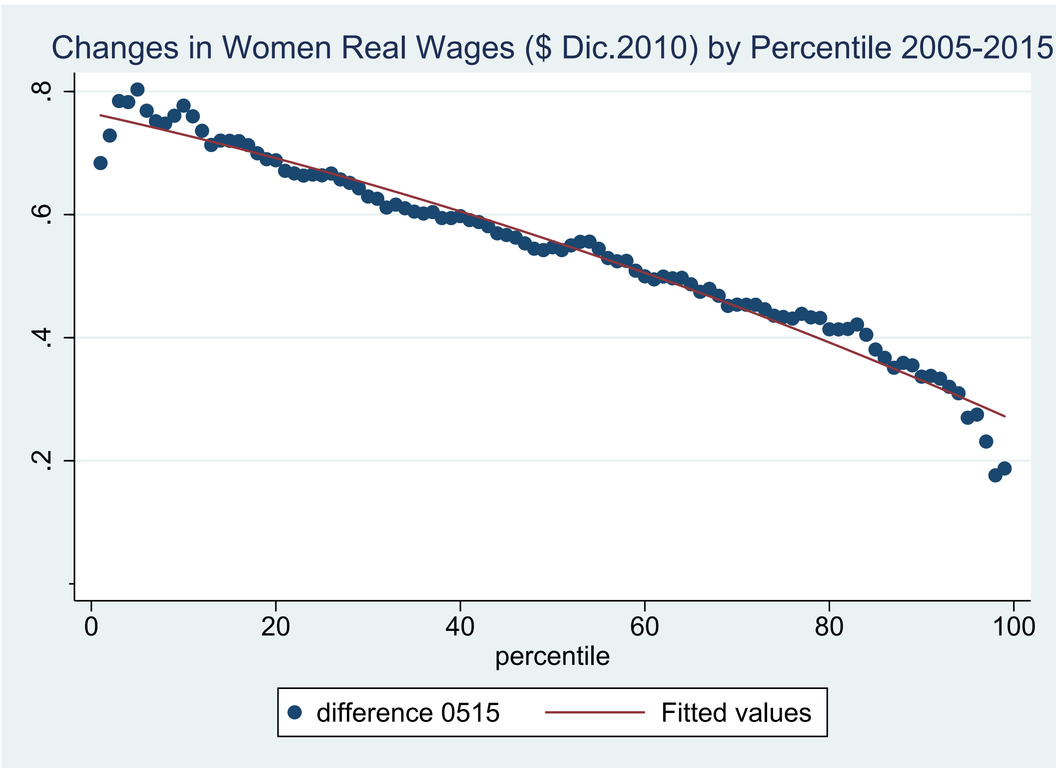
*** p<0.01, ** p<0.05, * p<0.1

Source: Compiled by authors based on ECH 2005, 2006 and 2014, 2015 data and O*NET. Number of observations 2005/2006: 17,875 ;2014/15: 23,144.

Figure 1: Difference in log-hourly wages between 2005 and 2015 (2010 prices) at each percentile

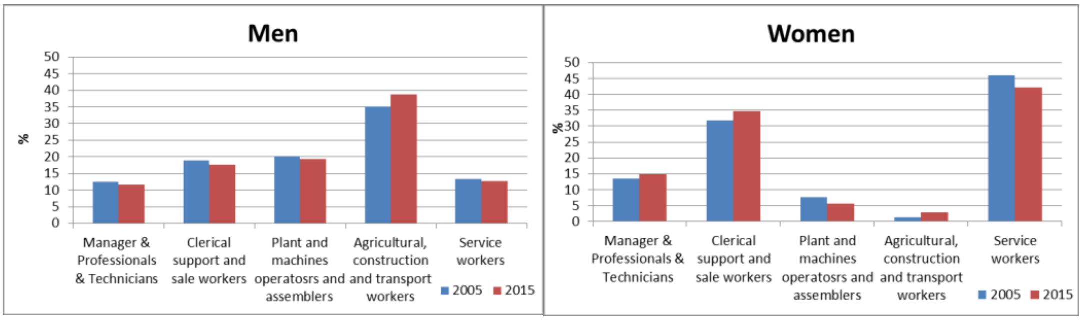


(a) Male



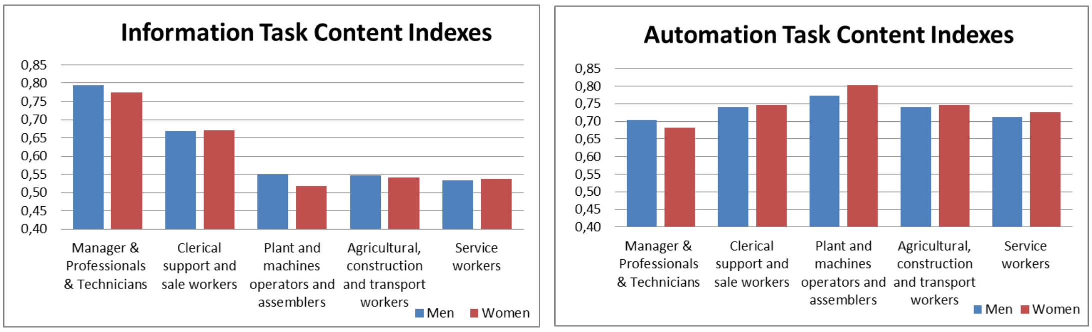
(b) Female

Figure 2: Occupational category by gender



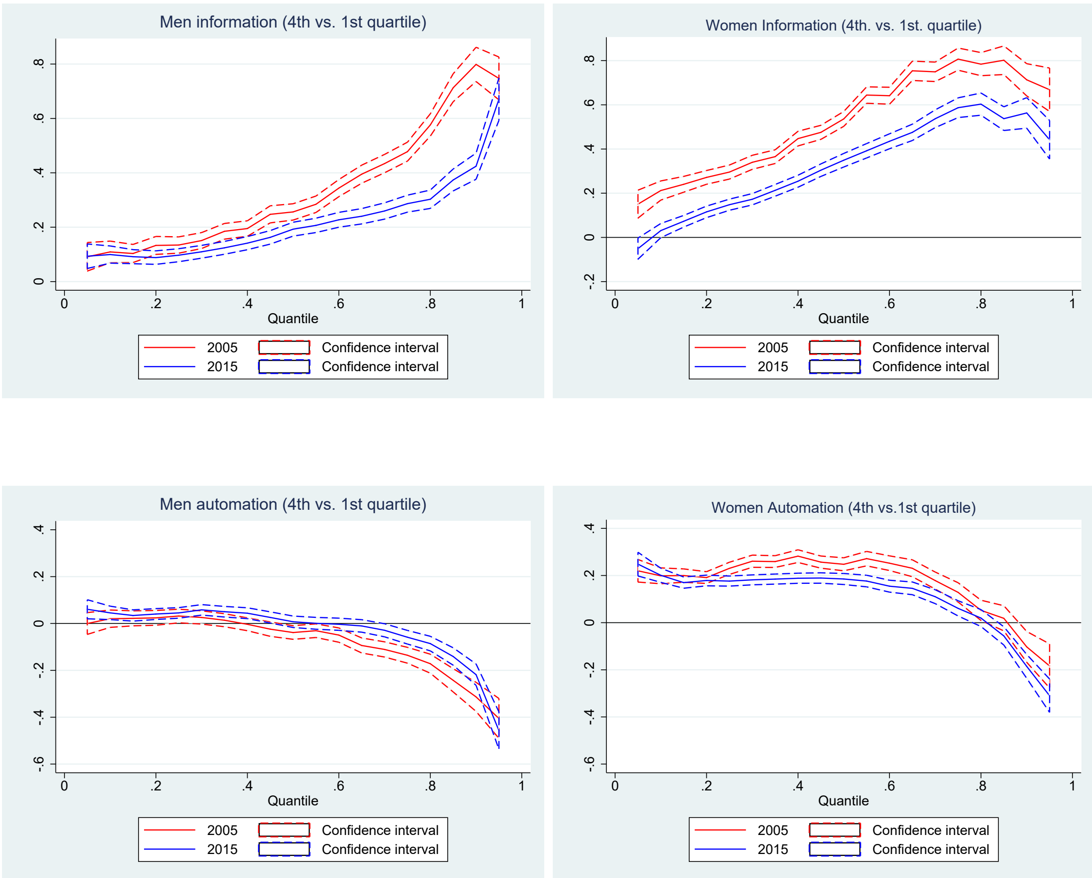
Note: Percentage of private workers by occupational category and gender in 2005 and 2015.

Figure 3: Task Content measure by Occupational Category



Source: Compiled by authors based on ECH-INE and National Center for O*NET Development.

Figure 4: Unconditional Quantile Partial Effects: Occupational Task 2005 – 2015. Forth vs First Quartile of Task Content



Notes: 1. Figures show the effect of the task indexes for the upper quartile when the bottom quartile is omitted. 2. Solid lines are point estimates, dashed lines are confidence intervals. Red and blue lines are for 2005 and 2015, respectively. 3. Partial effects are computed using Unconditional Quantile Regression of Firpo et al. (2018). Confidence interval are based on bootstrap standard errors using 200 replications. 4. Information/Automation covariates are defined as category variables that indicate the degree of information/automation task content of the job. Four quartiles are considered.

Figure 5: Unconditional Quantile Partial Effects: Selected Education Covariates

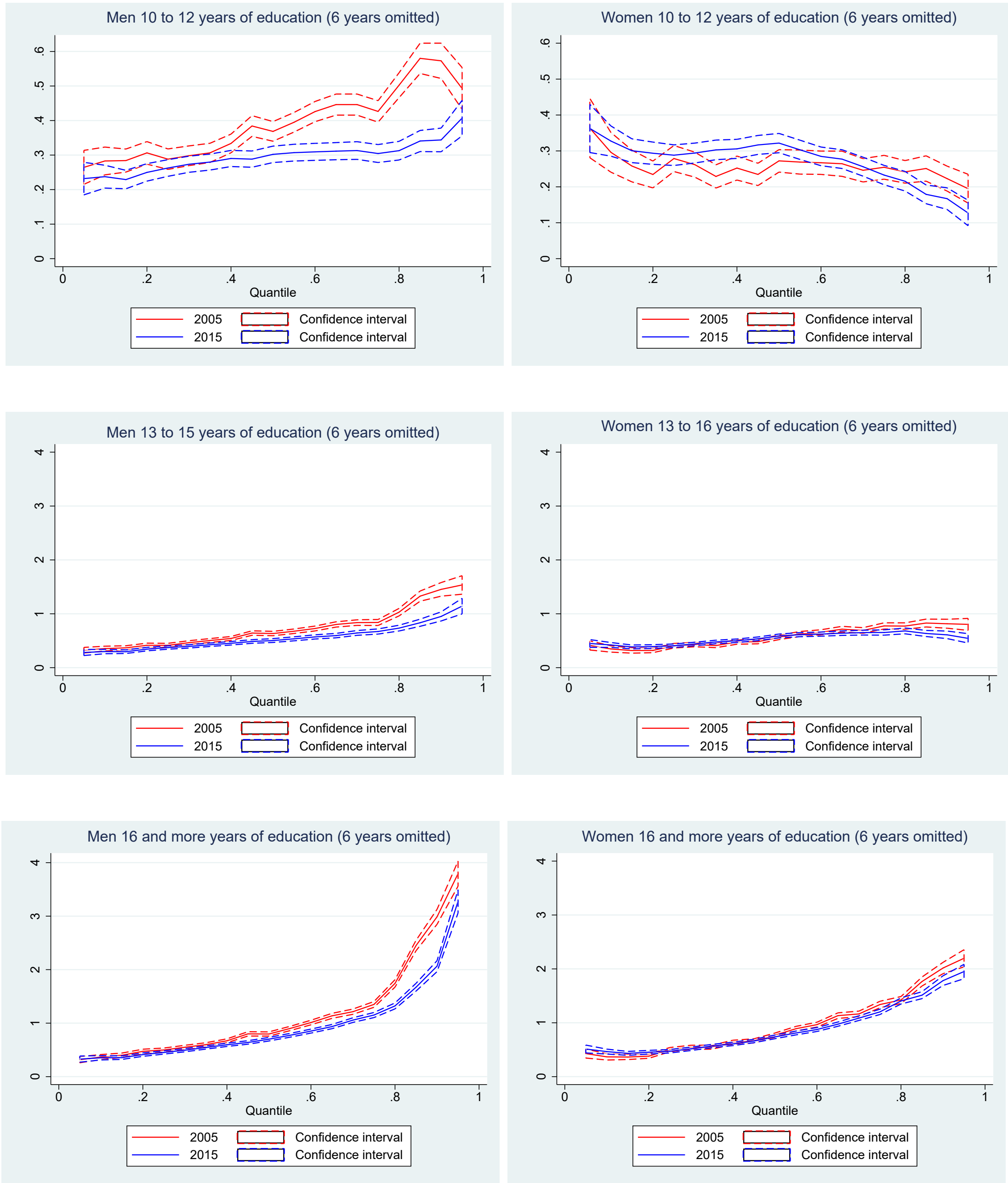


Figure 6: Unconditional Quantile Partial Effects: Selected Demographic Covariates

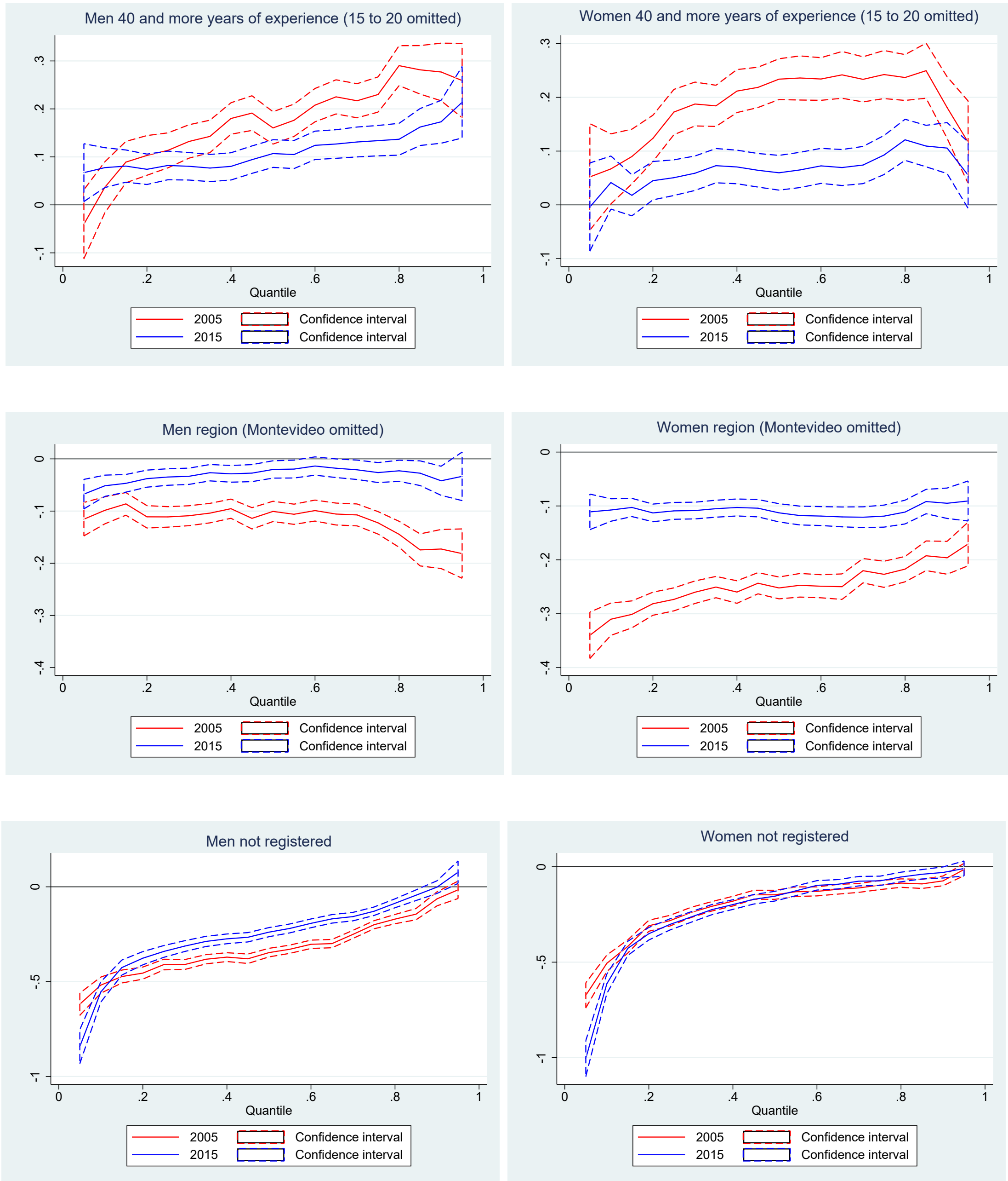


Figure 7: Decomposition of Total Change into Composition and Wage Structure Effects

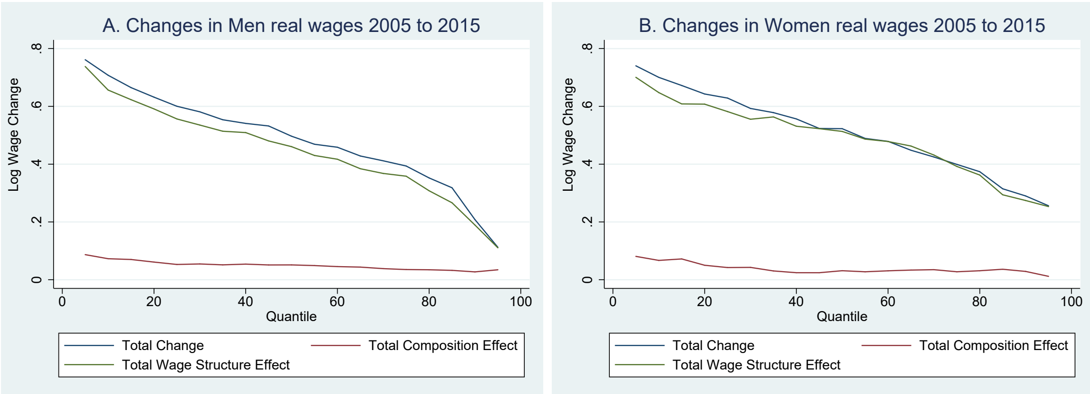


Figure 8: Detailed Decomposition of Composition Effects

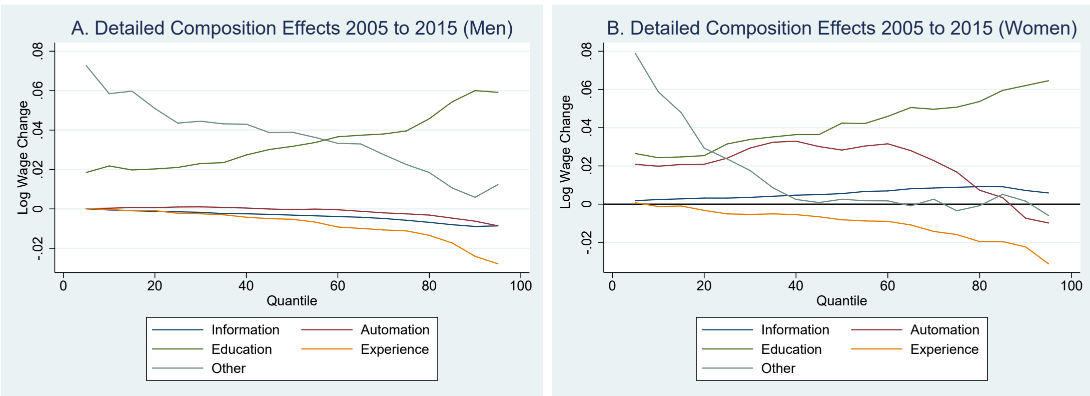


Figure 9: Detailed Decomposition of Wage Structure Effects

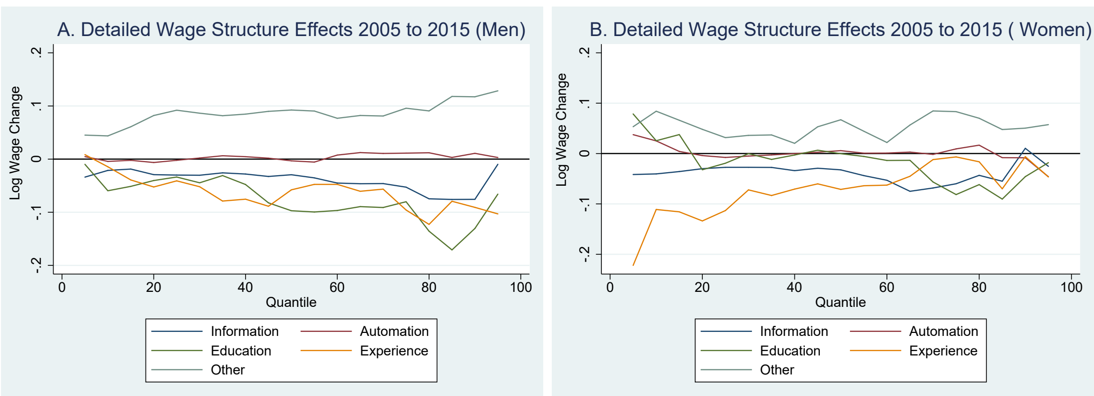


Figure 10: Technology Detailed Wage Structure Effects

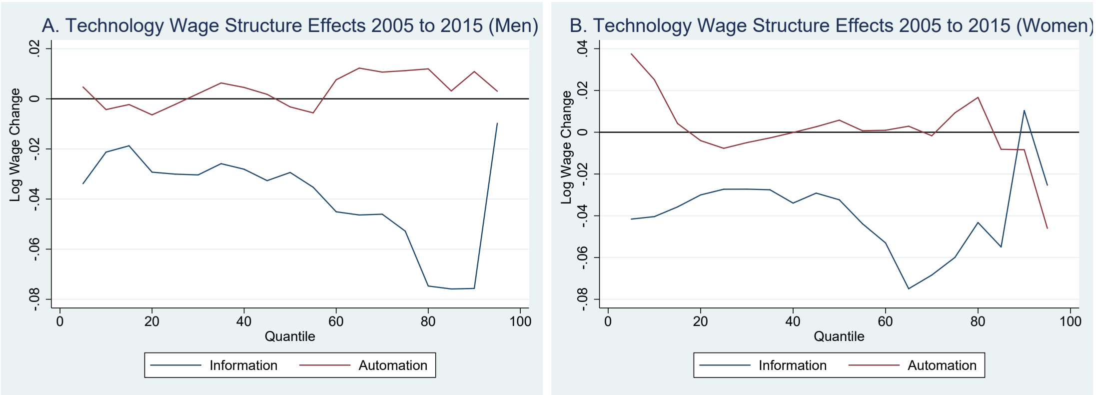
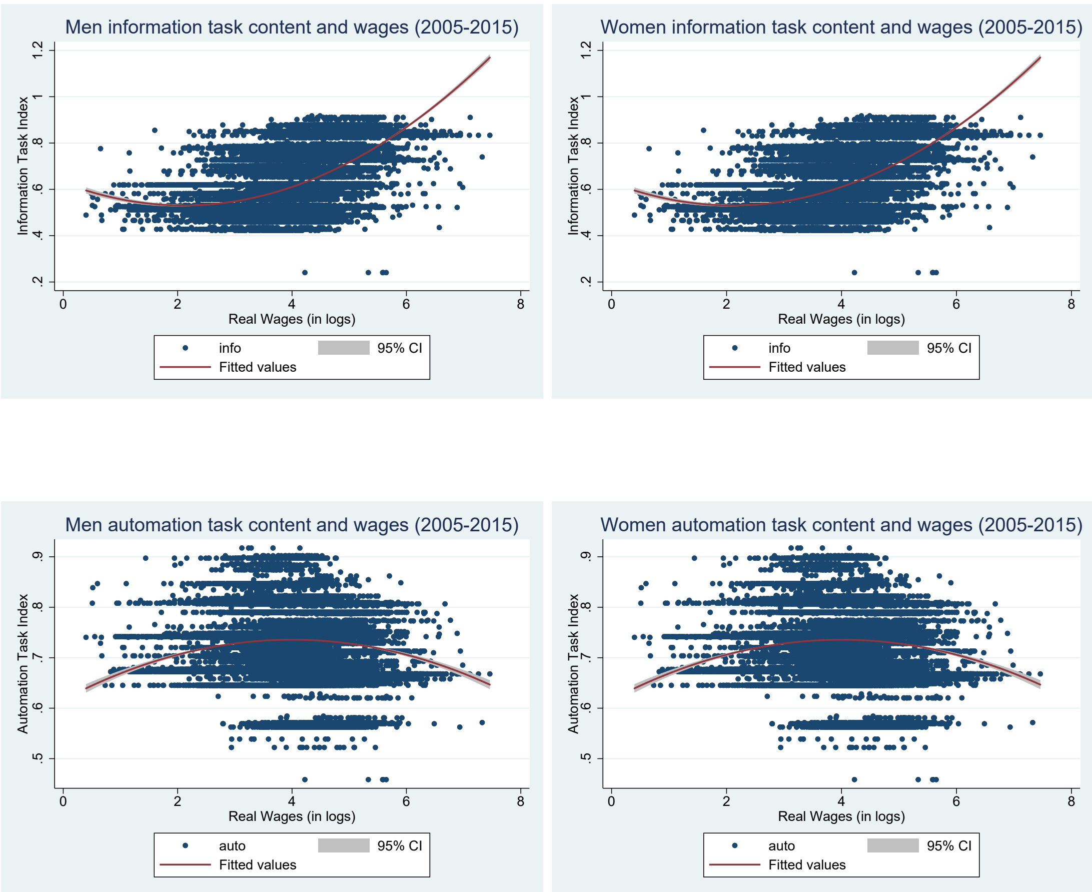


Figure 11: Wages and Task Content Indexes



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Facultad de Ciencias Económicas y de Administración

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