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TECHNOLOGICAL CHANGE AND THE LABOR MARKET IN ARGENTINA AND URUGUAY: A TASK CONTENT ANALYSIS[1]

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RESUMEN:

El objetivo de este documento es analizar las tendencias de los perfiles de empleo en Argentina y en Uruguay de acuerdo a las tareas realizadas por los trabajadores en sus empleos. El documento intenta lograr una aproximación del impacto del cambio tecnológico en el mercado laboral. Se utiliza la definición de un indicador que captura la importancia relativa de cuatro tipos de tareas, congnitivas/manuales y rutinarias/no rutinarias, basada en información de la *Occupational Information Network* y en encuestas de hogares. El análisis encuentra que en las últimas dos décadas la importancia relativa de las tareas cognitivas en el lugar de trabajo se ha incrementado en línea con la reducción de tareas manuales, particularmente entre las cohortes más jóvenes.

Palabras clave: cambio tecnológico, mercado de trabajo, productividad.

Clasificación JEL: J01, J22, J24

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ABSTRACT

The objective of this paper is to analyze the employment profile trends in Argentina and Uruguay according to the task content performed by the workers in their jobs. The paper aims to produce an approximation of the impact of technological change on the labor market. The paper uses the definition of an indicator that captures the relative importance of four types of tasks, cognitive/ manual and routine/non-routine, based on the information provided by *Occupational Information Network* and household surveys. The analysis finds that in the last two decades the relative importance of cognitive tasks in the workplace has increased in line with the reduction of manual tasks, particularly among the youngest cohorts.

Keywords: Technological change, Labor market, Productivity

JEL Classification: J01, J22, J24

1. INTRODUCTION

Technological change, such as the advance in digital technologies, communication and robotics, can lead to an improvement in the general well-being of the population and reduce poverty, thanks to the increase in global productivity of the economy. 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. Technological advance, together with the reduction of access cost to new forms of production, generates a potential displacement of a part of the traditional labor force through machines administered from computerized systems, while at the same time paving the way for the creation of new types of jobs.

The labor markets of Argentina and Uruguay are not exempt from this process. During the last 20 years, the labor force in both countries has moved from developing more in the area of intensive manual tasks to instead that of performing cognitive tasks. This allows us to suggest that, on average across the whole market, jobs are changing and with that the type of skills, and workers, required. This phenomenon is a characteristic of the change processes in the production functions of economies, in particular, of the adoption of new technologies such as robotics, which permit manual labor to be substituted in certain tasks.

The potential benefits of technological advance are important, both for workers and for consumers. Digital technologies, for example, can create jobs and increase benefits for small and medium-sized producers through the expansion of access to information and communication mechanisms, especially in those sectors which could be, or already are users of that technology. An example of this could be the creation of commercial platforms connected via the internet through which buyers and sellers can be brought together with minimum transaction costs.

From the point of view of consumers, the benefit coming from technological change is associated with the potential reduction in the price of products downstream - as a consequence of the profits gained from greater efficiencies – and the increase in the range of goods and services available, thus generating a positive variation in consumer surplus. The majority of these consumer gains come from reduced marginal costs of production and distribution when the productive sector incorporates technological innovation and automates productive processes taking advantage of the economies of scale which are generated.[2]

However, this new setting poses some challenges or new complementary investments for the labor force in order that the benefits offered by the technological change are realized. In other words, it demands an increment in the workers' productivity through an increase in their human capital in order to ensure their adaptation to and compliance with the new forms of production. In effect, the benefit generated by the use of the new production technologies is not automatic. Not only does access to information services and digital communication need to be improved, but also new basic skills need to be incorporated through the updating of education systems and continuous training.

However, technical progress, in particular the advance of robotics, means that certain activities run a high risk of becoming obsolete, since some of them, such as routine tasks, or those which can be replaced by code, can be easily automated, leading to what is commonly known as technological unemployment. Depending on whether the machines are capable of replacing only unskilled work, skilled work, or all work, the consequences will be distributed differently.

In this context, the objective of this study is to study past tendencies in the level of employment according to the types of tasks that the workers did in their jobs, in order to approximately assess the possible impact of technological change on labor demand and to prompt a discussion on the possible responses to this challenge in public policies.

The next section discusses the theoretical framework of analysis related to the relationship between technological change and the rhythm of substitution of productive factors. The third section presents the methodology and information used, and the fourth section analyzes the main results obtained. The fifth section discusses the challenges that these tendencies imply for public policies. Finally, some final reflections are made.

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2 However, the transfer of a technological improvement to final prices assumes a certain grade of competition in each market. In a market with a high concentration, profits from efficiency will be transferred to the profit margins of the companies.

2. THEORETICAL FRAMEWORK

The impact of technological advance on the performance of the labor market is discussed at length in the literature (Autoret *al.,* 2003 and 2013; Frey and Osborne, 2013; among others) in which it is suggested that there is a reduction in the level of employment in occupations high in routine tasks, that is, occupations which consist principally in tasks which follow well-defined procedures that can easily be performed by some sort of algorithm. This shows that not only technological advance, but also the reduction in cost of accessing these new production technologies, generates a potential displacement of a part of the labor force through machines administered by a computerized system. Therefore, technological change, in particular the advance of robotics, could give rise to an increase in technological unemployment.

Frey and Osborne (2013) distinguish between occupations at high, medium and low risk of being automated, and argue that close to 47% of the total work of the United States can be placed within the high-risk category. For its part, the World Bank (2016) estimates that an average of 50% of the current work in Latin America might not continue being performed by people in the future.

However, not all jobs are susceptible to being automated. The analysis of this phenomenon requires jobs to be differentiated, not by their levels of qualifications or skills, as may be suggested, but by the combination of tasks which are performed. This analysis framework, known as "task content", is the proposal of Autoret *al.* (2003) and Acemoglu andAutor (2011), among others. According to these authors, the tasks are not strictly the skills with which the worker is equipped, but those which are closely related with them.

Specifically, a task is defined as an activity which enables the creation of a product (Acemoglu and Autor, 2011). However, the workers need a series of skills to be able to carry out these tasks. As an example, an architect needs great numerical and mathematical skills to perform cognitive tasks which are generally non-routine, such as the design and development of plans. The skills may be seen as the ability of the workers to perform particular tasks.

Tasks can be classified in two large categories: routine or non-routine. A task is routine if its performance implies a clear and repetitive set of invariable actions. Many tasks, such as the temperature control of a steel production line or the transfer of a car part to its place in an assembly line, among others, have this characteristic. Since these tasks require the methodical repetition of a constant procedure, they can be clearly specified in a computer program and performed by a machine.

On the other hand, a non-routine task is that whose performance requires various actions to vary in time, and requires the ability to adapt to the context, using language, visual recognition and social interaction, among others. Following Polanyi (1966), this skill that says that a driver cannot be completely replaced; the knowledge that a person has about their own body differs completely from their knowledge of physiology; and the rules of rhyme and prose do not explain in themselves what a poem conveys. In this sense, the passage of a car through the traffic of a city, or the writing of a poem, fall into the category of non-routine tasks. The reason being that those tasks require the abilities of visual, socio-emotional and motor processing that cannot be described in terms of a set of programmable rules.

At the same time, the tasks in each of these two categories may be of a natural or cognitive nature, that is, that they are related to either physical work or to knowledge. From this, it is possible to establish four main categories of tasks:

1. Routine manual tasks: normally performed by low- or medium-skilled workers. Such tasks are highly codifiable and replaceable by automation, such as assembly line workers and manual factory workers.

2. Non-routine manual tasks: commonly performed by poorly-qualified workers. The performance of these tasks requires the ability to adapt to the situation, the language, visual recognition or social interaction. Drivers, mining workers and construction are examples of occupations which perform these types of tasks intensively. These workers have a low or zero probability of being computerized although Frey and Osborne (2013) suggested that some of these tasks, such as transport and logistics and administrative support, are at risk of being automated.

3. Routine cognitive tasks: are carried out by medium-skilled workers. In some occupations more than others, computers may be a substitution factor since they demand explicit and repeated sets of activities which could be coded in a computer program. The tasks performed by secretaries, salespeople, administrative staff and bank cashiers, among others, fall within this group.

4. Non-routine cognitive tasks: normally performed by highly-skilled workers. These tasks, which are often divided into two large subcategories, such as those of analysis and of personal relations, require abstract thought, creativity, the ability to solve problems and communication skills. Computers may complement the performance of these tasks, increasing the productivity of the skilled workers. These tasks are commonly performed by professionals such as managers, designers, engineers or information technology specialists, teachers, and researchers, among others.

All occupations, with differing levels of intensity, involve one or a combination of the tasks described. The intensity of the tasks may appear very heterogeneous between occupations. As an example, a car driver performs non-routine manual tasks the majority of the time but also performs personal non-routine cognitive tasks and routine cognitive tasks. In contrast a scientist dedicates the majority of their time to the performance of non-routine cognitive tasks but also preforms routine tasks with a lower frequency (cognitive and/or manual).

Owing to the decline in costs of access to new technologies, computer-controlled machinery could replace those workers that perform largely routine tasks, especially manual ones. This phenomenon is not new. This substitution has been seen since the first industrial revolution, but the technological revolution has developed in such a way that machines can perform cognitive tasks that decades ago were only performed by people. Following Bresnahan (1999), during the last three decades computers have replaced tasks associated with calculation, coordination of activities and communication, bank cashiers, telephone operators and other operators of repetitive information-processing tasks.

On the other hand, the ability of computers to replace workers employed in the performance of cognitive tasks is limited. The combination of tasks which demand flexibility, creativity, problem-solving and communication skills – non-routine cognitive tasks – are less susceptible to being automated. The need to establish a series of explicitly-programmed instructions constitutes a restriction.

Because computer technology is more adept at replacing workers who routinely perform routine tasks than non-routine tasks, it becomes a complementary factor for the development of non-routine tasks, and is even capable of increasing marginal productivity. To give an example, the ability to use a bibliographic search program through a networked computer increases the efficiency and quality of researchers that use such references as inputs.

Not all tasks are susceptible to being replaced by machines. The decision of the productive sector related to the optimum combination of production factors is found to be associated not only with the flexibility of the substitution between factors but also with the relative price of them. The simple model proposed by Autor *et al.* (2003) and also by Frey and Osborne (2013) allows these decisions to be formalized.

Assuming a Cobb-Douglas production function for work and capital in the following manner:

$$Q = (L_s + k)^{1-\beta} . L_n^{\beta}$$

Where L_s and k are the work intended to be performed by the tasks susceptible to automation and the capital that these tasks can realize, respectively. Both factors are perfect substitutes. L_n represents the value of the work required so that the tasks are not susceptible to automation. Assuming that the price of the product is the numeraire and that w_s, ρ and w_n are the salary of the work that can be automated, the price of the capital and the salary of the complementary work, respectively, of the first order conditions we can find the following expression.

$$Pmg_{L_r} = Pmg_k = (1-\beta).\frac{(L_s + K)^{-\beta}}{L_n^{-\beta}} = w_s = \rho$$

Where $\theta = \frac{(L_s+K)}{L_n}$ is the relationship between tasks susceptible and not susceptible to being automated within the production function. The optimal condition demands equality between the quotient of the marginal productivities of the factors and the relative prices:

$$\frac{Pmg_{L_s}}{Pmg_k} = 1 = \frac{w_s}{\rho}$$

Assuming a reduction of the price of capital, ρ, that implies that the technical substitution relationship is less than the relative prices, encouraging the company to seek a reallocation of productive factors in order to achieve economic efficiency. To do so, the company replaces labor with capital.[3] Simultaneously, a modification of the relative prices is generated, generating an increment of the redistribution L_s in relation to L_n. Of the first order conditions, we also have that

$$(1-\beta).\theta^{-\beta} = \rho$$

Taking the natural logarithm of both sides and differentiating completely we have that:

$$\frac{dln\theta}{dln\rho} = -\frac{1}{\beta}$$

Thus, a substitution effect is generated in favor of tasks susceptible to automation, and within these, in favor of those made by capital.

This change of relative prices, in addition to the effect generated by the substitution, would generate incentives around the type of job. Following Goos and Manning (2007), for the case of Great Britain, it is possible to see a tendency in the polarization in the work market, with growth in high-income cognitive work and low-income manual occupations, accompanied by a reduction in routine tasks with medium incomes. In this sense, given a reduction in the prices of computing equipment, problem-solving skills are becoming relatively more productive, which explains the growth in occupations which require the performance of cognitive tasks by a qualified labor force (Katz and Murphy, 1992 and Acemoglu, 2002).

3 In the case of additive production functions, the only effect in the face of an exogenous price shock is the substitution effect.

3. METHODOLOGY AND SOURCE OF INFORMATION

The source of information used in this study is the database developed by O*NET (Occupational Information Network), which provides information related to the content of occupational tasks. Since the year 2003 O*NET has been compiled in the United States for approximately 1,000 occupations based on SOC - Standard Occupational Classification, and since then, until the year 2014, it has been updated periodically.[4] Following Acemoglu andAutor (2011) four sets of O*NET data are used: skills, work activities, work context and capacities. Each one of them contains descriptors which aim to measure, using a scale of importance, the level, or extent, of the activity. For this, the O*NET data from 2003, 2005 and 2015 are used to try and identify the change in the content of the tasks within each occupation within that time period.[5]

At the same time, the Permanent Household Surveys from the years 1998, 2003 are 2015 are used for Argentina, and the Continuous Household Surveys from the years 1995, 2003 are 2015 are used for Uruguay.

In order to estimate the content of the tasks of the occupations, the elements of the tasks provided by O*NET are mapped to the classification of occupations coming from the household surveys from Argentina and Uruguay. In general, each country has its own specific version of the International Standard Classification of Occupations (ISCO) or at least, in the cases where a national classification is used, an equivalent to ISCO is applied.

The classifications used in the different household surveys are the National Occupation Classifications revision 2001 and 1991 (CNO 01 and CNO 91) in the case of Argentina and thecodes CIUO 2008, CIUO 88 and Cota70 in the surveys in Uruguay. Therefore, the mapping of the O*NET

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4 O*NET is the successor to DOT (Dictionary of Occupations) which is no longer updated. O*NET was started in 1998 on the OES base of codes Occupational Employment Statistics. In 2003 this was changed to SOC which means that the consistent measures of task content are calculated from 2003.

5 In this study it is assumed that the characteristics that describe each average occupation in Argentina and Uruguay are similar to those prevailing in the United States. This is not necessarily the case and so the results may have some bias.

data in their different versions with the corresponding information to the household surveys from Argentina and Uruguay required the correspondence tables SOC 2010- SOC 2000,[6] SOC-2010-CIUO 08,[7] CIUO 08- CNO 01,[8] NO 01 – CNO 91,[9] CIUO 08- CIUO 88[10] and CIUO 88- Cota 70.[11]

In many cases the correspondence tables do not determine a one-to-one correspondence between the occupation categories of O*NET and the household surveys. In these cases, the strategy used by Hardy *et al.* (2015) was followed. Four situations can be identified.

In the first case, there are situations where an occupational code of a specific classification corresponds to only one occupational code of the classification we want to map to. In this case the characteristics are attributed directly to the first code of the second classification.

In the second case, a specific code of a classification corresponds to more than one code of the classification we wish to map to. In this case, the characteristics of the same original code are attributed to all the occupations of the second classification.

In third case, various occupations from the original code correspond to the same code in the classification we are mapping to. In this case, the average value of the characteristics associated to the codes of the original classification are attributed to this last code.

The final case is where various codes in the original classification correspond to various codes in the mapped classification. In this situation, again an average value of the characteristics associated to the corresponding codes of the original classification is attributed to each code in the mapped classification.

6 To make the different O*NET bases compatible.
7 To perform the mapping with the Uruguayan household survey 2015.
8 To perform the mapping with the Argentinian household survey 2015.
9 To perform the mapping with the Argentinian household surveys 2003 and 1998.
10 To perform the mapping with the Uruguayan household survey 2003.
11 To perform the mapping with the Uruguayan household survey 1995.

Once the mapping has been done, following Acemoglu and Autor (2011) and Hardy et al. (2015) five measures of content or intensity of main tasks are constructed: non-routine cognitive analytical and interpersonal, routine cognitive and manual and non-routine manual. These are formed by the attributes of the activities which they involve. In this sense, some attributes were selected (elements) which are representative of each task. These are represented in Table 1.

Table 1. Construction of the measurement of the content of tasks

Task	Elements of the tasks *(t)*
Non-routine cognitive (analytical)	Information analysis Creative thinking Interpretation of information for others
Non-routine cognitive (interpersonal)	Establishment of personal relationships Leadership, management and motivation of staff Training / development of others
Routine / cognitive	Importance of repetition of the same task Importance of being exact or precise Being structured
Non-routine manual	Operating vehicles or operating machines Spending time using your hands to handle, control or feel objects Manual dexterity Spatial orientation
Routine manual	Rhythm determined by the speed of equipment Control of machines or processes Spending time doing repetitive movements

Source: Compiled based on Acemoglu andAutor (2011)

After assigning each attribute to each task, and these to the information from the surveys, the values of each element t are normalized in order to enable information to be comparable across time, using the following formula:

$$\forall i \, \forall j \in J \;\; t_{i,j}^{std} = \frac{t_i - \mu_j}{\delta_j} \quad (1)$$

Where J is the combination of the 16 tasks listed in Table 1 for the individual i and μ_j and δ_j represent, respectively. The weighted average and the standard deviation of the task j in the total of the period 1995-201 5are calculated in the following manner:

$$\forall j \in J \;\; \mu_j = \frac{\sum_{i=1}^{N} t_{i,j} . w_i}{\sum_{i=1}^{N} w_i} \tag{2}$$

$$\forall j \in J \;\; \delta_j = \left(\frac{\sum_{i=1}^{N} w_i (t_{i,j} - \mu_j)}{\sum_{i=1}^{N} w_i} \right)^{1/2} \tag{3}$$

Where w_i is the relative weighting attributed to the individual i.

To construct the measures of intensity of each task each one of the elements of the same group of tasks is added up and each one of the five measures of intensity is standardized.

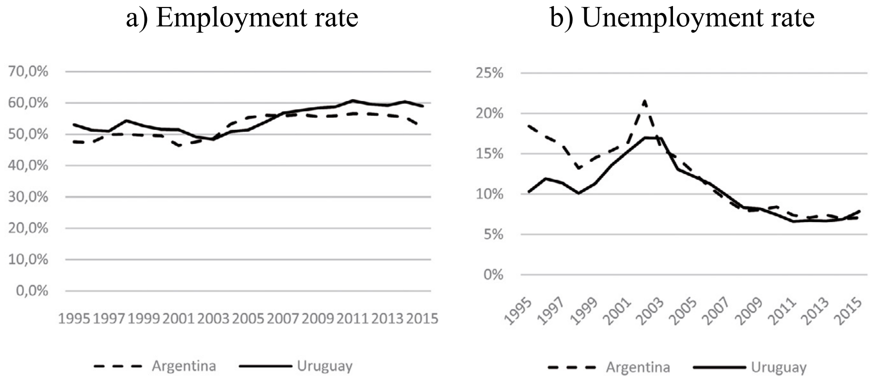
4. EMPIRICAL RESULTS

4.1 Relative importance of each task in the job

In this section we shall analyze job tendencies according to the relative importance of each type of task, starting from the implementation of the methodology just described. Specifically, the focus of attention is the evolution of the type of employment during approximately the last 20 years, which can be defined as the sum of persons employed in some occupation, which, in turn, is constituted by a set of tasks.

In order to put the labor market into context briefly, Figure 1 presents the employment rate and unemployment rate for the period between the years 1995 and 2015.

Figure 1. Employment rate and unemployment. Years 1995 – 2015



Source: Compiled based on World Bank-SEDLAC and Uruguayan National Institute of Statistics

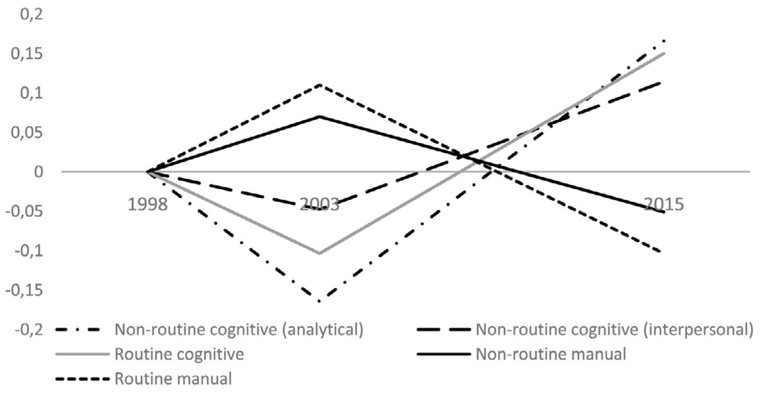
The most prominent fact of the labor market in the decade of the 2000s is a reversal in the negative trend seen in the 1990s. In effect, following a deterioration during the last half of the decade of the 1990s, which ended in 2002 with an unemployment rate which peaked at 21.5% in Argentina and 17% in Uruguay.As a consequence of the economic crisis in Argentina in that year and its spill-over effect on Uruguay, employment showed a very fast rate of growth, led especially by full-time employment.

Such change was a consequence of the configuration of a new macroeconomic stage, based on a type of competitive and stable change during the first post-crisis years in the case of Argentina, an in the significant increase in the price of commodities, the principal goods exported by both countries. From the dawn of this new context, the employment rate in both countries shows an upwards tendency, arriving in 2015 at 52.3% and 59% of the total population in Argentina and Uruguay, respectively. In the same way, the unemployment rate shows a significant fall throughout the period under scrutiny, arriving in 2015 at historical lows equivalent to 7% and 7.8% in Argentina and Uruguay respectively.

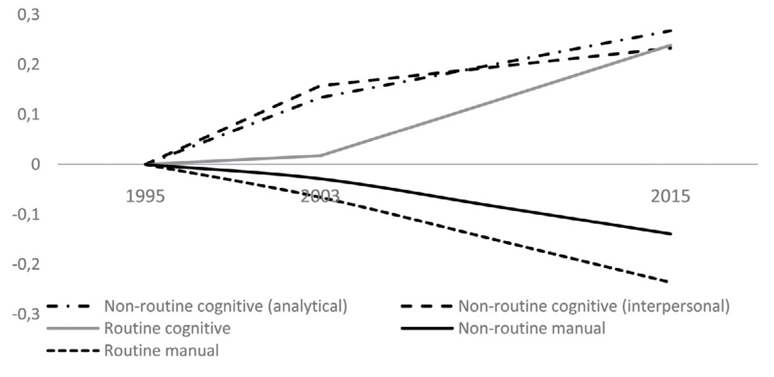
Figure2 shows the variation in intensity of tasks required in a job according to whether these are non-routine cognitive (analytical or interpersonal), routine cognitive, routine manual or non-routine manual.

Figure2. Intensity of the tasks performed in a job.

a) Argentina. 1998 - 2015



b) Uruguay. 1995 – 2015



Source: Our own estimation based on data from household surveys and O*NET

In observing the variation between the extreme years in each country, one can appreciate the increment in the intensity of cognitive tasks, both routine and non-routine, and a fall in the relative importance of manual tasks. However, in the case of Argentina in particular, the tendency is not strictly upwards, as there is a relatively important fall in cognitive tasks and a rise in manual tasks between 1998 and 2003. This can be associated with the economic crisis which the country experienced in 2001-2002. Given the extent of the crisis in the labor market, many workers were forced to carry out subsistence occupations in a situation of economic recession, which are generally intensive in manual tasks. The improvement in employment in subsequent years allowed this process to be reverted.

With respect to the non-routine cognitive tasks, the increase in the relative importance of analytical tasks in the workplace was greater than that observed for tasks associated with personal relations in the period studied, in both countries. This gap seen in the growth of both types of non-routine cognitive tasks appears relatively early on. Effectively, in the years 1990 and 2003 the intensity of analytical tasks in the workplace is already increasing at a greater rate than those associated with the development of personal relationships.

In the case of manual tasks, either routine or non-routine, their importance reduced during the period being studied. In the case of Uruguay, this fall was almost two times greater for routine tasks. In Argentina, and inversely to that observed for non-routine cognitive tasks, an increase in the intensity of manual tasks is seen between 1998 and 2003, although after the economic crisis, these begin to lose relevance in the average workplace.

The importance of routine cognitive tasks in the average workplace shows an increase in both countries during the period under analysis. In the case of Uruguay, this remains stable until the middle of the 2000s, during which period these tasks then begin to grow significantly in importance. In Argentina, just as with non-routine cognitive tasks, the importance of routine cognitive tasks decreases between 1998 and 2003, and then grows throughout the economic expansion and job creation process, particularly formal.

The results found suggest that in Argentina and Uruguay a change took place in the work profile, in terms of the intensity of the tasks that are performed as an average across all occupations, moving from jobs which are highly-intensive in manual tasks towards a greater intensity or content of cognitive tasks.

On average, these countries experienced a growth in the relative importance of non-routine cognitive tasks during the last 20 years. The intensity of the interpersonal cognitive tasks grew in both countries, but slightly less than for the analytical tasks. At the same time, the average intensity of manual tasks reduced, for both routine and non-routine tasks. All these changes can be found online in the findings reached in the most developed countries (Autor *et al.,* 2003, and Spitz-Oener, 2006), and with the results of Keister and Lewandowski (2016) for the case of Central and Eastern European countries and from Aedo et al. (2013) for the case of Brazil.

However, the direction of change in the relative importance of the routine cognitive tasks provides some room for discrepancy. Autor *et al.* (2003) show that the development of this type of task lost relevance within the workplace in the United States and Spitz-Oener (2006) obtained similar results for the case of Germany. However, a revision and update performed by Acemoglu and Autor (2011) for the case of the United States found various trends during specific time periods. In the same way, for Central and Eastern European countries, Keister and Lewandowski (2016) identify an increase in the intensity of routine cognitive tasks, while Aedo *et al.* (2013) obtained identical results for the case of Brazil.

4.2 Factorial decomposition of the change in the content of tasks

The variations in the content of observed tasks raise some concerns related to the mechanisms which operate in the change of the average job profile in both countries. In this sense, we can identify three main channels through which the changes in the importance of each task in the average job are generated.

The first of these is associated with the movement that workers make between economic sectors. As an example, a migration of the average worker from an economic sector such as agriculture, traditionally intensive in manual tasks, to the service sector which is intensive in cognitive tasks, results in a change in the profile of the tasks performed in the average workplace of the countries. This movement of workers between economic sectors can be seen as motivated by different causes such as the change in the terms of trade that affect the sector as a whole and puts them at a disadvantage in the face of international competition, the changes to global business centers and the appearance of other countries with greater comparative advantages in the sector, the urbanization processes which occur as people leave their jobs in rural areas to migrate to the big cities and join the industrial, service or business sectors, among others. However, technological change plays no minor role in this process. The incorporation of new production technology in the sector which displaces the labor force traditionally employed in the performance of manual tasks is exactly what forces this same labor force to seek opportunities in other lines of work.

The second channel of transmission of changes in the content of tasks performed by workers is the movement of workers between occupations within the same branch of activity. As an example, in the extreme, we could use the case of a worker who leaves his job as a bank cashier, a job primarily routine and cognitive, and begins to work in a restaurant or as a taxi driver (non-routine manual). This example highlights the importance technological change can have on the average job profile encouraging workers to move between occupations.

The third channel through which technological change affects changes in the average content of the tasks performed by workers are the changes within the specific occupations. In other words, the incorporation of new production technology in each occupation forces workers to reassign their roles within the workplace. The adoption of assembly machinery which is automated and administered from a computer program requires those tasks previously performed by the labor force to be reassigned. For example, dedicating the majority of their time to tasks relating to sales and merchandising.

In order to examine in detail the importance these transmission channels have had in the changes observed on the content of the different types of tasks performed in the average workplace in both countries, there follows below a factorial decomposition exercise. In order to do this, we took as reference the total changes in the intensity of the tasks between 1998 and 2015 for Argentina and 1995 and 2015 for Uruguay identifying three possible separate effects, namely:

(i) Structural change or effect between sectors (ES). The hypothesis behind this effect is that part of the change in the intensities of the tasks which the labor force performs is associated with a movement of the labor force between the sectors or branches of activity, being partly motivated by technological change, but also as mentioned by other exogenous factors.

(ii) Change between occupations or effect between occupations (EO). This effect is related to the movements of workers between distinct occupations with different combinations of tasks.

(iii) Changes within each occupation (IO). In this case we try to capture the contribution of the changes which are produced within each occupation, in terms of the combination of tasks required for the performance of the same.

The change in job profile according to types of tasks that workers perform is conditioned not only by the demand of work, that is, the current possibilities in the market which are affected by the production technology used in each occupation, but also by the capacity of the labor supply to modify the type of tasks that are performed and demanded. In this sense, the qualification level of the labor force allows it to re-adapt itself to the new conditions of the labor market through any of the three channels mentioned: moving between economic sectors, doing so between occupations in the same sector, or even within the same occupation. For this reason, the estimation of the participation of each effect in the total variation is controlled by the following additional factor:

(iv) Educational expansion (EE). This proposes that an improvement in the qualifications of the workers allows or encourages them to seek jobs which are more intensive in cognitive skills. The educational level of workers operates as a condition of the intensity with which technological change occurs.

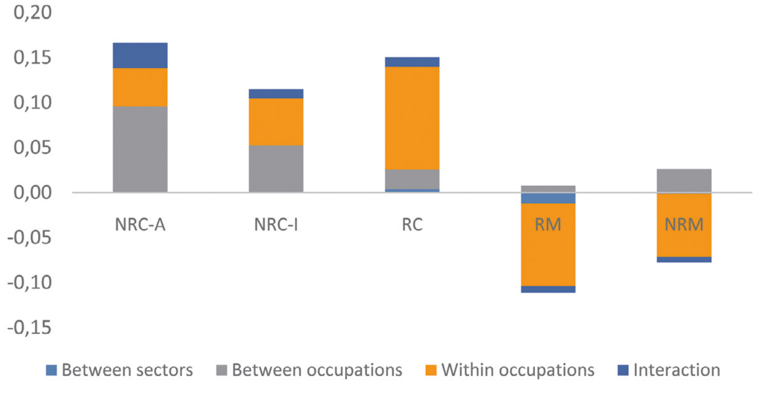
Finally, the interaction between factors is considered.

(v) The interaction of all of the above(INT).

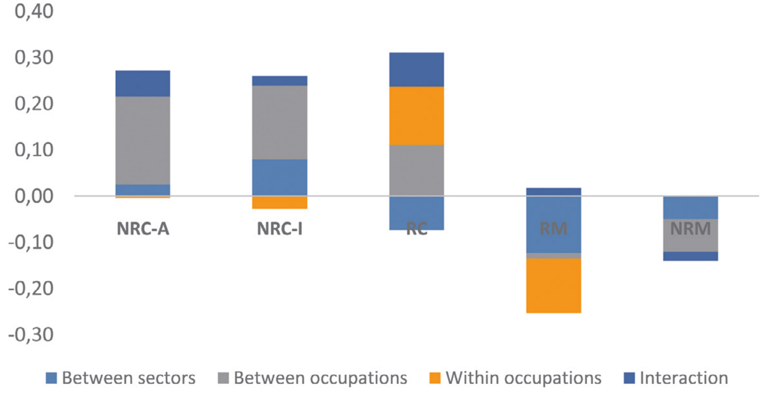
In the appendix the decomposition exercise methodology is described in detail while the results are presented in Figure 3.

Figure 3. Factorial decompositionof the change in intensity of tasks performed in the workplace

a) Argentina - 1998 – 2015



b) Uruguay - 1995 – 2015



Source: Our own estimation based on household surveys and O*NET

The results found allow us to suggest that the **intra-occupational effect**, that is, the changes in the combination of type of tasks within each occupation, constitute an important channel through which change is generated in the relative intensities of tasks in the average job. In this sense, 36% of the increase in non-routine cognitive tasks in Argentina is explained by this factor, although it is not significant in the case of Uruguay. In terms of the increase of the importance of routine cognitive tasks, 76% of this increase in Argentina, and 53% in Uruguay, comes from the changes generated within occupations. Inversely, this factor explains to a significant extent the reduction in the relative importance of manual tasks (both routine and non-routine).

On the other hand, the **between occupations effect** is also significant to explain the change in the relative importance of the tasks performed in the workplace in both countries. With respect to the non-routine cognitive tasks, 51% in Argentina and 70% in Uruguay of the changes observed are associated with movements of workers between occupations, moving from those which involve a higher proportion of manual tasks to those which involve morenon-routine cognitive tasks. In the same way, although with less significance, the effect between occupations explains the increase in intensity of routine cognitive tasks. Finally, the movement of workers between occupations explains the fall in the importance of non-routine manual tasks in Uruguay.

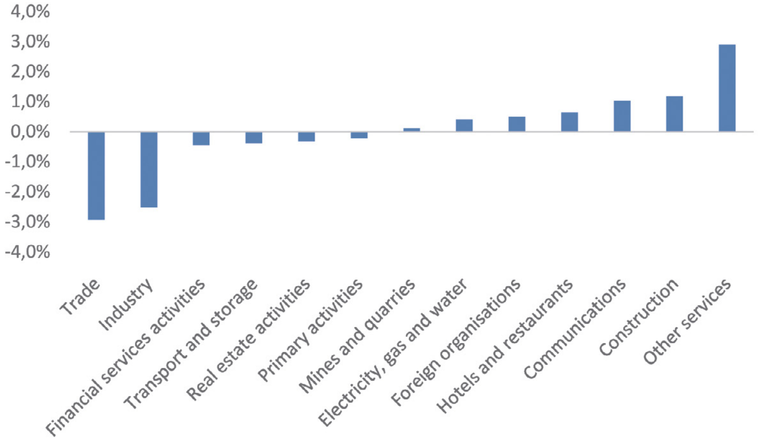
The third relevant factor which can be seen in the case of Uruguay, although not in Argentina, is that coming from the movement of workers **between economic sectors.** In terms of the increase in intensity of non-routine cognitive tasks, 22% of this change is explained by the change of work between branches of activity. In the same way, this effect explains 52% of the fall in the quantity of routine manual tasks and a 36% increase in non-routine manual tasks (although, in this case, it is compensated for by other effects).

The contribution of the structural change has been minimal in Argentina, since no significant movement between branches of activity has been identified (Figure 4a). In this sense, between 1998 and 2015 a small reduction in employment in sectors associated with Trade (3%) and Industry (2.5%), while an increase in employment can be seen in the sectors Other Services (3%) and Construction (1.2 %).

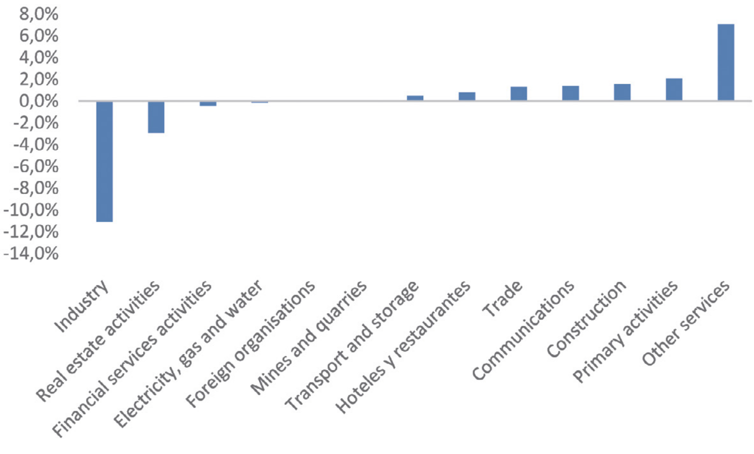
In contrast, in Uruguay, a significant shift in employment was seen between branches of economic activity (panel b.) which explains the importance of the structural change factor in the variations of the intensities of the tasks. A clear shift in employment can be seen from the industrial sector towards services. In the mid-1990s, 20% of total employment was within industry, while in 2015 this percentage had reduced to just 11.2%. In turn, while the service sector employed 32% of the labor force in 1990, in 2015 this had reached almost 40%.

Figure 4. Variation in employment according to branch of activity.
(In percentage points)

a) Argentina - 1998 – 2015



b) Uruguay - 1995 – 2015

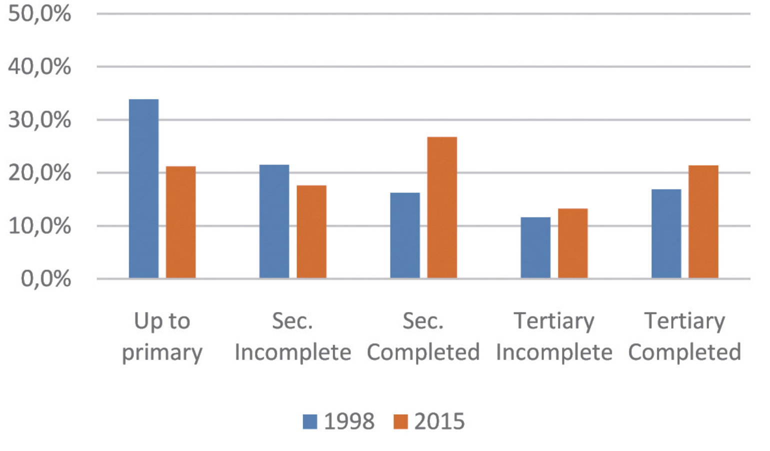


Source: Our own estimation based on household surveys.

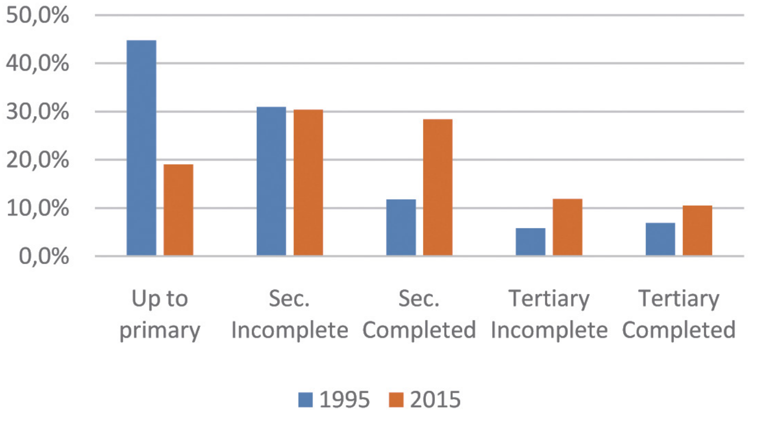
All these transmission channels, in particular that associated with the movement of workers between occupations, are enhanced by an increase in the educational level of the labor force, increasing the possibilities of changing occupation for those who are already active in the labor market, or by enabling the selection of an occupation richer in cognitive tasks for those who are about to enter it. Figure 5 shows an increase in the participation of workers for both countries who have completed secondary education, and completed or started tertiary education, to the detriment of those who have not completed secondary education or even primary education.

Figure 5. Distribution of those employed according to their level of education. Years 1995/1998 and 2015

a) Argentina



b) Uruguay



Source: Our own estimation based on household surveys

Figure 1.A in the appendix presents the results of the factorial decomposition exercise, segregating by the educational expansion effect described above. The results are convincing. If we subtract the effect due to the increase in educational level of the labor force, the contribution due to the movement of workers between occupations ceases to be significant. In other words, the increase in the proportion of workers with a better level of education generates an increase in the labor force with a greater probability of moving to jobs performing non-routine cognitive tasksto the detriment of manual tasks.

In this sense, the results suggest that the possibility of increasing the involvement of cognitive tasks in a sustained manner is strongly linked to the level of qualifications and skills that the workers have. In effect, from the point of view of the labor market, it is clear that space still exists in both countries to move from occupations intensive in manual tasks to those intensive in cognitive tasks if an expansion in the scope of the educational system can be achieved and if the school drop-out rate can be reduced, especially in middle and higher levels of education.

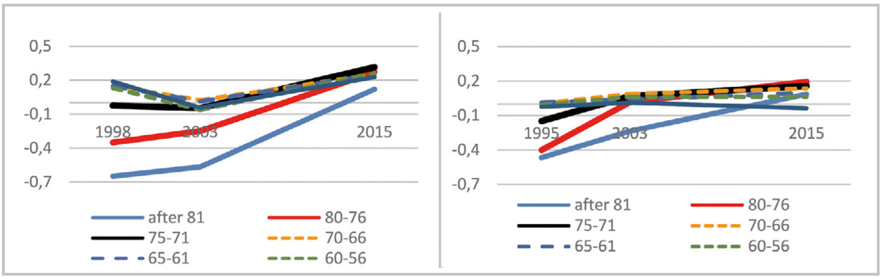
4.3 Changes from an intergenerational perspective

It could be suggested that it is the youngest generation of workers which has the greatest capacity to adapt to technological change, developing cognitive tasks more intensively which complement the new technologies. On the other hand, older generations could have greater difficulty in redefining tasks which are performed in their occupations, exposing themselves to greater risk of technological unemployment. In this context, a complementary approach is the analysis of the evolution of the content of tasks in the average occupation according to the cohort of birth of the workers. For that, Figure 6 shows the evolution of the relative intensity of each type of task in the average job, according the birth cohort of the workers.

Figure 6. Intensity index of the tasks in the job (t_j)according to the cohort. Years 1995/98 – 2015.

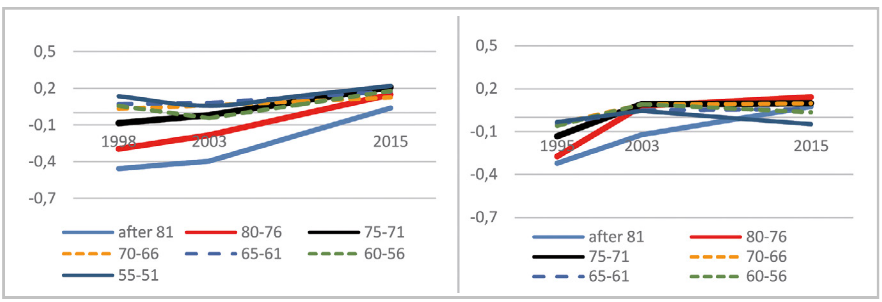
a) Non-routine cognitive tasks - analytical

Argentina Uruguay



b) Routine cognitive tasks –interpersonal

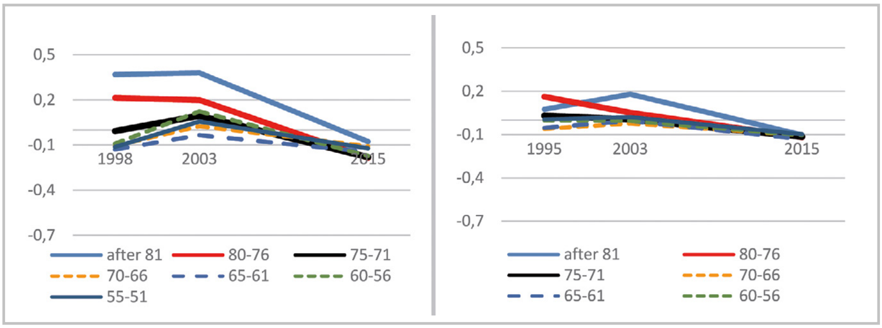
Argentina Uruguay



With respect to the intensity of the non-routine cognitive tasks in the job, both with the analytical and the interpersonal tasks, a clear stable trend can be seen for the cohorts before 1971. For its part, the relative importance of this type of task in occupations chosen by cohorts following this year shows a clearly positive trend. This suggests that older workers have greater difficulty in adopting and performing non-routine cognitive tasks than the young. For its part, the rapid growth in the importance of analytical cognitive tasks between the youngest generations could be attributed to two complementary factors: i) a greater capacity to adapt to change in the combination of tasks that are required, and ii) a composition effect, that is, the entrance of younger generations to the labor market is delayed since they spend more years in education and therefore their weighting in the average increases as they enter.

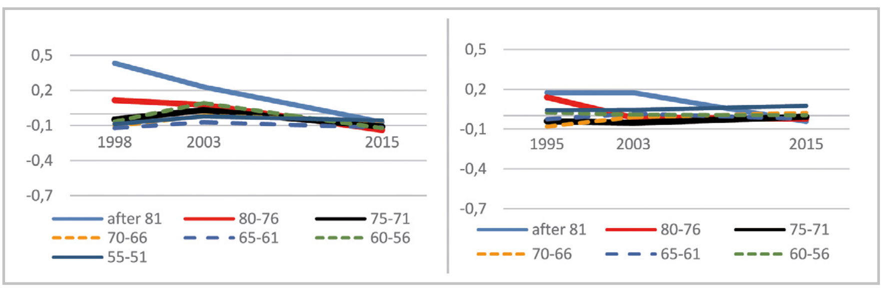
c) Routine manual tasks

Argentina Uruguay



d) Non-routine manual tasks

Argentina Uruguay

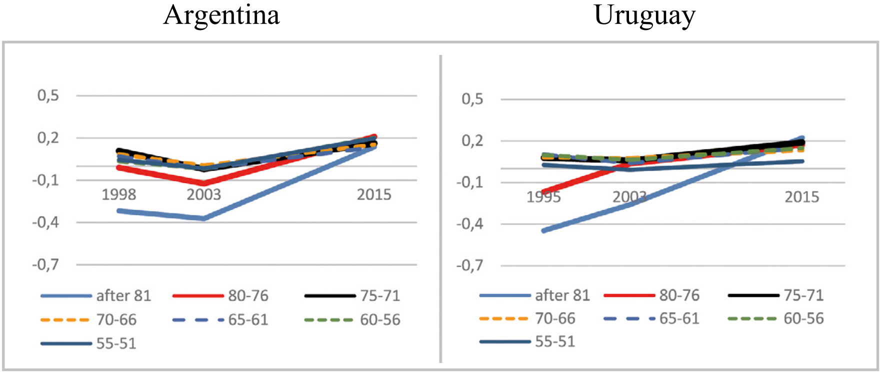


Conversely, in observing the variation in the relative importance of routine manual tasks in employment this suggests that although this shows a stable trend for all cohorts greater than 1971, the incline becomes negative for younger cohorts. Something similar, though of a lesser magnitude, is observed in the intensity of non-routine manual tasks.

In both cases, during the period under study a greater decline can be seen in the youngest cohorts, which suggests that on one hand, the young are directing their entrance into the labor market towards occupations which are less intensive in terms of non-routine manual tasks, and on the other hand, that as this group of workers has a greater capacity for adaptation they replace occupations intensive in these types of tasks with those more cognitively intense.

With respect to the relative importance of routine cognitive tasks, again the youngest cohort is that which defines the trend of the change, while the older generations remain relatively constant in the tasks which they perform in their occupations.

e) Routine cognitive tasks



Source: Our own estimation based on household surveys and O*NET

In summary, during the last two decades, the workplace in Argentina and Uruguay has experienced some changes in terms of the type of tasks which workers perform in their jobs. In this sense, we can detect an increase in the relative importance of non-routine cognitive tasks and a reduction in the intensity of manual tasks. In contrast with that seen in developed countries, work intensive in routine cognitive tasks has shown signs of growth. These variations correspond to various explanatory factors. On one hand, the process of technological change which incentivizes the modification of the optimum combination of tasks within an occupation. At the same time, and for the case of Uruguay, there is also still an effect of sectoral change, that is, the movement of work between branches of activity, moving from those which are more intensive in manual tasks to sectors with a greater emphasis of occupations intensive in cognitive tasks.

All changes are enhanced by the educational expansion that took place in the labor force, since as the workers increase their levels of qualification, they increase their chances of dedicating a larger proportion of their time to the performance of cognitive tasks. In any case, it is the young generations who dominate these trends, which suggests that they have a greater capacity for adaptation than the older generations.

4.4 Polarization of the labor market

The process of adopting new production technologies based on automation, robotics and digital communication would permit an increase in global productivity and therefore economic efficiency. However, that also implies a risk from the point of view of distribution. That being through the generation of a possible polarization of the labor market, since the transition from occupations which are intensive in manual tasks towards those more intensive in cognitive tasks demands a greater level of qualification from the labor force.

In this sense, this distribution risk is that the labor market remains represented by two large groups of workers. On one side, those who are highly-qualified, who perform tasks requiring an intensive use of non-routine cognitive tasks, of high productivity and high incomes. On the other side, a group of poorly-qualified workers, relegated to occupy those positions requiring intensive use of non-routine manual tasks, and therefore of low-productivity and low incomes. This will occur while workers with medium-level qualifications and incomes, face the risk of a reduced labor demand in the performance of routine tasks. This polarization may manifest itself through two complementary paths: employability (with increases in the extremities of the productivity distribution and falls in the center) and salary levels.

In order to provide an approximation of the effect that the changes in intensity of the tasks performed by the labor force have on the well-being of the workers, we have estimated here the significance of the relative importance of each task on the explanation of two key variables of workers' well-being: probability of becoming unemployed and level of income.

The identification of the determinants of the probability of becoming unemployed is done by the estimation of the following probit model:

$$Pr(d_i) = f\left(t_{i,j}, \Theta_i, u_i\right)$$

Where d_i takes the value of one if the individual finds themselves unemployed and zero if they are employed,[12] $t_{i,j}$ represents the intensity of the task j which the individual i performs and Θ_i is a vector of individual control variables such as age, a dummy variable which takes the value of one if the person is a man and the number of years of study.

The hypothesis states that those workers who perform routine tasks more intensively have a greater probability of finding themselves unemployed as a result of facing a greater risk of substitution, while those who perform more cognitive tasks have a lesser risk of finding themselves in that situation. The results of the estimation are presented in Table 2.

12 The household surveys conducted both in Argentina and in Uruguay include a question relating to the characteristics of the previous employment of the individual in the case that he is currently unemployed.

Table 2. Estimation of the probability of being unemployed. Year 2015

Variables	Argentina	Uruguay
Non-routine cognitive	-0.0514244*	-0.0172726*
	´(0.029028)	(0.0010277)
Routine cognitive	-0.1406224***	-0.0769139***
	(0.018459)	(0.009799)
Routine manual	0.3346739***	0.0505115***
	(0.041706)	(0.013147)
Non-routine manual	-0.1563471***	-0.0074673
	(0.038226)	(0.015701)
Man	-0.1227095***	-0.2669335***
	(0.034698)	(0.020472)
Yearsof education	-0.0014153	-0.045073***
	(0.005044)	(0.003176)
Age	-0.0233769***	-0.0244753***
	(0.001292)	(0.000695)
Constant	-0.791312***	-0.0257861
	(0.104482)	(0.044926)
Nº of observations	24299	53740
LR Chi2	902.52	1989.95
Prob> Chi2	0.0000	0.0000
Pseudo R2	0.1024	0.0787
Log likelihood	-3954.6	-11648.1

Source: Our own estimation based on household surveys and O*NET
Note: Standard error is shown in parenthesis. *** significant to 1%, ** to 5% and * to 10%.

The results found confirm the trends observed and partially confirm the hypothesis suggested for developed countries.

In this sense, the variable "Routine manual" has the positive sign expected and is significant to 1%. That suggests that the possibility of becoming unemployed increases as the relative importance of the routine manual tasks performed in that occupation grows. In other words, those workers in occupations that require a higher intensity of routine manual tasks face a greater risk of finding themselves unemployed, with this effect being greater in Argentina than in Uruguay. These results allow us to suggest that technological change, and therefore, the possibility of replacing tasks with automation, increment the probability of unemployment for those workers who spend the majority of their working hours performing routine manual tasks.

However, and in line with that discussed previously, no positive relationship is found between the probability of being unemployed and the intensity of routine cognitive tasks in the previous occupation. In effect, and in contrast to what has taken place in developed countries, in Argentina and Uruguay we have seen an increase in the relative importance of this type of task in the average workplace over the last 20 years.

With respect to the level of labor income, we propose the estimation of the Mincer equation (1974) in order to better understand the relationship between the relative importance of the tasks which workers perform in their jobs and their level of income per hour.

For this, the following equation is estimated:

$$\log w_i = \beta_0 + \beta_1 t_{i,cnr} + \beta_2 t_{i,cr} + \beta_3 t_{i,mr} + \beta_4 t_{i,mnr} + \beta_j \Theta_i + u_i$$

Where w_i is the salary per hour,

$t_{i,j}$ is the index of intensity of each task j Θ_i is a vector of individual control variables: work experience, work experience squared, a dummy variable which takes the value of one if the individual is a man, the years of education, and a dummy variable which takes the value of one if the worker has formal employment.

The results of the estimation through the Ordinary Minimal Squares (Table 3) are as expected. Workers in occupations which require a greater relative importance of cognitive tasks have an output, in terms of hourly salary, greater than those who perform a greater intensity of manual tasks. In both countries, non-routine cognitive tasks have a greater remuneration than routine ones.

The results found allow us to suggest that the changes observed in the workplace, in terms of the types of tasks that the labor force performs, and the changes to be expected in the future while the access costs to new technologies decrease and the capacity to adapt to them increase, could imply a greater risk of polarization of the labor market.

A greater insertion of new technologies of automated production has two direct effects on the market. On one hand, the increase in probability of unemployment (technological unemployment) among those workers in occupations intensive in routine manual tasks. On the other hand, a reduction in the level of income for those who work in occupations which are intensive in manual tasks, and an increase in income for those workers in occupations intensive in cognitive tasks, especially non-routine.

Table 3. Ordinary least squares–Mincer's Equation. Year 2015

Variables	Argentina	Uruguay
Non-routine cognitive	0.138261***	0.0571613***
	(0.006626)	(0.003453)
Routine cognitive	0.0579983***	0.0297189***
	(0.004752)	(0.003486)
Routine manual	0.0430737***	-0.0182148***
	(0.012302)	(0.004679)
Non-routine manual	-0.0248547**	-0.0263061***
	(0.0105)	(0.005292)
Experience	0.012084***	0.0247491***
	(0.000921)	(0.000736)
Experiencia2	-0.000134***	-0.0002611***
	(0.000002)	(0.000001)
Man	0.0722601***	0.2277636***
	(0.009096)	(0.006925)
Years of education	0.0371603***	0.0808401***
	(0.001416)	(0.001138)
Formal	0.4958803***	0.3572354***
	(0.00881)	(0.008088)
Constant	2.571179***	3.188941***
	(0.02658)	(0.01651)
Nº of observations	21707	49256
Statistic F	1053.0	2143.1
Prob > F	0.0000	0.0000
R2	0.30	0.28
R2 adjusted	0.30	0.28

Source: Our own estimation based on household surveys and O*NET
Note: Standard error shown in parenthesis. *** significant to 1%, ** to 5% and * to 10%.

5. IMPLICATIONS FOR PUBLIC POLICY

The process of technological change could generate a reduction in the employment demand for those on middle incomes (in general associated with routine manual tasks), establishing a polarization of the labor market, creating two large groups of employment: one of poorly-paid activities, related to the performance of non-routine manual tasks, and the other of higher incomes related to non-routine cognitive tasks.

In this technological race, there is a clear challenge laid out for public policy associated with the need of low-skilled workers to reassign their tasks towards others not susceptible to automation, that is, towards those that require an intensive use of creative or social intelligence.

In the last 20 years the labor markets of Argentina and Uruguay experienced a substantial change, moving from manual work to cognitive work, which can largely be attributed to an improvement in the qualification levels of the labor force, the modernization within the occupations themselves and, in the case of Uruguay, to a movement of workers between sectors. As in the United States, Germany, and the countries of Central and Eastern Europe, the importance of non-routine cognitive tasks in the average workplace has shown signs of considerable increase in the Argentina and Uruguayan economies. However, a fundamental characteristic which distinguishes these two countries from the labor markets of the United States and Germany, was the growth in the intensity of routine cognitive tasks.

Two effects of technological change and its reduced access cost can be seen: one more short term and one of medium or long term but which requires immediate action.

The first is associated with a lower requirement for routine manual tasks and therefore, an increase in technological unemployment in some segments of the labor force. The second is related to the challenge of preparing the younger generations, in their process of acquiring human capital, for the performance of occupations which do not exist yet but will certainly incorporate a major component of non-routine cognitive tasks.

In relation to technological unemployment, the policies aimed at confronting the negative effects of the movement of employment from intensive production in routine manual work towards intensive production in technological capital and cognitive work are of crucial importance. The transition may be confronted from two different perspectives, one from the point of view of labor demand and the other from supply.

From the perspective of labor demand, that is to say the actual productive sector which chooses the combination of factors which maximizes its benefits, the transition could be attenuated through regulations which limit the substitution of labor force by capital. These regulations could be enhanced by the political economy itself in each economy. As an example, unions play an important role in the political economy with the ability to apply pressure on the productive sector and the state in order to prevent changes in production functions. An example of that is the frustrated attempt of the Central Bank of Argentina in 2016 that the commercial banks gradually substitute printed summaries of accounts with those in digital format. This constituted a risk of reduced labor demand for the postal and delivery workers. Confronted with such a risk, the truck drivers union opposed, and managed to block the implementation of the initiative proposed by the monetary authority. In another similar case, in 2008 in Uruguay, an attempt was made to replace the bus conductors with automatic ticket dispensing machines, but the transition was never completed in order to avoid the effect that it would have on the level of employment in that occupation.

Alternatively, the authorities could design fiscal incentive mechanisms, such as subsidiary schemes for sectors or occupations which require tasks of a routine nature. In this way, the state would indirectly modify the relative prices of the production factors, discouraging the replacement of labor force by capital.

However, whichever initiative is adopted from this perspective, it must take into account the social costs and benefits which are generated. In this sense, it is essential to analyze the costs of these decisions (for example, in terms of increased production cost and reduced well-being of the consumers who pay higher market prices) and the benefits (maintaining employment levels in certain occupations). In the same way, it is important to stress that technological change is a continuous phenomenon and therefore the access cost will continue to decrease. That implies that the trend towards automation is growing over time, which implies that the costs of its deterrence shall too. In other words, to maintain its effect, this type of intervention will need to increase over time as the process of technological change advances, accepting ever greater costs of intervention.

On the other hand, and as shown by the factorial decomposition exercise in section 4.2, the movement of workers between occupations, encouraged by the increase in level of education of the labor force, is the most important channel through which changes in the work profile will be affected. So, in order to be effective, the labor protection policies should be oriented towards regulating and offering incentives that affect the production function of companies, instead of protecting productive sectors, since the greatest change will take place within these areas.

Alternatively, public policy could focus its efforts of labor supply. Both Argentina and Uruguay have a continuous training system for working adults. In this sense, the consistent challenge in the strengthening of the spaces or instruments of re-adaptation of the labor supply, that is, redesigning continuous training systems taking into account the new labor demands. That should consider the promotion of public-private cooperation, not only in terms of financing, but also in terms of defining the training strategy and taking advantage of economies of scale on training tasks. For that, it is necessary to clearly identify the factors which put the success of this type of initiative at risk, above all, between older workers.

The medium-term challenge, but which in reality needs to be addressed immediately, is the preparation of the young generations, in their process of accumulation of human capital, for the performance of roles which still "do not exist". Beyond the potential creative destruction of employment, and its consequential technological unemployment, this process could be a step towards an increase in global productivity of the economy and to the generation of new occupations which are currently unknown.[13]

Economic growth takes place as jobs become more productive, but also as more productive jobs are created and those less productive disappear.

13 As was the machinist after the Industrial Revolution and the web designer at the beginning of the 21st century.

In the latter instance, these benefits may be as a consequence of new products, new methods of production and transport and new markets, but they appear through a constant restructuring and redistribution of resources, including the labor force. Since economies grow as high productivity jobs are created and low productivity jobs disappear, the relationship between increases in productivity and the creation of jobs is not mechanical. Even if in the short term the innovations may imply increases or reductions in levels of employment, in the medium term the increase in employment will tend towards being closely aligned with economic growth.

In a context where many of the jobs that shall be performed by the children of today still do not exist, it is not possible to plan specific training for such occupations. The challenge, however, consists of preparing their cognitive skills in such a way as to generate their capacity to create and adapt to whatever situation presents itself.

To achieve this, it is essential to rethink the educational system at all levels, achieving rapid adaptability of subjects to labor demand as it arises. In this sense, we suggest that it is necessary to switch focus from one which bases educational systems on the paradigm of acquiring knowledge (memorizing) to one which prioritizing the development of cognitive and socio-emotional skills, through problem-solving, as a foundation to gain technical skills in a continuous form.

The challenge consists in recognizing the importance and generating the paths for the development of a mechanism of study associated with the development of critical thought (argue, think, analyze), that is, the generation of transferable/adaptable skills which are useful in different activities, that is, with a great capacity for fast adaptation.

It is crucial that all students of the educational system develop and learn their basic skills, above all the numeric skills and problem-solving, since cognitive deficiencies developed at an early age are extremely difficult to overcome later in life. This must be accompanied by a constant update process, not only of the tools but also of the vocabulary itself. As an example, Internet access has a minimum requirement of a new kind of literacy (cognitive and digital).

6. FINAL REFLECTIONS

Technological innovation, such as the advance of the digital technologies, communications and robotics, may imply an improvement in the general well-being of the population and reduce poverty by increasing the overall productivity of the economy. However, if this process is not accompanied by complementary investments, that is to say institutional reforms and public policies directed at making the most of its advantages, the technological advance could also deepen a situation of inequality.

From a study of the employment profile trend in the last 20 years it is possible to see a significant increase in the relative importance of cognitive tasks in the workplace to the detriment of manual tasks. In effect, these changes are generated through changes produced within the occupations in terms of the combinations of types of tasks which are performed to produce a good or service; and structural changes – especially in Uruguay – that is, movements of workers between branches of activities, moving from branches which are more intensive in manual tasks to sectors intensive in cognitive tasks. This process is encouraged by the level of qualification of the labor force, which enables the adaptation of the workers and the change of the type of work that is required, especially among the younger generations.

It is possible to expect a deepening of these trends, in favor of non-routine cognitive tasks to the detriment of routine manual tasks, as technological change advances and it may be appropriate and adapted by the productive sector of developing countries.

Clearly, this will imply a reduction in specialized labor demand in routine manual tasks, generating technological unemployment in the short term. However, any technological change which replaces workers with machines will have effects on all the product and factor markets. An increase in production efficiency which allows the costs of production methods to be reduced could generate an increased demand in other goods and services.

Therefore, technological progress has two effects on the level of employment. In the first place, a destructive effect, as technological change replaces the labor force; and in second place, an effect of creating new jobs, as the number of production units that internalize new technologies increases and productivity increases, complementary employment in these sectors expands and other occupations are generated that meet new demands for goods and services.

In this context, it is key to define two different strategies, one short term and one long term but which requires immediate action. With respect to the potential situation of technological unemployment it is important to orchestrate mechanisms which permit a strengthening of the continuous training system in a way that allows the re-adaptation of the labor supply. In other words, it is important to redesign the systems of continuous training considering the new labor demands. This should take into account the promotion of public-private cooperation not only in terms of financing but also the definition of a training strategy and the use of economies of scale in training.

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APPENDIX. DECOMPOSITION OF THE VARIATION OF THE INTENSITY OF THE TASKS IN THE JOB

For each country there are 65 cells that emerge from the combination of 13 sectors/branches of activity and 5 educational categories. For each task *i* the change is decomposed (between 1995 and 2015) of the average intensity of the task per worker, IT_i, considering the contribution of five factors:

i. Changes in the sectorial structure (effect between sectors), ES_i;
ii. Changes in the educationalstructure (education effect), EE_i;
iii. Changes in the occupationalstructure (inter-occupation effect), EO_i;
iv. Changes in the intensities of the content of each task within a particular occupation (intra-occupation effect), IO_i; Y
v. The interaction between those changes in the structure of work and the intensities of the associated tasks, INT_i.

The decomposition is calculated for each country according to the formula:

$$IT_{i\in T}\left(IT_i^{2015} - IT_i^{1995}\right) = \left(\sum_{j\in S}\sum_{k\in E} t_{i,j,k,15}^{15}\, h_{j,k}^{15} - \sum_{j\in S}\sum_{k\in E} t_{i,j,k,03}^{95}\, h_{j,k}^{95}\right)$$

$$IT_{i\in T}\left(IT_i^{2015} - IT_i^{1995}\right) = ES_i + EE_i + EO_i + IO_i + INT_i$$

$$\forall_{i\in T} ES_i = \sum_{j\in S}\left[t_{i,j,k,03}^{95}\left(h_j^{15} - h_j^{95}\right)\right]$$

$$\forall_{i\in T}\ EE_i = \sum_{j\in S}\left(\sum_{k\in E} t_{i,j,k,03}^{95}\left(\frac{h_{j,k}^{15}}{h_j^{15}} - \frac{h_{j,k}^{95}}{h_j^{95}}\right)\right) h_j^{95}$$

$$\forall_{i\in T}\ EO_i = \sum_{j\in S}\sum_{k\in E}\left(t_{i,j,k,03}^{15} - t_{i,j,k,03}^{95}\right) h_{j,k}^{95}$$

$$\forall_{i\in T}\ IO_i = \sum_{j\in S}\sum_{k\in E}\left(t^{15}_{i,j,k,15} - t^{15}_{i,j,k,03}\right) h^{95}_{j,k}$$

$$\forall_{i\in T}\ INT_i = \sum_{j\in S}\sum_{k\in E}\left(t^{15}_{i,j,k,15} - t^{95}_{i,j,k,03}\right)\left(h^{15}_{j,k} - h^{95}_{j,k}\right) + \sum_{j\in S}\sum_{k\in E} t^{95}_{i,j,k,03}\left(h^{15}_{j,k}\left(1-\frac{h^{95}_j}{h^{15}_j}\right) + h^{95}_{j,k}\left(1-\frac{h^{15}_j}{h^{95}_j}\right)\right)$$

Where:

$t^{y}_{i,j,k,15}$ and $t^{y}_{i,j,k,03}$ represent the average value of the intensity of task *i* for the worker *j*, with education *k*, in the year y = [1995,2015], calculated from the use of O*NET 2015 and 2003, respectively. Those variables which omit the sub index *k* refer to the sector average.

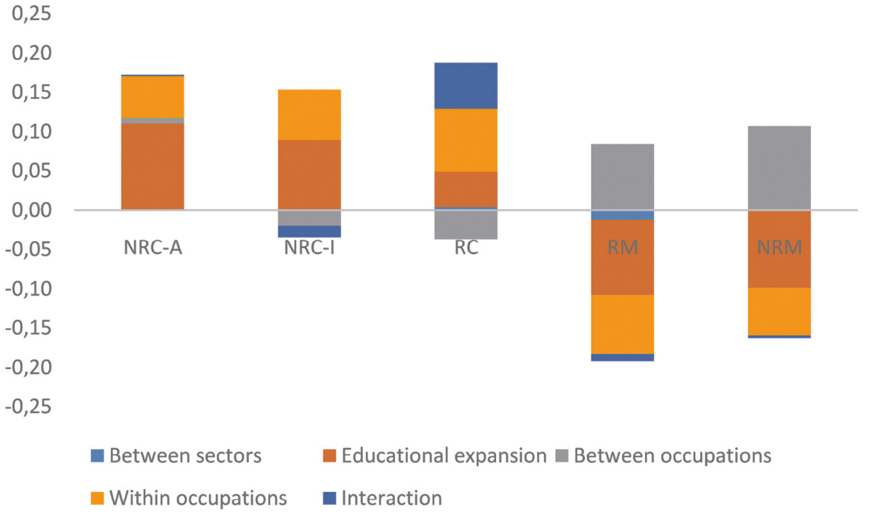
$h^{y}_{j,k}$ represents the percentage of the work in sector *j* with educational level *k*.Those variables which omit the subindex *k* refer to the sector average.

T is the combination of the five tasks defined.

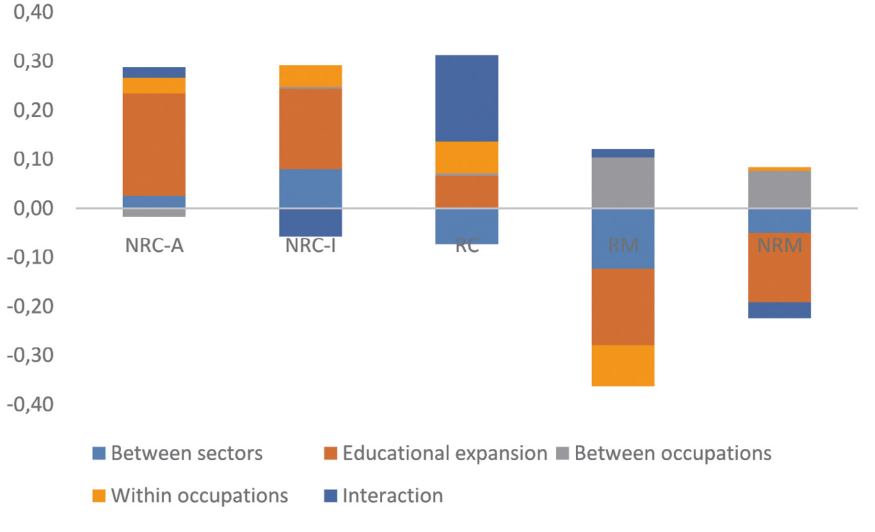
S is the combination of 13 sectors, defined from ISC to one digit, and *E* is the combination of five educational levels (primary completed or less, secondary incomplete, secondary completed, tertiary incomplete, tertiary completed).

Figure 1.A. Factorial decomposition of the change in intensity of the tasks performed in the job. Discriminated educational expansion effect

a) Argentina - 1998 – 2015



b) Uruguay - 1995 – 2015



Source: Our own estimation based on household surveys and O*NET