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# Technological change in Uruguay. Labor polarization and distributional effects

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## Tabla de contenido

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## Abstract

Technological change, particularly the automation processes, although it could achieve increases in the economy's overall productivity, also brings with it a distributive risk. This potential phenomenon could be as a consequence of the displacement of human labor due to the automation of particular tasks, especially those of a routine nature. This work explores the hypothesis of labor polarization in Uruguay between 2003 and 2017. The results found suggest the existence of a very incipient process of polarization of the labor force. Contrary to what has been observed in developed countries, with the exception of employment in high-skilled occupations and therefore high productivity, which has increased its participation in total employment between 2003 and 2017, the rest of the Uruguayan labor force still maintains stability in their shares or with insignificant reductions. On the other hand, those occupations with lower productivity show a moderate process of aging of their workers, while reducing the average age of workers in higher productivity occupations or intensive in non-routine cognitive tasks. Finally, the changes occurred in terms of the contents of tasks performed by the workers have not had an impact on the distribution of labor income. Indeed, the inequality has decreased during our period under study and this has been particularly as a consequence of the drop in returns to education in those occupations with higher qualifications.

**Keywords**: Technological change, Labour polarization, task content.

**JEL Classification**: J01, J22, J24.

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# 1. Introduction

The technological change process that Uruguay is going through implies a great opportunity in terms of achieving increases in the global productivity of the economy. This is particularly important in economies such as the Uruguayan, which are at an advanced stage of their demographic transition and require productivity increases to sustain the growth rate of GDP per capita in a context of reduction in the size of the labor force. However, if this process is not accompanied by complementary investments, that is, institutional reforms and public policies aimed at capitalizing on the advantages that this process permits, then the technological advance could also deepen a situation of inequality. This potential phenomenon could be as a consequence of the displacement of human labor due to the automation of particular tasks, especially those of a routine nature. This type of task requires the methodical repetition of a constant and time-invariant procedure and, for this reason, they are very susceptible to being specified in an algorithm and executed from a computer program.

During the last twenty years there has been a change in the profile of employment in Uruguay in terms of the tasks content performed by workers in their occupations. The average job went from performing intensively routine manual tasks to routine and non-routine cognitive tasks. Apella and Zunino (2018) define an indicator that captures the relative importance of four types of tasks, cognitive/manual and routine/non-routine, based on the information provided by the O*NET database and household surveys. Authors observe that in the last two decades the relative importance in the use of cognitive tasks (including those that are routine) has increased while the prevalence of manual tasks has been reduced.

In this technological race, the challenge for public policy is associated with the need for low and medium-skilled workers to reassign their tasks to others that are not susceptible of automation. This group of workers, that is, those who intensively perform routine tasks in their occupations, represent a large proportion of the labor market. Although during the last two decades there has been a significant reduction in the importance of routine manual tasks in employment, at the same time there was an increase in those routine cognitive tasks. These tasks have a high exposure to the risk of automation and therefore the workers who develop them would require readjustment to perform other types of non-automated (non-routine) tasks.

In a context of changes in the task content performed by workers in their occupations there is a risk of polarization of employment. The automation of routine tasks, both manual and cognitive, could modify the structure of the labor market, remaining in the limit represented by two large groups of workers. On the one hand, those with high qualification working in occupations intensive in the use of non-routine cognitive tasks, with high productivity and high labor income. On the other hand, a group of low-skilled workers, relegated to occupy positions in occupations intensive in non-routine manual tasks, with low productivity and therefore low labor income. This would happen while the workers with middle level of qualification generally performing routine tasks (manual and cognitive) face a lower demand of employment. In this sense, occupations intensive in this type of tasks, such as credit analysts, office assistants, cashiers, vendors, publishers, or even translators, are those through which mid-skilled workers are located.

Given the change in the profile of employment that has been observed in Uruguay in recent decades, the objective of this paper is to identify the existence of a tendency to a polarization of the employment biased towards non-routine tasks and the distributive effects that this process implies. For this purpose, we analyze the labor market in Uruguay during the period between 2003 and 2017, focusing on the evolution of the occupational structure according to the task content, and its effects on the distribution of labor income.

A better understanding of the implications of technological change on the labor income distribution of labor is important for several reasons. First, in Latin America, labor income inequality is the main reason of changes in income inequality (Lustig et al., 2013, Cord et al., 2017). Likewise, changes in labor income have consequences on poverty and social mobility. Third, technological change is a phenomenon that, although it had an impact on the employment profile, has not been complete and would still have more intense effects. For this reason, this work tries to anticipate the shocks and think and design public policy strategies aimed at mitigating the adverse effects.

This paper is structured as follows. The following section presents the theoretical framework and review the literature associated with the potential impact of technological changes on the labor market and the associated impact in terms of labor income distribution. The third section describes the methodology and the source of information. In section four the results are presented in terms of the changes in the occupational structure according to the task content and the potential trend of polarization. The fifth section describes the recent changes in labor income and presents a decomposition exercise of these changes in order to estimate the how much is attributable to technological change, in comparison with other characteristics of workers and changes in the returns to these characteristics. Based on the results found, the following section presents some public policy suggestions. Finally, the main conclusions are presented in summary.

## 2. Theoretical framework

A key idea present in recent literature is that technological change, especially automation, replaces human labor in the performance of tasks within occupations. Bresnahan (1999) and Autor et al. (2003) provide evidence showing that new production technologies are frequently used to automate routine tasks, both cognitive and manual. This is because this type of tasks is repetitive and follows an explicit set of rules that can be easily coded and run using computer software.

In some cases, automation is considered a problem of machines replacing human work completely. For example, Frey and Osborne (2013) started evaluating 70 occupations to determine which can be "completely automated" using equipment controlled by any state-of-the art software. In collaboration with a group of researchers specialized in machine learning, they proposed in 2013 that, with current production technology, 37 occupations are susceptible to full automation, including several which are very popular today, such as accountants, auditors, bank loan agents and mailmen. Based on this analysis, authors project that nearly half of all jobs are susceptible to full automation in the near future.

However, a distinction that frequently leads to different diagnostics about the impact of technological change on the labor market is noteworthy. Following Bessen (2016), automating a task is not a synonym of automating a full occupation. Occupations involve a combination of tasks that are performed by workers. New production technologies do not automate occupations; they rather automate the tasks that may be specific to an occupation or similar in different occupations. Therefore, in an occupation, automation may be partial (if only some tasks are automated) or full (if all tasks are automated). The economic difference between these concepts is important: full automation implies a net loss of jobs; partial automation does not. In the 19$^{th}$ century, 98% of the labor required to weave a unit of cloth was automated, however, the number of weaving jobs increased (Bessen 2016). This happened because of the increased efficiency obtained with the incorporation of new production technologies, which was reflected in lower final prices, which, due to the highly elastic demand, translated into an increased demand for textiles and, therefore, in a net increase of employment.

The paradigmatic example of this phenomenon in modern times is the implementation and expansion of automatic teller machines (ATMs) of US commercial banks. These ATMs would allow substituting most of the tasks performed by a bank employee. However, since the massive expansion of ATMs in the 90s, the number of full-time bank employees has also increased[4]. This phenomenon has been explained by the lower costs of opening new banking branches generated by the possibility of using ATMs, which encouraged the operation of new branches and, therefore, an increasing demand for employment (Bessen 2016).

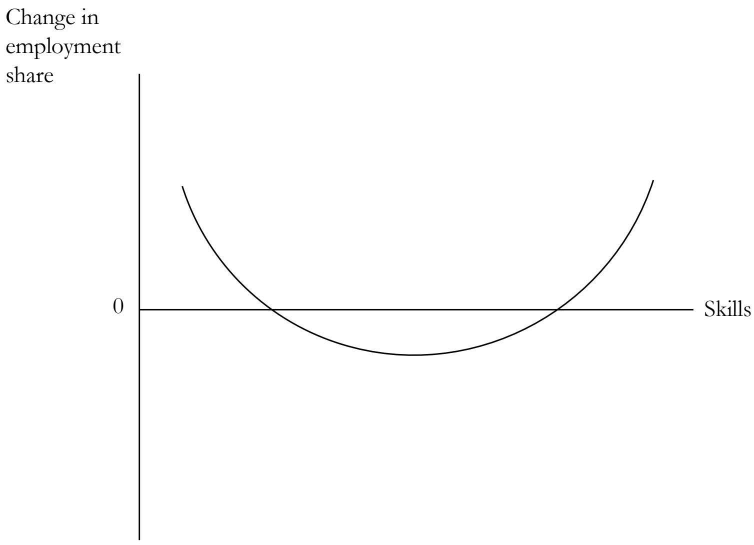
It seems clear that while the net effect of technical change on aggregate employment demand is not obvious, a change of profile can be expected. In this respect, technological change poses a risk for the labor market, which is not so much associated with the concept of technological unemployment as it is with its distributive impact. This discussion comes from the approach known as “task-biased technological change”. According to this hypothesis, technological change tends to automate “routine tasks” that follow procedures that can be easily defined and specified following a series of instructions that can be run using computer equipment. Autor et al. (2008) proposed the hypothesis of biased technological change as an explanation of labor polarization.

This may lead to a polarization process, with employment concentrating in two main groups of workers. On the one hand, high-skilled, high-productivity, high-wage workers performing non-routine cognitive intensive tasks; on the other hand, a group of low-skilled workers relegated to non-routine manual intensive tasks and, therefore, with low

[4] Between 1999 and 2009, 200 thousand ATMs were deployed in the US financial sector, while the demand for bank tellers increased at a 2% annual rate.

levels of productivity and low wages. In turn, mid-skilled and medium-wage workers, generally performing routine tasks (manual and cognitive) would face a lower demand for labor (Acemoglu and Autor, 2011; Acemoglu, 2002; Autor and Dorn, 2009; Autor, 2015). Diagram 1 represents this phenomenon in theory.

Diagram 1. Polarization of the Labor Market




This shift from routine tasks increases the relative demand for labor with higher concentration in non-routine cognitive tasks that require creativity, strong problem-solving or interpersonal skills and non-routine manual that require situational adaptability, visual recognition, language use, and interpersonal skills. These two types of non-routine skills lie at the opposite ends of the skill/income distribution: cognitive skills are usually performed by high-skilled workers, while manual tasks require a low level of qualification and, therefore, imply lower incomes.

Polarization is one of the main characteristics of the shifts observed in the occupational structure in the US and Western Europe: over the last three decades, there was a trend towards an increasing share of both low- and high-skilled jobs (Goos and Manning, 2007). Bussolo et al. (2018) obtained similar results for Germany and Spain. Using harmonized data from the European Union Labor Force Survey, Goos et al. (2008) found that in 14 of the 16 European countries for which there is available data, high-wage occupations grew compared to medium-wage occupations between 1990 and 2000, and in all 16 countries, low-wage occupations grew relative to medium-wage occupations.

According to the literature, polarization of employment is a phenomenon mainly of developed countries. In emerging economies, there is a lower number of available jobs and evidence is not consistent with the results found for developed countries. In fact, Keister and Lewandowsky (2016) for Central and Eastern Europe, and Messina et al. (2016) for Latin America did not find evidence of labor polarization. In this group of countries, routine cognitive task intensive employment requiring medium-skilled workers increased its share in overall employment. Complementarily, Maloney and Molina (2016) found that only in two of the twenty-one developing countries analyzed there is evidence of labor polarization.

In fact, the evolution of wage distribution during the 2000s is opposite to the predictions of the biased technological change hypothesis. In the labor markets of the countries of the region, including Uruguay, there has been a reduction in wage inequality during the first decade of the 21st century, mainly associated with a decrease in the returns to skills, particularly in the returns to secondary education level (Messina and Silva, 2018).

In Uruguay, previous studies show that the reduction in income inequality during the first decade of the 2000s is mainly explained by changes in the returns of formalization and education. Amarante et al (2016) show that the composition effect, that is to say, the differential in salaries attributed to the change in the characteristics of workers and their occupations - classified according to their task content -, has little impact. This is because that increase in formality induces wage increases in the first percentiles of the distribution and lower inequality, but the increase in the educational level causes a greater variation in the highest salaries, with an increase in inequality. These two combined effects result in the low impact of the composition effect. In the case of returns, both the formalization and the educational level have an impact in the same sense: the change in the formality award influences the higher wages in the lower size of the distribution and the returns to education level also have a positive effect on wage changes in the lower part of the distribution. But these effects become negative in the upper size of distribution.

The most direct antecedent to this study is the work of Rodriguez Lopez (2014) based on a “task approach” that shows that the tasks content in the different occupations contributes marginally to explain the changes in the salary distribution of the men in Uruguay between the end of the 90s and the beginning of the 2000s. However, it is not the automation, but the information content of occupations that seems to be behind the found effect.

# 3. Methodology and source of information.

## 3.1 Task content and labor polarization

An empirical measurement of polarization involves ranking occupations based on the income or qualification level. This work addresses the analysis of the labor polarization hypothesis through two complementary empirical approaches to the extent they rest on different strategies to rank occupations according to the qualification level required: the first strategy uses mean wages to measure polarization, while the second one look at the prevalence of different task types in different jobs.

For the first approach, considering that the correlation between wage and schooling years (skill level proxy) is not only significant and positive, but also ordinally stable, literature has used mean wage as a variable to rank occupations to analyze the changes in the occupational structure (Autor and Dorn 2009; Goos, et al., 2014). Furthermore, it is assumed that hourly wage represents a good approach of occupation average productivity, which is also positively related to the workers' skill level.

Based on this proposed definition and methodology, we ranked occupations by their average hourly wage at the beginning of the analyzed period and grouped them into 40 intervals (40-tiles)[5]. Then, we have calculated the change in the employment share of each occupational 40-tiles over the 2003-2017 period. The polarization hypothesis would be consistent with a simultaneous growth in the relative share of occupations with higher and lower-level productivity (hourly wages) in the labor market, as the relative share of mid-level productivity occupations decreases.

An alternative option to analyze the potential incidence of a non-neutral technical change process is that developed by Bussolo et al. (2018). In this case, building on the conceptual framework proposed by Acemoglu and Autor (2011), the authors classify occupations into three categories: occupations relatively intensive in routine tasks, occupations relatively intensive in non-routine, cognitive tasks, and occupations relatively intensive in non-routine, manual tasks.[6]

The main source of information used is the Continuous Household Survey, complemented with the O*NET database (Occupational Information Network), which provides information referring to the task content of occupations.

## 3.2 Decomposition based on Recentered Influence Functions (RIF) Regressions

The decomposition method proposed by Fortin, Firpo and Lemieux (2011), abbreviated as FFL, is based on a regression estimate where labor income –the independent variable– is replaced with a transformation thereon, the recentered influence function (RIF). The RIF allows to measure, in distributional statistics –for example, deciles– the effect of small changes in the underlying distribution. One of the greatest advantages of this type of decomposition is that it enables to calculate the unconditional marginal effect of marginal changes in an explanatory variable of labor income from different parts of the distribution.

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5 Although occupations are usually grouped in hourly wage percentiles, the analysis in this work is based on 40 intervals. This lower number of categories is due to the fact that, in practice, the information of the CHS for the period does not allow to monitor occupations at that level of disaggregation. Specifically, it works with the three-digit ISCO code, which entails monitoring a total of 132 occupations.

6 Grouping occupations into three exclusionary categories is a limited approach because, to a lesser or greater extent, each occupation involves different types of tasks. In this regard, this grouping strategy necessarily implies identifying the most relevant tasks on a case-by-case basis. This could mean, however, that occupations characterized in a certain way could be at the same time characterized by a significant intensity in other types of tasks. This grouping strategy, i.e. building statistics that summarize the average task content for each of the categories, is included in the Annex to this work.

Following FFL, for each decile of the labor income distribution FY, v(F) measures the importance of each observation in the conformation of the value of such statistic. In general terms, a RIF-regression coefficient can be interpreted as the contribution of one observation to the individual statistic of interest.

$$\mathrm{RIF(Y) = v(F) + IF(Y)}$$

In the case of quantiles, the influence function IF $(\mathrm{Y}; \mathrm{Q}_\tau)$ is given by $(\tau - \mathrm{I}\{\mathrm{Y} \leq \mathrm{Q}_\tau\})/\mathrm{f_Y}(\mathrm{Q}_\tau)$, where I$\{\cdot\}$ is an indicator function, $\mathrm{f_Y}(\cdot)$ is the density of the marginal distribution of Y, and $\mathrm{Q}_\tau$ is the population quantile of the unconditional distribution of Y. Therefore, RIF$(\mathrm{Y}; \mathrm{Q}_\tau)$ equals $\mathrm{Q}_\tau + \mathrm{IF}\ (\mathrm{Y}; \mathrm{Q}_\tau)$, and can be rewritten as:

$$\mathrm{RIF}(\mathrm{Y}; \mathrm{Q}_\tau) = \mathrm{Q}_\tau + \frac{\tau - \mathrm{I}\{\mathrm{Y} \leq \mathrm{Q}_\tau\}}{\mathrm{f_Y}(\mathrm{Q}_\tau)} = \mathrm{c}_{1,\tau} \cdot \mathrm{I}\{\mathrm{Y} > \mathrm{Q}_\tau\} + \mathrm{c}_{2,\tau},$$

Where $\mathrm{c}_{1,\tau} = 1/\mathrm{f_Y}(\mathrm{Q}_\tau)$, and $\mathrm{c}_{2,\tau} = \mathrm{Q}_\tau - \mathrm{c}_{1,\tau}(1-\tau)$. We can observe, then, that except for the constants $\mathrm{c}_{1,\tau}$ and $\mathrm{c}_{2,\tau}$, the RIF for a quantile is simply an indicator $\mathrm{I}\{\mathrm{Y} \leq \mathrm{Q}_\tau\}$ when the outcome variable is smaller or equal to the quantile of interest. In other words, the RIF can be computed empirically through a local inversion that specifies whether the value $\mathrm{Y}$ is smaller or equal than $\mathrm{Q}_\tau$. After calculating the RIF for the statistic of interest, we obtain a value of the variable transformed for each observation of the sample. These values are used to estimate a regression of Ordinary Least Squares (OLS) of the RIF variable in a vector of explanatory variables under the assumption that the conditioned expected value of the RIF function can be shaped as a linear function of the explanatory variables, and that the effect of the change in the distribution of an explanatory variable in the statistic can be expressed, ceteris paribus, as the average partial effect of that variable on the conditioned expected value of its RIF function. The coefficients obtained in the OLS regression can, therefore, be interpreted as the effect of an increase in the mean of an explanatory variable in the quantile of interest.

Specifically, this study estimates two sets of unconditional regressions where the explanatory variables include workers' observable characteristics, such as age, educational level, economic activity sector; and five variables that (approximately) have a zero mean and variance equal to 1, according to the task-content of each ISCO-08 occupation and which capture the occupational intensity in tasks classified as: Routine Cognitive (RC), Routine Manual (RM), Non-Routine Cognitive - Analytical (NRCA), Non-Routine Cognitive - Interpersonal (NRCI), Non-Routine Manual (NRM).

The estimated coefficients in the regression described above are used to calculate a standard Oaxaca-Blinder decomposition in each statistic. This decomposition can be described as follows:

$$\Delta_\mathrm{v} = (\overline{\mathrm{X}}_\mathrm{s} - \overline{\mathrm{X}}_\mathrm{t})\hat{\theta}^*{}_\mathrm{v} + \left\{\overline{\mathrm{X}}_\mathrm{s}\left(\hat{\theta}_\mathrm{t,v} - \hat{\theta}^*{}_\mathrm{v}\right) + \overline{\mathrm{X}}_\mathrm{t}\left(\hat{\theta}^*{}_\mathrm{v} - \hat{\theta}_\mathrm{s,v}\right)\right\}$$

Where $\Delta_v$ represents the difference in the statistic v between the wage distributions for the years t and $s$; $\overline{X}_t$ and $\overline{X}_s$ are the average characteristics of each year, and $\hat{\theta}_{s,v}$ and $\hat{\theta}_{t,v}$ denote the coefficients estimated on the basis of the RIF regression of the statistic v over the set of explanatory variables for the years t and s. The first component of the equation, $(\overline{X}_s - \overline{X}_t)\hat{\theta}^*{}_v$, is the effect of the differences in the statistic of the difference in characteristics, also known as the "explained" component or composition effect. The second component, $\overline{X}_s(\hat{\theta}_{t,v} - \hat{\theta}^*{}_v) + \overline{X}_t(\hat{\theta}^*{}_v - \hat{\theta}_{s,v})$, known as the "unexplained" component, belongs to the effect of changes in coefficients.

## 3.3 Data

In the present work, we analyze the evolution of the labor market in the last 14 years (2003-2017).[7]To carry out this analysis, we use the information available in the O*NET (Occupational Information Network) database in combination with the Continuous Households Surveys releved by the National Statistic Institute of Uruguay. This database provides information referring to the content of tasks of the occupations. Since 2003, O*NET data have been collected in the United States for approximately 1000 occupations based on the Standard Occupational Classification (SOC), and it has been updated periodically.[8]

Following the work of Acemoglu and Author (2011) four sets of O*NET data are used: skills, work activities, work context and skills. Each of them contains descriptors that try to measure the importance, level or scope of the activity from a scale. For this, data from O*NET 2003 and 2015 are used in order to capture the content change of the tasks within each occupation over time.

In order to estimate the content of the tasks in the occupations, the elements of the tasks provided by O*NET are mapped to the corresponding occupations of four digits in the International Standard Classification of Occupations (ISCO). This is combined with individual labour force data from household surveys. In general, each country has a specific version of the ISCO or, at least, in cases where a national classification is used, an ISCO equivalence is applied. On the other hand, O*NET follows a modified version of the Standard Occupational Classification (ONET-SOC). In order to be able to combine the appropriate occupational attributes to the household survey data, an equivalence table between these two classifications is used.

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[7] The period is limited by the ability to track the different occupations. Prior to 2003, the continuous household survey identifies occupations using the Cota 70 code, which does not have a unique correspondence with the ISCO classification. The selection of the period forces to restrict the analysis to populations of 5000 or more habitants, because at the beginning of the period the surveys only covered these populations.

[8] O*NET is the successor of DOT (Dictionary of occupational titles) which is no longer updated. O*NET was launched in 1998 on the basis of the BLS Occupational Employment Statistics codes. In 2003, it was changed to SOC which implies that the consistent measures of task content are calculated from 2003.

Previous studies have worked with the sample of men in the labor force to avoid the selection problem in the labor market.[9] This study considers both men and women aged 15 and over who are active in the labor market and receive remuneration for their main occupation. To address the selection problem, we estimate labor income equations adjusted by selection in labor market participation. Also, in an extension of this work, an alternative methodology is used to construct simulated salary distributions in which the decision to participate in a specific occupation is included based on explanatory variables related to marital status and the demographic characteristics of the household (see annex 2).

## 4. Labor polarization in Uruguay

An empirical measurement of polarization involves ranking occupations based on the income or qualification level. This work addresses the analysis of the labor polarization hypothesis through two complementary empirical approaches to the extent they rest on different strategies to rank occupations according to the qualification level required: the first strategy uses mean wages to measure polarization, while the second one look at the prevalence of different task types in different jobs.

For the first approach, considering that the correlation between wage and schooling years (skill level proxy) is not only significant and positive, but also ordinally stable, literature has used mean wage as a variable to rank occupations to analyze the changes in the occupational structure (Autor and Dorn 2009; Goos, et al., 2014). Furthermore, it is assumed that hourly wage represents a good approach of occupation average productivity, which is also positively related to the workers' skill level.

Based on this proposed definition and methodology, we ranked occupations by their average hourly wage at the beginning of the analyzed period and grouped them into 40 intervals (40-tiles)[10]. Then, we have calculated the change in the employment share of each occupational 40-tiles over the 2003-2017 period. The polarization hypothesis would be consistent with a simultaneous growth in the relative share of occupations with higher and lower-level productivity (hourly wages) in the labor market, as the relative share of mid-level productivity occupations decreases.

An alternative option to analyze the potential incidence of a non-neutral technical change process is that developed by Bussolo et al. (2018). In this case, building on the conceptual framework proposed by Acemoglu and Autor (2011), the authors classify occupations into three categories: occupations relatively intensive in routine tasks,

[9] See Rodriguez (2014) for the case of Uruguay

[10] Although occupations are usually grouped in hourly wage percentiles, the analysis in this work is based on 40 intervals. This lower number of categories is due to the fact that, in practice, the information of the CHS for the period does not allow to monitor occupations at that level of disaggregation. Specifically, it works with the three-digit ISCO code, which entails monitoring a total of 132 occupations.

occupations relatively intensive in non-routine, cognitive tasks, and occupations relatively intensive in non-routine, manual tasks.[11]

The main source of information used is the Continuous Household Survey, complemented with the O*NET database (Occupational Information Network), which provides information referring to the task content of occupations.

Figure 1 shows that occupations that had a higher hourly wage level in 2003 are, in turn, the ones that had a larger increase on employment share in the period under analysis (2003-2017). Beyond the increasing share of high-level productivity occupations, figure 2 depicts another relevant aspect. The ratio between the change in employment share and the initial productivity level (hourly wage) is not linear, but has a J-shaped curve. In other words, the employment share in occupations with initial lower productivity is mostly stable (variation close to zero), declines for occupations in the mid-low productivity segment and increases for those with medium and high productivity.

Figure 1.

Change in Employment Share by Occupational Hourly Wage 40-Quantiles (smoothed)

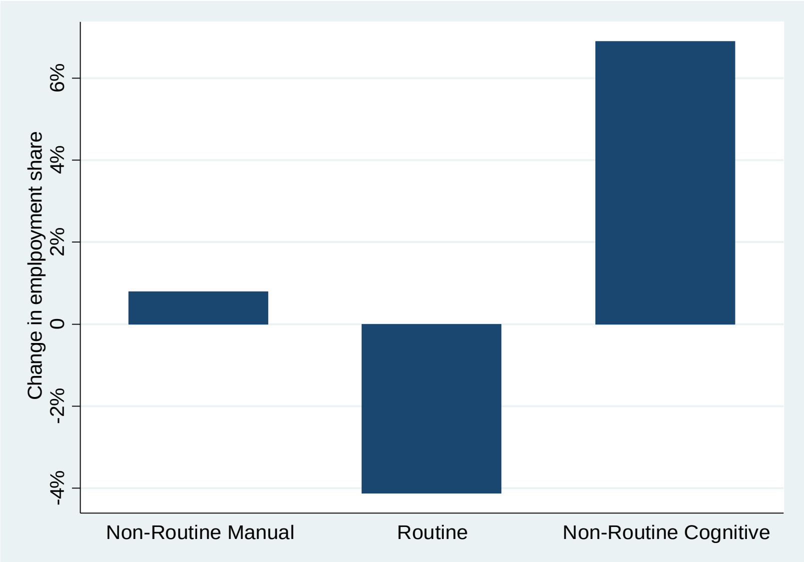

Source: own elaboration based on the Continuous Household Survey

11 Grouping occupations into three exclusionary categories is a limited approach because, to a lesser or greater extent, each occupation involves different types of tasks. In this regard, this grouping strategy necessarily implies identifying the most relevant tasks on a case-by-case basis. This could mean, however, that occupations characterized in a certain way could be at the same time characterized by a significant intensity in other types of tasks. This grouping strategy, i.e. building statistics that summarize the average task content for each of the categories, is included in the Annex to this work.

The empirical approach based on the second methodological approach presents evidence that confirms the incipient process of occupational polarization in the Uruguayan labor market. Non-routine, cognitive task intensive occupations[12] (which are linked to high qualification and wage levels) show a strong growth in their relative share in the labor market over the period under analysis (Figure 2). At the same time, routine task intensive occupations[13] linked to a mid-qualification and wage levels exhibit a reduction in their labor market share, and non-routine, manual task intensive occupations[14], characterized by lower qualification and wage levels, exhibit a slight increase in their total employment share.

Figure2.

Change in Employment Share by Occupational Categories




Source: own elaboration based on the Continuous Household Survey and O*NET

These findings are consistent with those obtained using labor income as a proxy for productivity. In both cases, the labor demand seems to have remained stable for low productivity workers, declined for those in the middle of the distribution and increased for high productivity level occupations or higher qualification requirements. This shift pattern in the labor market could be posing difficulties for people who have attained middle-school level and, therefore, bring about relevant distributional consequences.

12 This group includes occupations such as production and operations department managers, nursing and midwifery professionals, different professionals such as medical doctors, biologists, agronomists, biologists, veterinaries, pharmacologists, accountants and business administration specialists and computer programmers and computer systems analysts.

13 This group includes occupations such doorkeepers, watchpersons and related workers, sewers, embroiderers and knitters, general office clerks and secretaries, typists and word-processor and related operators and machine and tool operators.

14 This group includes occupations such as mining and mineral processing plant operators, fashion and other models, treasury and social security officials and locomotive engine drivers and switch operators)

However, as in the results obtained with the first methodological approach, the variations observed in occupational relative share are not large. In other words, although the tendency in labor market shares significant point of contact with the findings in developed economies, the size of the variations determines that it is still premature to talk about a labor polarization phenomenon. Indeed, the evidence gathered could suggest the existence of an incipient labor polarization process that could materialize in the decades to come.

In a nutshell, the empirical analysis conducted suggests that the labor market evidences a process of change in the required occupational profile, although this process is still incipient. This is consistent with the non-neutral technical change hypothesis and could be evidencing the first signs of an occupational polarization process similar to that found in developed countries.

This process does not fully match the polarization scenario observed in more developed countries because there is not a notorious increase in the share of lower-level productivity occupations. In turn, occupations evidencing a greater loss in the relative share in the labor market tend to situate in the mid-low wage distribution level, without reaching occupations situated above the distributional median.

## 5. Distributional effect

While evidence for polarization is not clear, the existence of some indications that it might be starting makes relevant whether it is having an impact on income distribution, as demand for occupations in the mid-low range of productivity has declined and demand for occupations in the high productivity range has increased in relative terms. Theory indicates that this change in demand, coupled with a shift in labor supply that would result in a slow increase in highly skilled workers and mid and low-skilled workers now competing for the low productivity jobs could result in an increase in labor income inequality, as high-range salaries would grow faster.

Descriptive evidence in Uruguay shows that the growth in real wages between 2003 and 2017 was slightly positive and inequality contracted sharply during the period under analysis. Figures 3 and 4 show the evolution of the distribution of wages and monthly labor pay over the 2003-2017 period. In terms of distribution, the Gini index for wage distribution went from 0.48 to 0.40 between 2003 and 2017 while, for labor income distribution (including the self-employed and employers) went from 0.44 to 0.36.

Figure 3.
Wage Distribution,
2003 and 2017

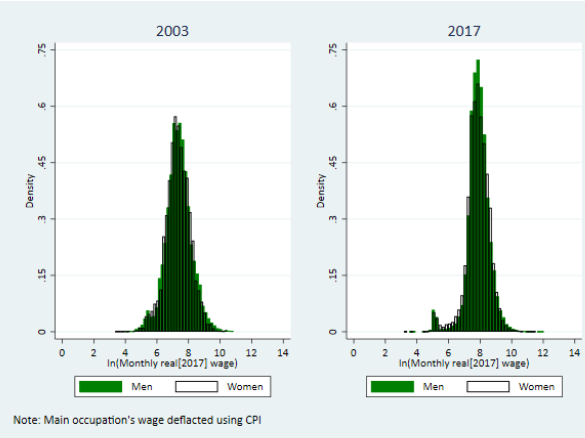
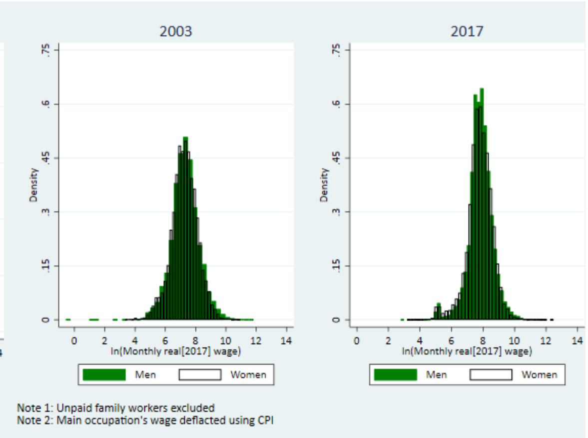



Figure 4.
Labor Income Distribution,
2003 and 2017




Source: own elaboration based on the Continuous Household Survey

The observed improvement in the income distribution is associated with a decrease in the inequality between the deciles of higher income, as well as a reduction in the differential between deciles 5 and 1.

Table 1.
Labor monthly income distribution.2003-2017

| | Salaried, Self-Employed and Employers | | | Salaried | | |
|---|---|---|---|---|---|---|
| Decile | 2003 | 2017 | Variation 2017-2003 | 2003 | 2017 | Variation 2017-2003 |
| 1 | 472,0 | 984,3 | 512,3 | 566,4 | 1211,2 | 644,8 |
| 2 | 708,0 | 1416,7 | 708,7 | 807,3 | 1600,0 | 792,7 |
| 3 | 915,2 | 1726,0 | 810,8 | 1019,5 | 1881,2 | 861,7 |
| 4 | 1132,8 | 2000,0 | 867,2 | 1211,7 | 2168,4 | 956,8 |
| 5 | 1358,9 | 2346,5 | 987,6 | 1416,0 | 2471,0 | 1055,0 |
| 6 | 1618,3 | 2683,4 | 1065,1 | 1685,6 | 2819,7 | 1134,1 |
| 7 | 1931,9 | 3156,0 | 1224,1 | 1982,6 | 3236,2 | 1253,6 |
| 8 | 2373,7 | 3750,0 | 1376,3 | 2424,9 | 3822,7 | 1397,8 |
| 9 | 3089,5 | 4662,0 | 1572,5 | 3072,9 | 4661,0 | 1588,1 |
| 10 | 4692,0 | 6380,4 | 1688,4 | 4455,3 | 6195,2 | 1739,9 |
| Gini | 0.48 | 0.41 | -0.07 | 0.44 | 0.37 | -0.07 |

Source: own elaboration based on the Continuous Household Survey

In terms of wage evolution for occupations characterized according to their task content, table 2 shows that, on average, higher manual task intensities –both routine and non-routine– receive lower pay than higher routine cognitive task intensities. However, these differences have narrowed over the past 15 years, which would evidence a relative wage improvement in less qualified occupations, consistently with the polarization hypothesis. On the other hand, occupations classified as non-routine cognitive analytical are the ones that show higher positive difference, and this difference relative to the reference category (routine cognitive) increased in 2017 compared to 2003. Occupations classified as non-routine cognitive interpersonal have shifted from having a lower average wage than the reference category in 2003 to having a higher average wage in 2017. These changes are very small (and the statistical significance is low in all cases), but they seem to be consistent with the trends in polarization discussed earlier, as wages in the extremes of the distribution grew faster than those in the middle (i.e. the routine-cognitive intensive occupations).

Table 2.
Average Wage in Each Occupational Category as a Proportion of Wage in Routine Cognitive (RC) Task Intensive Occupations

| Type of task | 2003 | 2017 |
|---|---|---|
| Routine cognitive (RC) | 1 | 1 |
| Routine manual (RM) | 0.65 | 0.70 |
| Non-routine cognitive – analytical (NRCA) | 1.56 | 1.71 |
| Non-routine cognitive – interpersonal (NRCI) | 0.91 | 1.10 |
| Non-routine manual (NRM) | 0.71 | 0.85 |

Source: Own elaboration based on the Continuous Household Survey and O*NET
Note: Occupations are classified according to their task-content intensities.

A complementary, more rigorous approach to this discussion is to measure the changes in labor income for different groups. By considering the changes across the income distribution percentile, Figure 5 shows that, in the period analyzed, income grew consistently faster for those in the lower part of the distribution. Furthermore, it is possible to decompose these changes, identifying the portion attributable to technological change and those attributable to returns to labor.

This empirical analysis, based on Fortin, Firpo and Lemieux (2011)[15] allows to break down the changes in labor income estimating the portion attributable to changes in (i) workers' observable characteristics, including occupational categories by task content (commonly known as the composition effect); and (ii) the return of these characteristics on wages (commonly known as the wage structure effect).

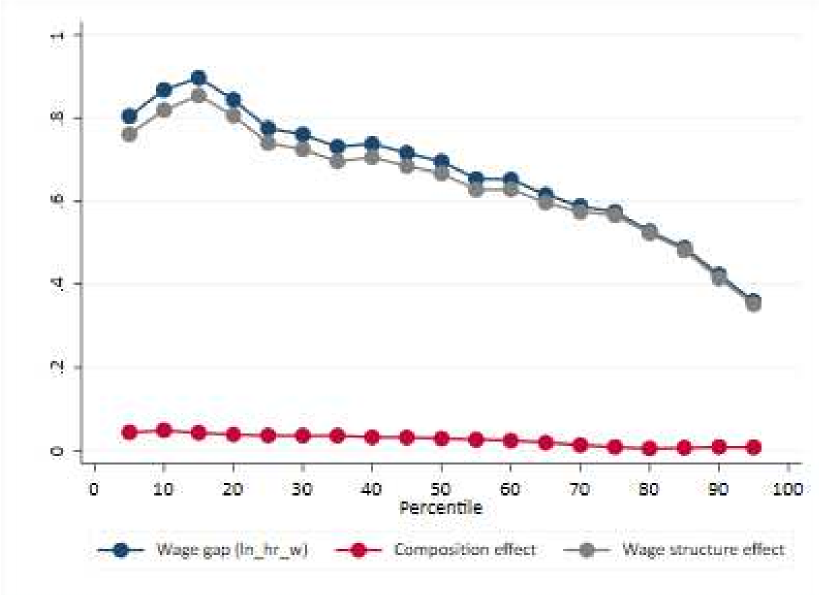
The results of this analysis show that increases in real wages between 2003 and 2017 were stronger in the lower part of the distribution and weaker in the higher part, resulting in a reduction of wage inequality. Most of this change is accounted for by the

15 See Annex II for a methodological discussion.

effect on returns, that is, individual wages. The composition effect (which reflects the impact of technological change) appears to be very weak, that is, the changes in the workers' characteristics account for a little part of the change in wages, and this contribution occurs homogeneously throughout the distribution.

Figure 5.

Aggregate Decomposition of the Change in Monthly Labor Income, 2003-2017




Source: own elaboration based on the Continuous Household Surveyand O*NET

The results of the decomposition suggest that the change in the composition of employment -which includes in this case the effect of the change in occupations categorized by their task content- contributed very little in net terms to an increase in wages and in a relatively homogeneous way throughout the salary distribution.

The change explained by the coefficients includes the greatest impact on the growth experienced in practice by real wages between 2003 and 2017, with a greater effect on the left tail of the distribution. These results imply that changes in returns benefited workers with lower wages to a greater extent, which is consistent with several institutional changes in Uruguay after the 2002 crisis.[16] Along with the rapid economic growth during the analysis period, wages were affected in Uruguay by important institutional changes, for example, increases in the minimum wage, establishment of wage councils, and tax and health system reforms. As of July 2007, tax reform was applied that introduced income taxes and had a direct impact on the wages of workers in the upper part of the distribution.

The next step in this study is the analysis of the detailed decomposition that allows estimating the contribution of each of the variables to the effects of composition and the salary structure. Figure 13 shows the composition effect of the variables grouped into four categories: age, educational level, branch of economic activity and job content of

16 See Amarante, Arim and Yapor (2016)

the occupations. As the figure shows, changes in the educational composition of workers are those that explain to a greater extent the changes in real wages between 2003 and 2017. These changes have a positive effect on the left tail of the distribution, but show less importance around deciles 3, 4 and 5. The composition of occupational characteristics according to the content of tasks does not seem to explain changes in real wages in the period analyzed.

On the other hand, the contribution of each variable to the effect of changes in coefficients is presented in figure 6. The effect of the coefficient on the age variable is negative throughout the distribution and presents greater intensity in the less advantaged deciles. This implies that as the worker's age increases, his returns were penalized between 2003 and 2017, and this in greater measure for workers with lower wages. Increases in the wages of workers in the lower part of the distribution are explained by positive changes in the returns to the branch of economic activity where they participate. On the contrary, in the upper half of the distribution, the changes in the returns to the branch of economic activity are negative.

In relation to the contribution of the different tasks performed by the workers on salaries, the returns to non-routine cognitive interpersonal tasks have changed in such a way that individuals in the lower part of the salary distribution have slightly more income than what the individuals in the upper part. However, the specific contribution of returns to occupations according to their routine content is fairly close to zero in a homogeneous manner throughout the distribution.

The contribution of the education coefficient is positive especially in the first two deciles of the distribution and then loses importance. It should be noted that the aggregate effect of changes in salary returns is also explained, to a large extent, by the effect of the constant (which includes the effect of those unobservable characteristics, for example, institutional changes), which was positive especially for the lower part of the distribution (table 3).

The presented results do not show a relevant role of the occupational change in the changes of the salary distribution. However, an important criticism is that the applied methodological approach assumes as exogenous the occupational structure in the two points of time analyzed. Indeed, the choice of a worker to participate in an occupation with specific task content is not exogenous and in fact, depends on its characteristics.

Figure 6. Detailed decomposition of the composition effect or explained component of the change.

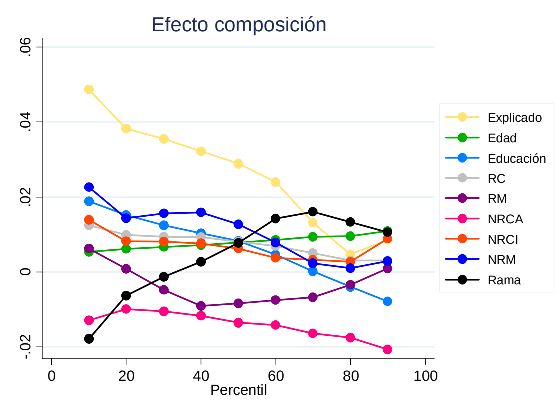
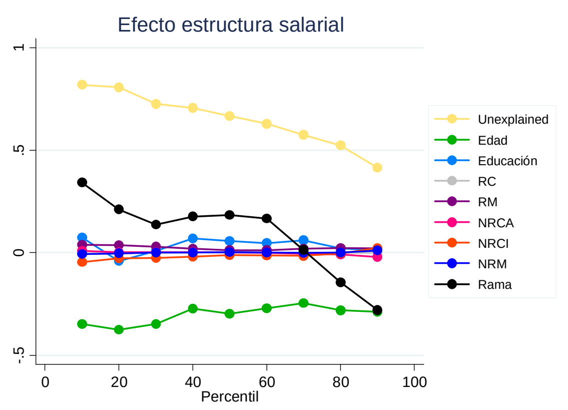



Figure 14. Detailed decomposition of the effect of unexplained wage structural component.




Source: Own elaboration based on ECH 2003 and 2017

Table 3.
Decomposition of changes in quantiles and inequality 2003-2017

| | (1) Percentile 10 | (2) Median | (3) Percentile 90 | (4) Gini index |
|---|---|---|---|---|
| 2003 | 5.988*** | 7.004*** | 8.121*** | 0.0688*** |
| | *(2198.42)* | *(3059.86)* | *(2589.94)* | *(850.25)* |
| 2017 | 6.856*** | 7.700*** | 8.544*** | 0.0536*** |
| | *(4055.93)* | *(7112.88)* | *(6017.76)* | *(1154.06)* |
| Difference | -0.868*** | -0.696*** | -0.423*** | 0.0152*** |
| | *(-270.72)* | *(-274.70)* | *(-122.93)* | *(163.02)* |
| | | Explained | | |
| Age | -0.00539*** | -0.00783*** | -0.0109*** | 0.0000798*** |
| | (-28.16) | (-30.88) | (-31.03) | (-21.40) |
| Education | -0.0189*** | -0.00823*** | 0.00789*** | 0.000737*** |
| | (-35.05) | (-17.28) | (10.57) | (59.96) |
| RC | -0.0124*** | -0.00812*** | -0.00305*** | 0.000253*** |
| | (-42.65) | (-42.33) | (-23.76) | (37.70) |
| RM | -0.00623*** | 0.00832*** | -0.000906* | 0.000123*** |
| | (-11.55) | (24.18) | (-2.21) | (8.74) |
| NRCA | 0.0129*** | 0.0136*** | 0.0207*** | 0.000101*** |
| | (39.61) | (48.08) | (49.14) | (13.26) |
| NRCI | -0.0139*** | -0.00618*** | -0.00886*** | 0.000158*** |
| | (-29.09) | (-19.74) | (-19.78) | (11.46) |
| NRM | -0.0226*** | -0.0127*** | -0.00290*** | 0.000556*** |
| | (-43.98) | (-36.89) | (-6.63) | (38.10) |
| Branch of Activity | 0.0178*** | -0.00767*** | -0.0106*** | -0.000950*** |
| | (19.40) | (-11.58) | (-12.19) | (-35.20) |
| Total | -0.0486*** | -0.0289*** | -0.00858*** | 0.000898*** |
| | (-40.86) | (-28.47) | (-6.22) | (28.64) |

| | | | | |
|---|---|---|---|---|
| | Unexplained | | | |
| Age | 0.348*** | 0.299*** | 0.288*** | -0.00509*** |
| | (29.29) | (33.48) | (25.05) | (-15.06) |
| Education | -0.0745*** | -0.0582*** | -0.0126* | -0.00213*** |
| | (-10.19) | (-11.48) | (-2.05) | (-10.59) |
| RC | 0.00386*** | -0.00215*** | 0.00130*** | -0.0000147* |
| | (12.24) | (-8.84) | (3.99) | (-2.09) |
| RM | -0.0390*** | -0.0124*** | -0.0221*** | 0.000820*** |
| | (-27.58) | (-11.07) | (-14.19) | (19.49) |
| NRCA | -0.00977*** | -0.000389 | 0.0203*** | 0.000773*** |
| | (-14.77) | (-0.77) | (25.94) | (33.10) |
| NRCI | 0.0463*** | 0.0114*** | -0.0226*** | -0.00176*** |
| | (44.24) | (13.12) | (-16.57) | (-50.32) |
| NRM | 0.00588*** | -0.00220*** | -0.0113*** | -0.000265*** |
| | (8.83) | (-4.23) | (-15.41) | (-12.97) |
| Branch of Activity | -0.343*** | -0.184*** | 0.279*** | 0.0153*** |
| | (-12.37) | (-7.68) | (8.87) | (20.49) |
| Constant | -0.757*** | -0.717*** | -0.935*** | 0.00671*** |
| | (-23.69) | (-26.82) | (-27.17) | (7.97) |
| Total | -0.819*** | -0.667*** | -0.415*** | 0.0143*** |
| | (-253.47) | (-274.07) | (-124.27) | (149.27) |
| N | 61165 | 61165 | 61165 | 59836 |

t statistic in parentheses

*p< 0.05, **p< 0.01, ***p< 0.001

Education summarizes the contribution of 5 binary variables for different levels
Branch of activity summarizes the contribution of 13 binary variables for different branches of economic activity.

Source: own Elaboration based on ECH 2003 and 2017

**Construction of counterfactuals modeling participation in different occupations**

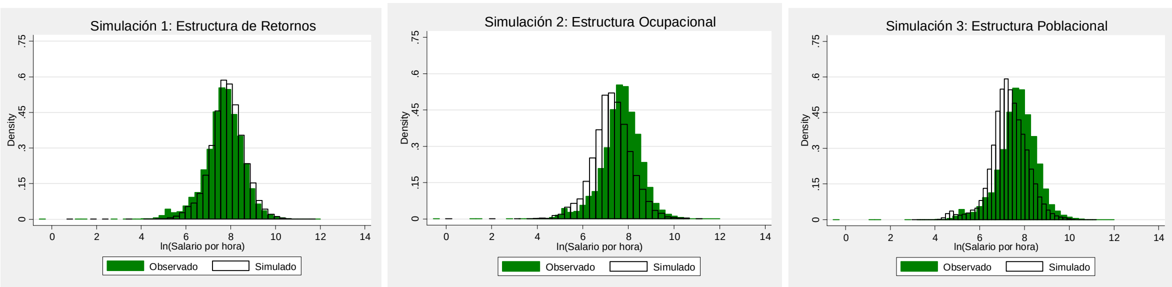
In an approximation similar to that of Bussolo et al. (2018) and taking into account the main limitation of applying the FFL methodology, taking as an exogenous the participation in the different occupational categories according to their task content, for the case of interest in this study, salary distributions are modeled taking into account explicitly the election of occupations based on characteristics of workers. Following the methodology of Bourguignon et al. (2005) and Bourguignon et al. (2008) the simulated distributions are constructed for the case of Uruguay. A more detailed summary of the methodology is presented in Annex 2.

Following Bourguignon et al. (2005) we estimate: (i) the coefficients of the Mincer equation; (ii) the coefficients of the multinomial regression logit in which the dependent variable is the occupational categories according to the content of the tasks; (iii) the residuals of the Mincer equation; and (iv) the residuals of the multinomial logit regression. The latter does not arise directly from the estimate since they are not a difference between the data and the prediction as in the case of an estimate by Ordinary Least Squares (OLS). In particular, the aim is to take into account the non-observable part of the theoretical model of utility maximization that motivates the logit multinomial.[17]

Once these parameters are estimated, the simulated distributions are constructed. Specifically, these simulations are created by exchanging returns and residuals (or unobservable) between one year and another to generate the different salary distributions.

Figure 7

Simulated salary distributions incorporating the modeled occupational choice



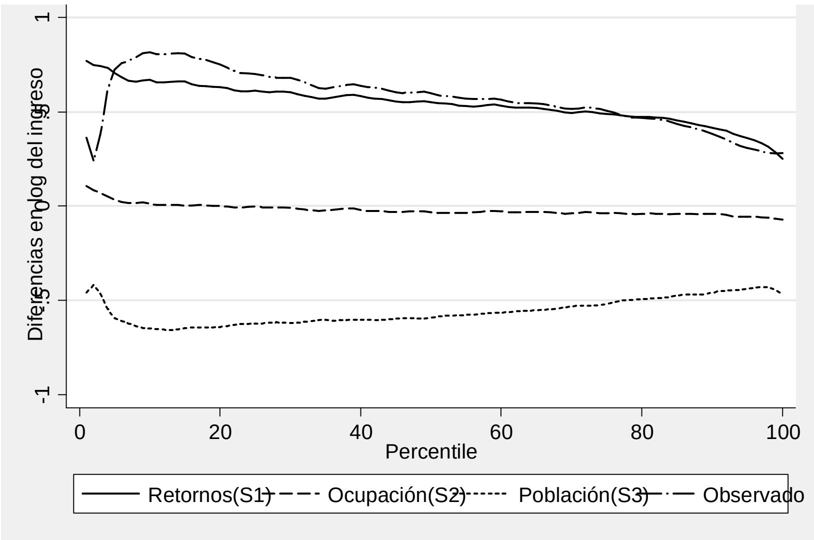

Source: Own elaboration based on ECH 2003 and 2017

The next step is to compare the changes in salaries based on the simulated distributions taking into account the parameters of the occupation choice model. The results suggest that changes in the salary distribution between 2003 and 2017 are virtually null if only the distribution of occupations has changed according to their task content. In fact, most of the observed changes in the salary distribution are explained by changes in the returns to the characteristics of the workers and by the change in the demographic characteristics of the individuals in the labor market (Figure 8).

17 According to which individuals choose occupation in such a way that $I = 1$ si $\boldsymbol{X}\beta i + \varepsilon i > Max(0, \boldsymbol{X}\beta j + \varepsilon j), \forall j$. The epsilons are the parameters of interest.

Figure 8.

Comparison of the change observed in salaries and the results of the simulations to isolate different sources of change




Source: Own elaboration based on ECH 2003 and 2017

Notes: Returns (S1) refers to the simulation in which it is assumed that only the returns (wages) of workers change while everything else remains constant; Occupation (S2) refers to the simulation in which it is assumed that the distribution of workers in the different occupation categories changes according to their main task content, keeping the rest constant; Population (S3) refers to the simulation in which the characteristics of the sociodemographic workers of the workers change and the rest remains constant.

In conclusion, Uruguay's labor market might be experiencing the early stages of a polarization process, that could accelerate if technological changes that replace routine cognitive tasks are introduced at a faster pace in the future. Distributional impacts appear to have been limited so far. Jobs with higher incidence of tasks that require mid-level skills seem to have lost returns in comparative terms, but this effect is very weak and not enough to offset the impact of other changes that, in the last fifteen years, explain an important improvement in income distribution.[18] Hand in hand with the rapid economic growth during the period under analysis, wages in Uruguay were affected by significant institutional changes, such as increases of the minimum wage, the establishment of wage councils and the introduction of reforms in the tax and health systems[19].

18 See Amarante, Arim and Yapor (2016)

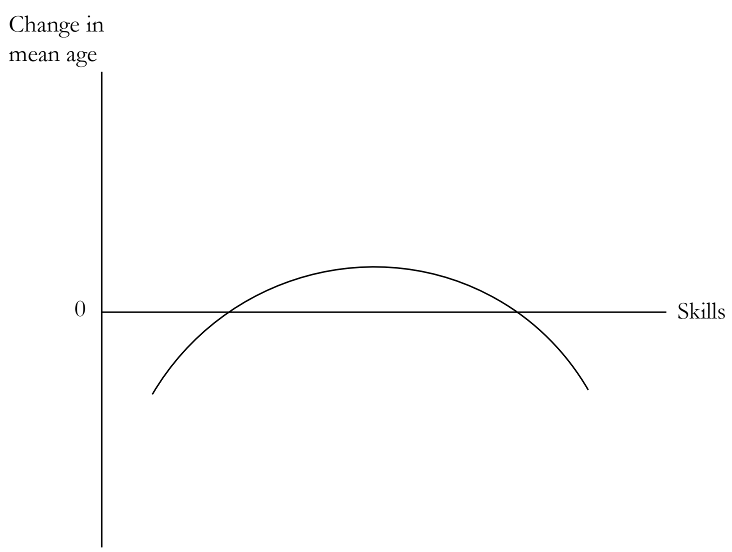
19 In July 2007, a reform was put in place that introduced taxes on income and had a direct impact on workers in the higher part of the wage distribution.

# 6. The aging of tasks hypothesis

One of the concerns usually arising from the existence of workforce polarization processes is associated with the characteristics of the individuals affected by such process. As polarization does not affect all workers equally, identifying the socio-demographic profiles of affected groups is important to understand the phenomenon and propose public policies responses. A particularly interesting aspect is the age structure of these workers, because this is relevant to design State measures. For example, if most workers at risk are youngsters entering the labor market for the first time, policies should focus on ensuring that the educational system provides training for other skills. In turn, in the case of young adults, policies should focus on helping them upgrade their skills. Finally, in the case of adults near the retirement age, it may be more effective to offer efficient social security schemes that help them complete their work life and make an organized transition to retirement.

Autor and Dorn (2009) pose the hypothesis of routine occupation aging. According to this hypothesis, young workers do not have incentives to enter contracting jobs, and if already employed, to keep them. In addition, older workers, given the difficulties they face to upgrade their skills and reenter the labor market, have incentives to remain in such jobs, especially when they already have many years of experience. The outcome of these different incentives based on age ranges is known as relative aging of occupations with declining share in the labor market (Diagram 2).

Diagram 2. Aging of tasks




Observing this hypothesis would condition the effectiveness of policies designed to develop and upgrade workers' skills. In the extreme of cases, it can be stated that if workers performing routine task intensive occupations that are reducing their share in overall employment grow older and, at the same time, non-routine task intensive occupations are taken by younger cohorts, the target population of training programs should be the latter, while adult workers could keep their jobs until they reach their retirement age.

In fact, contrasting the hypothesis of aging of tasks would lead to focusing attention on readapting the needs of young and middle-aged workers, being in the end cost-effective to protect routine task intensive occupations developed by people approaching their retirement (e.g. bus guard) because the job offer for such tasks will naturally decrease.

Understanding the demographic profile of those working on occupations more expose to automation is critical to design effective public policies. Technological change may result on the total or partial substitution of human work, and while this may have positive impacts in terms of aggregated productivity and output, it also creates relevant challenges as public policies aim at protecting workers and facilitate their transition to more productive jobs. Policies should differ depending on the demographic profile of affected workers, as in some cases it would be critical to provide basic skills to those entering the labor force, in others the focus should be to re-train more mature workers and in others to ensure a smooth transition to retirement.

Assessing whether there is a specific demographic profile among those in jobs more exposed automation is difficult, due to definition issues (we can identify what tasks may be replaced, but jobs include an ever changing combination of tasks and as such they may adapt to new conditions) and lack of adequate data. However, we may consider some proxy variables, such as the age profile by productivity (proxied by salary level or occupation's task contents).

The average age of workers on lower productivity occupations has increased in the last 15 years, while the age of those in higher productivity occupations has declined, as shown in Figure 9. This would confirm the existence of a task aging process, provided that the occupation's mean wage is a good proxy for productivity. Younger workers tend to concentrate more than before in higher productivity jobs, while older workers have moved in the opposite direction.

However, we should note that the relationship between the variation of the occupational average age and their hourly wage level does not exhibit an inverted J shape, as could be expected from the analysis of occupational employment share. The possible explanations for this are twofold. On the one hand, younger workers might not have been encouraged to do this low-wage jobs that are non-routine, manual task intensive. On the other, these types of occupations have worked as a shelter for middle-aged and older workers that have been crowded out from routine-intensive or middle-wage jobs.

Figure 9.

Variation in the Occupational Average Age by Hourly Wage 40-Quantiles (smoothed) 2003-2017

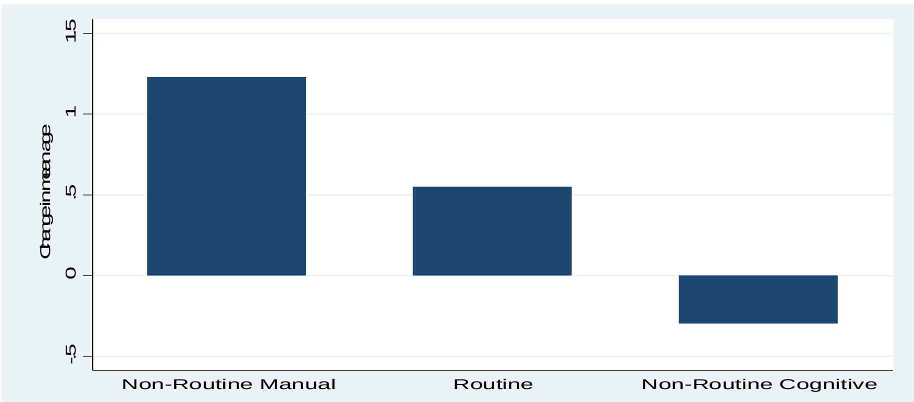

Source: own elaboration based on the Continuous Household Survey

The same pattern can be observed if the task content of occupations is used as a proxy for productivity (Figure 10). The average age of those working in non-routine cognitive task-intensive occupations declined by more than 0.25 years between 2003 and 2017, while those working on routine task-intensive occupations are now more than 0.5 years older than 15 years ago. These observations are consistent with the hypothesis proposed by Autor and Dorn (2009) about routine tasks growing old.

However, non-routine manual task-intensive occupations suffered the fastest aging in Uruguay (more than 1 year), which is inconsistent with that hypothesis. This could be explained if these occupations work as a shelter for middle-aged and older workers who have been crowded out from routine-intensive occupations. While changes occurred in the direction predicted by this hypothesis, the magnitude was small, indicating that this might be the early stages of a process that could accelerate in coming years.

Figure 10.

Variation in the Occupational Average Age of Occupations by Task-Content Categories




Source: own elaboration based on the Continuous Household Survey

# 7. Public policy discussion

Technological innovations may result in sustained increases in productivity, an effect that Uruguay, as other countries going through a population aging process, needs to continue growing and improving the population's welfare. However, these changes may also result in the replacement of human work with automation, generating risks such as technological unemployment and labor market polarization.

The empirical evidence indicating that these processes are happening in Uruguay is very limited, partly because not enough data is available to assess the magnitude of some of them, and partly because the available data indicates that changes in aggregated labor demand and market polarization produced by technological changes are still small. While available information does not indicate that this has been a serious problem for Uruguay recently, it is less clear whether it will become more relevant as innovations continue to be introduced and disseminate throughout the economy. Hence, discussing possible public policies that would respond to these trends in Uruguay is relevant, as they might become critical to ensure continued economic and welfare growth in coming years.

Technological innovations are affecting the way tasks are done by workers across the economy, as well as creating new tasks and making obsolete others. These trends imply changes in labor demand, forcing workersto upskill and upgrade their knowledge and abilities to maintain their competitiveness in the market throughout their working lives.

The incipient changes in labor demand observed in Uruguay, along with changes in employment profiles, tasks performed by workers, and skills required to that end are associated with the growing importance of non-routine cognitive tasks in jobs throughout the economy. As mentioned before, this shift in tasks and required skills has been slower in Uruguay than in more developed economies, and routine cognitive tasks continue to be an important part of day-to-day activities for most workers. Following Apella and Zunino (2018) this slower adaptation process might be explained by a "relative price" effect: the cost of acquiring new production technologies would be higher than the cost per worker to be borne by firms.

However, the shift in demand from workers with abilities to perform in routing cognitive tasks to those with abilities better fit for non-routine tasks is likely to happen in the future, and policy makers should consider strategies to facilitate the upskilling of these workers, that must go beyond the formal education systems, that reach younger generations. Therefore, Uruguay should have a lifelong learning program that offers training and upskilling to workers throughout their lives. New skills should respond to the changing labor demand. Implementation does not need to be an exclusive State responsibility: while the programs should be part of a public policy strategy, the private sector may have an important role as it provides on-the-job training, and other forms of lifelong learning services.

The literature suggests that the results of adults training depends, to a great extent, on prior life experiences[20]. Although skill acquisition is generally associated with formal education systems, these constitute one of the many ways in which individuals develop their abilities. People spend an average of 30 to 40 years in the labor market, and the investment in human capital over those years is essential to increase and maintain productivity. In a constantly transforming labor market, individuals continue accumulating skills outside the formal education system. Indeed, the training opportunities that emerge after individuals have entered the labor market are of utmost importance.

Several factors determine the effectiveness and quality of training during adulthood and working life. Age and education levels play an important role, as younger workers with a higher education level are more likely to learn from their partners more easily. The size of the workplace is also relevant, for workers in larger companies have more training offers.

Continuous training policies should address two coexisting realities. The first one is that education and training programs should assist less educated workers in closing the skills gap existing between them and others with higher qualifications. The second is that such policies also need to offer reskilling to currently employed workers that are in occupations that will be more expose to task automation. Therefore, we should highlight that lifelong learning policies should be addressed both to the employed and the unemployed.

In general, low quality jobs are closely matched to workers with low human capital. Insufficient human capital not only impact on current employment, but also on individuals' capacity to search for alternative jobs. For this reason, employment policies should ensure that people acquire proper skills to fill positions in a changing and competitive environment. Demographic trends demand that labor force participation increases by incorporating currently inactive persons and upskilling workers who lost their jobs. There are three policy strategies to achieve this objective. First, intermediation services provide information and facilitate the link between individuals and their potential employers. The second strategy focus on providing on-the-job training, while the third one focuses on more formal training services through classes or workshops. Current policies combine these approaches to maximize their impact.

Developing an effective skill training program for adult workers is a serious challenge, as it requires not only adequate funding, but a strategic vision, implementation capacity and a network of quality providers. Uruguay has an institution, created in 2008, that is responsible for public policies aimed at professional training. The National Institute of Employment and Professional Education is a tri-partite public entity (as its directive council is integrated by representatives of workers, employers, and the government) with the mandate to provide professional training activities and monitor productive sectors demands for qualifications. While INEFOP has the mandate and it is well funded to provide training, its focus is mostly on technical skills that are in high demand in the short term, and not on longer term strategic reskilling. A growing number of

[20] CAF (2017)

studies note that, in the new labor context, demanded-for skills go beyond technical or occupation-specific but are more in the area of softer, basic skills. Employers give priority to basic-skilled workers over specifically skilled technical workers. While these workers may be not as ready to work on the required tasks immediately, their flexibility and ability to learn and adapt is more valued (Lankard Brown, 2002; Griffiths and Guile, 2004). These profiles are scarcer in the labor market and the lack thereof translates as a barrier to employment for many individuals (Peddle, 2000).

This discussion has implications for active skill-development policies. The private sector has incentives to invest in workers' technical skill training, as long as they have soft and basic skills. Technical skills are not only specific to each productive sector or occupation, but also change over time. In fact, many of these skills are more likely to be developed in the individual's interaction with his or her work environment and being more specific to the particular job makes easier for employers to recover the investment in training. On the other hand, soft skills are relevant across the economy and, as such, incentives for individual employers to provide them are much lower, requiring a public institution such as INEFOP to take the responsibility.

In order to generate training and education initiatives to help workers and firms to adapt to current and future technological changes, the interaction between the different players involved is crucial: private sector, unions, education and training institutions, government must dialogue and cooperate to monitor skills demand trends and provide them when necessary in an effective way.

# 8. Conclusions

Technological change, particularly the automation processes, although it could achieve increases in the economy's overall productivity, also brings with it a distributive risk. The distribution risk is a result of the displacement of labor due to the automation of certain tasks, especially those of a routine nature. This type of task requires the methodical repetition of a constant and time-invariant procedure and, for this reason, they are very susceptible to being specified in an algorithm and executed from a computer program.

The results found in the present work suggest the existence of a very incipient process of polarization of the labor force. Contrary to what has been observed in developed countries, with the exception of employment in high-skilled occupations and therefore high productivity, which has increased its participation in total employment between 2003 and 2017, the rest of the Uruguayan labor force still maintains stability in their shares or with insignificant reductions.

On the other hand, those occupations with lower productivity show a moderate process of aging of their workers, while reducing the average age of workers in higher productivity occupations or intensive in non-routine cognitive tasks.

Finally, the changes occurred in terms of the contents of tasks performed by the workers have not had an impact on the distribution of labor income. Indeed, the inequality has decreased during our period under study and this has been particularly as a consequence of the drop in returns to education in those occupations with higher qualifications.

The incipient changes in the configuration of the labor force according to the workers' qualification, with a curve of variation of the participation in the employment in the form of "J", and the null impact of the changes in the employment profile in the distribution of labor income are associated with the evolution that has maintained the relative importance of routine cognitive tasks in the combination of tasks performed by workers in their occupations. In this sense, and as mentioned above, during the last decades and contrary to what has been observed in the developed countries, technological change, particularly the production processes based on automation, has not yet penetrated deeply into Uruguay to automate much of the routine cognitive tasks. Following Apella and Zunino (2018) a hypothesis that would justify this phenomenon is the existence of an effect "relative prices": the cost of acquisition of new production technologies aimed at automating this type of task would be higher than the cost that firms must face by worker.

However, the increase in the content of routine cognitive tasks in average employment in Uruguay, as in several countries in the region, poses a medium-term challenge associated with the automation risk that this type of tasks faces. The fact that the labor force carries out this type of task with greater intensity today implies a risk in the medium term of displacement of a part of the said workforce due to automation. As new production technologies, based on the automation of routine cognitive tasks, are standardized, the adoption cost would decrease and with this would increase the probability of substitution. Usually, this type of tasks is developed by workers at the intermediate level of education and who achieve average labor income, which implies that, in the face of a process of automation and displacement of the labor force, a situation of distributive inequality would deepen.

From this, the possibility of taking advantage of technological change implies a clear challenge for public policies, associated with the need for workers to move towards the development of tasks not susceptible to automation, that is, to non-routine tasks, in particular, cognitive. Consequently, the acquisition and updating of skills and knowledge of the workers constitutes the main strategy in that direction and the strengthening of the programs of continuous training of the population in active age is the instrument.

The speed with which technological change happens demands a faster adaptation response by workers. Likewise, this context of constant adaptation to different tasks suggests that the training process does not end with the formal education system, but rather is a process that accompanies the worker throughout his working life. Therefore, it is imperative that Uruguay strengthen its continuing education program in order to offer training and skills upgrading to job supply throughout the career.

The strengthening of spaces and instruments for readapting the job supply must be based on the consideration of new labor demands in terms of tasks. Although this initiative is part of the family of public policies, it should not be promoted and supported only by the public sector. It is necessary to promote public-private cooperation, not only in terms of financing but also in the definition of the training strategy and the use of economies of scale in the training tasks.

In this sense, the private sector is the one with clear incentives to invest in the training of its workers in terms of technical skills, through on-the-job training (learning by doing). This type of skills are not only specific to each productive sector or occupation, but also are changing over time and therefore no other agent involved in the production process has incentives to finance training. On the other hand, there is a set of cross-cutting skills throughout the productive sector, the so-called soft skills, such as agility and adaptability, interpretation, writing, arithmetic, communication, coordination of activities and conflict resolution, to mention a few. These types of skills are not appropriated by all agents, but exclusively by the worker, and for this reason, the public sector becomes the ideal responsible for the training process.

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## Annex 1.

## Classification of occupations according to task content

The strategy to group occupations into three exclusive categories, that is, intensive occupations in cognitive non-routine tasks, intensive occupations in routine tasks and intensive occupations in manual non-routine tasks, is carried out following the strategy proposed in Bussolo et. al (2018).

The first step of this strategy consists of constructing, based on information from the O * NET base, following the methodology proposed by Acemoglu and Autor (2011), five indicators that measure the content of occupations tasks: i) non-routine content cognitive analytical (NRCA); ii) non-routine cognitive interpersonal content (NRCI); iii) routine cognitive content (CR); iv) manual routine content (RM) and vi) manual non-routine content (NRM).

Second, from these indicators that summarize the task content of the occupations, an index of intensity of routine tasks of the occupations (RTI index, "routine task intensity") is calculated, following Autor, Levy and Murnane (2003) , where RTI = (RM + RC) / (NRCA + NRCI). This RTI index is computed for each of the 132 identified occupations (ISCO 88 at three digits). Subsequently, the occupations are ordered according to their RTI index. The occupations belonging to the third with the highest value of the index will be identified as intensive occupations in routine tasks.

Third, the remaining two-thirds of occupations will be ranked according to the NRCA indicator that measures the importance of non-routine cognitive tasks. Within this subset of occupations, the 50% that present the highest level of the NRCA indicator will be identified as intensive occupations in non-routine cognitive tasks, while the remaining 50% will be considered as intensive occupations in non-routine manual tasks.

The grouping strategy leads us to have a third of the occupations in each category, which could artificially be forcing a certain task to be categorized as intensive occupations (for example, non-routine cognitive) when they present a strong content of other types of tasks (for example, example, cognitive routines). In order to have a clear idea of the average task content of each of the categories, the average value of the five indicators proposed by Acemoglu and Autor (2011) is summarized for each group. Remember that according to the O*NET information, these indicators take values between 1 and 5 where a higher value of the indicator establishes a greater intensity of this type of task.

Table A1. Task content by Occupation Categories.

| | Variable | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Routine** | | | | | |
| | NRCA | 1.82 | 0.25 | 1.40 | 2.61 |
| | NRCI | 1.54 | 0.26 | 1.23 | 2.19 |
| | RC | 2.85 | 0.27 | 2.24 | 3.32 |
| | RM | 3.09 | 0.40 | 2.21 | 3.83 |
| | NRM | 2.91 | 0.35 | 2.07 | 3.62 |
| **Non-Routine Cognitive** | | | | | |
| | NRCA | 3.50 | 0.31 | 3.06 | 4.15 |
| | NRCI | 3.20 | 0.53 | 2.22 | 4.01 |
| | RC | 3.67 | 0.31 | 2.60 | 4.22 |
| | RM | 1.98 | 0.42 | 1.14 | 3.12 |
| | NRM | 1.93 | 0.42 | 1.26 | 2.83 |
| **Non-Routine Manual** | | | | | |
| | NRCA | 2.49 | 0.30 | 1.75 | 3.02 |
| | NRCI | 2.36 | 0.38 | 1.58 | 3.06 |
| | RC | 3.37 | 0.47 | 2.25 | 4.21 |
| | RM | 2.44 | 0.46 | 1.38 | 3.64 |
| | NRM | 2.60 | 0.59 | 1.64 | 3.82 |
| **Total Employment** | | | | | |
| | NRCA | 2.60 | 0.75 | 1.40 | 4.15 |
| | NRCI | 2.37 | 0.79 | 1.23 | 4.01 |
| | RC | 3.30 | 0.49 | 2.24 | 4.22 |
| | RM | 2.50 | 0.62 | 1.14 | 3.83 |
| | NRM | 2.48 | 0.62 | 1.26 | 3.82 |

Source: ECH 2003 y O*NET.

# Annex 2.

## Construction of counterfactual distributions simulating decisions to participate in the labor market[21]

The analysis consists of comparing the observed distributions of labor income with a set of simulated distributions that allow exploring which are the components that could explain most of the change in labor income between 2003 and 2017. The methodology that is followed includes two stages. First, following Bourguinon et al. (2008), the parameters that determine the choice of occupational category made by individuals and the corresponding labor income are estimated, adjusting for the endogeneity bias that implies the use of parameters that simultaneously affect the choice of individuals and their wages. Second, alternative labor income distributions are simulated using the parameters estimated in the first part and following the methodology of Bourguignon et al. (2005) and Bourguignon et al. (2008).

In the first part, to capture the intensity of the tasks, we define an occupation as intense in a specific task category according to the highest value of the five continuous variables used as occupation categories (see table A1). Mincer equations are then calculated for 2003 and 2017, and each of the five categories of occupations in order to obtain the returns to the control variables, which are: gender, age cohort indicators (16-25 years as a base ), indicators of educational level (incomplete or complete primary, incomplete secondary, complete secondary, university or equivalent without finishing, university or equivalent finished), indicators for branch of economic activity (agricultural, industrial and services) and a variable that indicates whether the place of residence is Montevideo.

The choice of occupation is modeled using a multinomial logit regression, where the dependent variable is the five occupational categories according to the content of the task and the explanatory variables contain characteristics of the workers (age, gender, educational level and branch of economic activity).

In the second part, the set of simulations includes:

**S1**. Return structure simulation. The objective of this simulation is to understand how the distribution of labor income would have changed if the only thing that had changed between 2003 and 2017 were the labor returns to the characteristics of the workers.

**S2**. Occupation simulation. The simulated distribution is generated allowing individuals to change occupational category according to an underlying utility maximization model and using the multilogit probability model, the distribution of what would be the occupational and salary structure is generated as if the only thing that had caused changes between 2003 and 2017 outside of technological change.

**S3**. Simulation of population characteristics. This simulation is generated assuming that the only thing that changes between 2003 and 2017 are the characteristics of the workers (age structure, education and branch of economic activity). The simulation implies some changes in occupation because it includes the estimation of how the individuals would have chosen occupation and what wages they would have obtained. I understand that said choice is a function of the characteristics of the workers that have changed between the initial year and the final year.

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[21] This annex is based on an extension to this work (Apella, Morales, Rodríguez-Chamussy and Zunino) in process.

## Annex 3. Intensive occupations in routine tasks

1. Farmers and Skilled Crop Workers
2. Skilled forest workers
3. Fishermen, hunters and trappers
4. Subsistence agricultural and fishing workers
5. Miners, stonemasons, gluers and stone workers
6. Construction officials and operators
7. Painters and facade cleaners
8. Molders, welders, sheet metal workers, boilermakers, assemblers of metal structures
9. Blacksmiths, toolmakers
10. Electrical and electronic mechanics and adjusters
11. Potters and glassware operators
12. Craftsmen of wood, fabrics, leather and similar materials
13. Officials and operators of the graphic arts
14. Food Processing Officers and Operators
15. Officers and operators of the treatment of mothers and cabinetmakers
16. Officials and operators of textiles and clothing
17. Operators of metal processing facilities
18. Glass and ceramic operators
19. Operators of wood processing and papermaking facilities
20. Operators of chemical treatment facilities
21. Domestic staff, cleaners Operators of energy production facilities
22. Operators of machines for working metals and mineral products
23. Operators of machines for manufacturing chemicals
24. Machine operators to manufacture rubber and plastic products
25. Machine operators to manufacture textile products and leather and leather articles
26. Assemblers
27. Other machine operators and assemblers
28. Operators of mobile agricultural machinery and other mobile machinery
29. Sellers
30. Washers and ironers
31. Janitors
32. Mining and construction laborers
33. Laborers in the manufacturing industry

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