BRAZIL'S AUTOMATABLE JOBS: THE IMPACT OF INFORMATION TECHNOLOGY[1]

João Pedro Lima Delgado
PUCRS, Business School, Porto Alegre, Brazil; e-mail: jplimadelgado@gmail.com

Silvio Hong Tiing Tai
RITM, Paris-Sud University, Orsay, France; and PUCRS, Business School, Porto Alegre, Brazil

Niels-Hugo Blunch
Department of Economics, Washington and Lee University, Lexington, VA 24450, USA; Institute of Labor Economics (IZA), Bonn, Germany

Abstract: This paper investigates the impact of recent advances in the technological frontier on Brazilian workers' income. To this end, a new classification of automatable occupations that considers the use of disruptive technologies has been used. We use employer-employee microdata from the Brazilian Formal Sector from 2013 contained in the Annual Social Information Report *(Relação Anual de Informações Sociais* - RAIS). We estimate the impact a firm's use of information technology has on the salaries of employees in occupations deemed to be automatable by current standards. This cross-sectional analysis provides evidence that the substitution of labor by information technology can be observed through the statistically significant reduction in income, even in a developing country with low wages relative to computational costs.

Keywords: automation; labor substitution; information technology; artificial intelligence; computerization.

TRABALHOS AUTOMATIZÁVEIS DO BRASIL: O IMPACTO DA TECNOLOGIA DA INFORMAÇÃO

Resumo: O presente artigo investiga o impacto dos recentes avanços na fronteira tecnológica no salário de trabalhadores brasileiros. Para este fim, uma nova classificação de profissões automatizáveis que considera o uso de tecnologias disruptivas foi utilizado. Foi feito uso de microdados referentes a empregadores e empregados do setor formal brasileiro de 2013 contidos na Relação Anual de Informações Sociais – RAIS. Nós estimamos o impacto que a utilização de tecnologia da informação tem no salário de empregados em ocupações consideradas automatizáveis nos padrões atuais. Esta análise em corte transversal fornece evidências de que a substituição do trabalho por tecnologia da informação pode ser observada por meio de significante redução na renda, mesmo em uma economia em desenvolvimento com baixos salários relativos em relação a custos computacionais.

Palavras-chave: automação; substituição do trabalho; tecnologia da informação; inteligência artificial; computadorização.

JEL classification: J23, J24, J3

Área: Economia do Trabalho

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1 INTRODUCTION

Historically, technological changes have provoked intense debate about the impact they produce in society. The benefits of innovations such as the steam engine, electricity, computers, and more recently, robotics and artificial intelligence are accompanied by ruptures with the underlying historical context that may lead to unforeseen and undesirable outcomes for a portion of the population. Such outcomes may be represented, for example, by a reduction in the income of certain workers by virtue of the introduction of disruptive technologies. Concern about the substitution of human labor by capital has existed, at least, and incontestably, since the Luddite movement in England between 1811 and 1816 (FREY and OSBORNE, 2013, AUTHOR, 2015).

This debate has been reinvigorated with each technological evolution imposed on society, especially those in which the pace of penetration and change in labor relations is intense. Technological developments such as the steam engine and electricity replaced physical capacity, as pointed out by Leontief (1983), while the computer has allowed the automation of complex and routine tasks. The latest advances in robotics and artificial intelligence offer the possibility of replacing the human being in tasks with a greater cognitive demand, such as writing legal texts and driving cars. There is evidence of an ongoing substantial transformation of the capacity for automation. We have reached the point where ‘self-learning’ computational systems are superior to ‘human-taught’ computational systems (SILVER *et al.*, 2018). What impacts are felt by workers as we see an increasingly qualified range of professions being targeted by automation via Robotics or Artificial Intelligence?

This article estimates the impact of information technology use (ITU) by firms on the relative wages of workers with occupations considered automatable by current standards, according to the recent literature. Using Brazilian employer-employee date from the 2013 RAIS (*Relatório Annual de Informações Sociais* - Annual Social Information Report), we identify the automatable occupations and a proxy variable for each firm’s information technology use, captured by the proportion of employees dedicated to the information technology sector. The article is believed to be novel in terms of this type of study in the Brazilian context, which presents harder conditions to replace workers by ITU, comparing to developed countries. On the one hand, the computer hardware cost is relatively high;[2] on the other hand, the level of wages is substantially lower than developed countries. Nevertheless, the econometric findings show the wages of individuals in automatable occupations are reduced in firms that make intensive use of information technology, suggesting there is a substitution effect between those workers and information technology.

Depending on the technological innovation, some sectors of the labor market benefit while other sectors are penalized. Therefore, the relationship between technological advance and the labor provided by human beings changes over time. For example, during the 19th century, the adoption of new productive methods led to the replacement of the then relatively skilled worker (represented by craftsmen) by machines that allowed the work activities to be broken down into several simpler tasks that were amenable to replication. Capital thus complemented unskilled labor, while replacing the skilled labor of specialized craftsmen. However, from the late nineteenth and early twentieth century, with the paradigm shift represented by the replacement of steam power by electrical power in manufacturing, there was a rupture in the pattern of employment of labor. During this period, in contrast to the nineteenth century, there was a trend towards a greater demand for skilled labor. Electricity allowed many tasks previously performed manually by low-skilled workers to be fully automated, which in turn increased the demand for skilled labor – better complemented the available capital (GOLDIN and KATZ, 1996 and 1998).

The late twentieth century was marked by notable advances in the use of computer science or information technology in the workplace; first with the introduction of mainframes in 1970, later with the expansion of the use of personal computers in 1980 and finally with the growth of the use of networks in

[2] Brazil presents relative high level of taxes (BAER; GALVÃO, 2008), which increases consumer prices. Indices of international products, as *iPad* from Apple, recurrently places Brazil with the highest nominal price (MAZUNDER, 2016).

1990 (AUTHOR, LEVY and MURNANE, 2002). The so-called Computational Revolution[3] is considered one of the main variables responsible for the augmenting complementarity between capital and skill (KRUEGER, 1993, AUTHOR *et al.*, 1998, BRESNAHAN *et al.*, 2002). Bresnahan *et al.* (2002) show that reduced Information Technology prices allowed for its increasing adoption in the workplace, generating greater organizational innovations in the firm and expanding the demand for skilled workers.

Nevertheless, some authors explore the nature of work computers *could* substitute. Autor *et al.* (2003) expands the analysis by Levy and Murnane (1996)[4] and assume that computational capital is a substitute for human labor in routine tasks (whether manual or cognitive)[5] that are performed following explicit, well-defined rules. They also assume that computational capital is complementary to human labor when the tasks required for its accomplishment are non-routine, involving communication and resolution of complex problems. [6] This model predicts that labor intensive industries and jobs will routinely invest relatively more in computational capital as its cost decreases. In this sense, there will be a shift towards a demand for non-routine work. It is important to note that although the reduction in the prices of information technology is the main determinant behind the increased popularity of its use, it is not a sufficient condition for the adoption of these technologies everywhere.

On that note, Zeira (1998) shows that the cost of computing capital needs to be relatively lower than the cost of the labor to be replaced for a technology to be adopted. Therefore, wage levels have a positive impact on the adoption of new technologies, since they create an incentive for producers to substitute this factor with factors with a lower relative cost. This conclusion implies that not all countries will adopt the new technologies, even though they may be already available, as adoption requires a greater input of capital into the productive process, which will only be justified in countries with sufficiently high wages. While this is certainly the case of the most developed countries, further investigation is necessary for developing countries, as Brazil, which presents an intermediary situation. Although the World Bank classifies this country as upper-middle income economy[7], it presents only 26% of United States GDP per capita.[8]

Since the beginning of the 21st century, the fields of Artificial Intelligence and Robotics have led to a shift in the way we think about the machines used, both in the production process and in our daily lives. It challenges us to rethink the way they have been seen as merely tools that increase worker productivity (Ford, 2015). Rather, machines are now seen as having the explicit purpose of replacing humans in any and all physical or cognitive tasks (NILSSON, 1984). The substitution of workers by computational capital, be it embodied in the form of machine, algorithms or artificial intelligence, is the natural continuation of the long process of automation that began in the nineteenth century (KORINEK and STIGLITZ, 2017).

In the present century, research into Artificial Intelligence has already reached a level of sophistication that seeks to understand and build agents endowed with rationality, that is, systems capable of acting with instrumental rationality, given the information to which they have access, to achieve a goal. Thus, Machine Learning systems could adapt to new circumstances and detect and extrapolate patterns[9]. In

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[3] The Computer Revolution began between 1960 and 1990, facilitated by the continuous decline in cost per computation – on average 37 percent between 1945 and 1980 and 64 percent between 1980 and 1990 – as pointed out by Nordhaus (2007).

[4] Levy and Murnane (1996) argued that computer networks are capable to substitute human work in "routine tasks" rather than in "exceptional tasks". The latter comprising all those tasks in which human labor has a comparative cost advantage, whereby automating them would be either too expensive or impossible.

[5] The insight about how computers would be able to reproduce routine tasks had already appeared since the first remarks regarding a "universal machine" in Turing (1936, p.242), "[…] each step could be carried out by referring to these rules. We have only to regard the rules as being capable of being taken out and exchanged for others and we have something very akin to the universal machine."

[6] Since 1960, computer systems in the workplace would have been responsible for the regularization and "routinization" of simpler, repetitive tasks, as opposed to more complex idiosyncratic tasks (BRESNAHAN,1999).

[7] Source: https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html. Accessed on 16 September 2019.

[8] In 2018 purchase parity power. Source: https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD. Accessed on 16 September 2019.

[9] In such systems, the initial set up may contain some *a priori* knowledge of the environment in which it is inserted, but as the system gains experience, that knowledge may change or increase (RUSSEL and NORVIG, 2004).

addition, the advance of Big Data technology, in particular, enables engineers to develop increasingly accurate and effective codes – as they benefit greatly from the amount of data available online and in which such Machine Learning mechanisms are employed to increase the quality of the results.

Activities, such as driving automobiles, that until recently were considered intrinsically non-automatable are today seen as automatable activities. In 2010, Google announced it had modified a fleet of cars to become completely autonomous, traversing more than 1,600 kilometers of roads in the USA without any human guidance. Despite being an extremely complex task, requiring extreme reflexes and care, Google's team of technicians managed to solve the steering problem using the vast amounts of data collected from Google Maps and Google Street View (BRYNJOLFSSON and MCAFEE, 2014).

Given recent technological achievements, Frey and Osborne (2013) propose incorporating these advances to Autor's (2003) task model, as more and more previously non-automatable tasks were becoming automatable. Thus, their analysis continued to include two types of tasks, but in this case, they are treated as susceptible to computerization (automation) and non-susceptible to computerization. The latter are those tasks that still present technological bottlenecks[10] with respect to engineering that prevent their total automation. Even with these bottlenecks, Frey and Osborne (2013) estimate that about 47 percent of US jobs are at risk of being fully computerized in the coming decades.

The traditional idea that only simpler and lower paid tasks would be subject automation and, therefore, substitution, needs to be questioned. Acemoglu and Restrepo (2018) propose a theoretical model that allows both skilled and unskilled labor to be replaced by capital. The authors argue that given the recent advances in the technological frontier (i.e., Artificial Intelligence, Machine Learning, Big Data, etc.) capital could compete with both types of work available in the market, leading to the depreciation in the wages for the type of work that will be directly affected by automation.

Based on the literature studied, we perceived the existence of new prospects regarding the introduction of technology in the labor market. In addition, there is a need to consider the idiosyncrasies of each country when analyzing an issue as delicate as this. The impacts of a possible replacement of labor by capital – in a generalized way – would be felt differently in countries in different stages of development (ZEIRA, 1998), since they depend on several factors, such as the skills of the workforce and institutional issues (GOLDIN and KATZ, 1998, ACEMOGLU, 2002, AUTOR, 2015, BOUND and JOHNSON, 1992).

The remainder of the paper is structured as follows. Section 2 presents the methodology and describes the data. Section 3 reports on the empirical results, while Section 4 draws some conclusions.

2 METHODOLOGY AND DATA

2.1 Econometric Specification

Firms are incentivized to replace human labor for information technology, since the former's cost is remarkably high, as it is the case of developed countries. To our knowledge, there is no evidence in the literature concerning developing countries. We investigate if wages are sufficiently high in Brazil in order to provide such a substitution effect. Conversely, it may be assumed that costs related to computer hardware, logistics and human resources specialized in information technology will decrease with the level of development, which would suggest that the replacement of automatable work using information technology should be easier. These two explanations converge to predict that the adoption of new technologies depresses the relative wage of automatable occupations if countries experience high levels of development. In this context, the adoption of new technologies is less accessible in developing countries, like Brazil. Thus, theoretical arguments may support the adoption of new technologies or not, and the verification of depression in the relative wage of automatable occupations turns to be an econometric issue.

The econometric specification should compare the logarithm of the wages of individuals with automatable occupations with the logarithm of the salaries of individuals with non-automatable

[10] The technological bottlenecks highlighted by the authors can be divided into three categories: creative intelligence, perception and manipulation and social intelligence.

occupations. This comparison is possible by regressing the logarithm of wages into dummy variable (A_0) that is worth one if the occupation is automatable and zero if not.

$$\ln(W_i) = \alpha_1 A_0 + \boldsymbol{\beta'X} + \mathbf{F.E._i} + \mathbf{F.E._f} + \mathbf{F.E._t} + \varepsilon_i \tag{1}$$

Where **X** is a vector of control variables (which is detailed below), $\mathbf{F.E._i}$ are individual fixed effects, $\mathbf{F.E._f}$ are firms fixed effects and $\mathbf{F.E._t}$ are time fixed effects.

Goodman-Bacon (2018) shows that the coefficient α_1 is the weighted average of all possible 2×2 difference-in-differences estimators. It accounts for the difference of two differences: the outcome difference of treatment group (e.g. those individuals that change A_0 from zero to one in a given period), and the outcome difference of control group (e.g. those individuals that do not change A_0).[11] In other words, the difference-in-differences estimator assesses the relative wage variation of individuals that were allocated to automatable occupations, compared to those individuals that were not allocated to automatable occupations.

This study is interested in the wage difference between groups arising from automation through the computational capital invested by the firm in its automation. Since this data is not available, information technology use will be used as a proxy (see the subsection below). Thus, the econometric specification includes a variable that measures each firm's information technology use (ITU_f), and that variable's interaction with the variable automatable occupation (A_0).

It is reasonable to consider that automatable occupations status A_0 may be correlated with Supervisor status within a given profession, or differences between professions (see details in section 2.3 below), or years of education. Thus, the coefficient of A_0 and its interactions may incorporate biases due the wage difference between Supervisor and Non, between professions, and between different levels of education. Thus, we address this issue by controlling for the interactions of ITU_f with these three variables: Supervisor status, years of education, two-digit CBO occupation ($\mathbf{F.E._{occ}} \times ITU_f$). CBO stands for *Classificação Brasileira de Ocupações* - Brazilian Classification of Occupations – see the complete three-digit list and distribution in the supplementary online appendix.

Thus, the equation to be estimated is:

$$\ln(W_i) = \alpha_1 A_0 + \alpha_2 ITU_f \cdot A_0 + \alpha_3 ITU_f + \boldsymbol{\beta'X} + \mathbf{F.E._i} + \mathbf{F.E._f} + \mathbf{F.E._y} + \mathbf{F.E._{occ}} \times ITU_f + \varepsilon_i \tag{2}$$

Where W_i is the hourly wage of individual i, $\boldsymbol{X}$ is a control vector, $\boldsymbol{\beta'}$ is a vector of coefficients and ε_i is an error term. The controls include years of education, years of education interacted with ITU_f, Supervisor, Supervisor interacted with ITU_f, age, age-squared, time in employment, and time in employment-squared, $\mathbf{F.E._i}$ are individual fixed effects, $\mathbf{F.E._f}$ are firms fixed effects and $\mathbf{F.E._t}$ are time fixed effects and $\mathbf{F.E._{occ}} \times ITU_f$ are 2-digit occupation fixed effects interacted with ITU_f.

The interaction $ITU_f \cdot A_0$ assumes that the impact of variable A_0 depends on the variable ITU_f. This relationship occurs because firms with greater ability to use information technology tend to automate the activities to a greater degree, which may be reflected in the depression of the wages of individuals with automatable occupations. Thus, by calculating the marginal effect of automation (A_0) of an occupation on the wage, it is possible to see how the ITU_f acts on the remuneration of those individuals, linearly changing the impact of A_0 on the wages logarithm.

[11] Treatment status is time variant; thus, this weighted average includes many comparisons that are possible in a given period. For example, we can compare individuals who changed from non-automatable occupation to automatable occupation within the period with individuals that are not changing her occupation, but they had already changed it in past periods.

$$\frac{\partial \, ln\, Wage}{\partial A_0} = \alpha_1 + \alpha_2 ITU_f \qquad (3)$$

To perform this analysis, the microdata from the Identified RAIS for 2010, 2011, 2012 and 2013[12] from all Brazilian states is used, since each state has socioeconomic peculiarities. Therefore, a complete analysis of the entire country is necessary, otherwise the results found for a specific state might not precisely represent all of them. Using this database allows the adoption of several available control variables and, more importantly, the identification of the firms and individuals across time. However, this database only includes the formal sector, which corresponds to approximately 50% of the Brazilian labor market (ULYSSEA, 2010, p.87).

2.2 Information technology use

The estimable equation (2) is analogous to the specification used by Krueger (1993), who had a specific question about the use, or otherwise, of computers at work per individual. As there is no similar study in Brazil that applies this question at the individual level, we propose the use of an indirect measure using a proxy variable. The model used in this study does not include the variable that would be most appropriate to obtain the most precise results, namely: computational capital invested specifically in automation in each firm. Instead, we assume that the computational capital of a firm is reflected in its use of information technology, which in turn can be captured by the proportion of employees dedicated to the information technology sector in a firm. The rationale being that the amount of invested computational capital requires a proportional amount of skilled labor. Hence, the Identified RAIS microdata from 2013, pertaining to IT-related occupations, is used to create a variable with the proportion of those employees in each firm. These occupations were identified at the most detailed level of the Brazilian Classification of Occupations (CBO), namely to 4 digits. Table 1 shows all the IT-related occupations.

There are at least two limitations with this variable. On the one hand, the variable *Information Technology Use* may include information technology professionals, but whose workforce is not necessarily used for the purposes of task automation. On the other hand, companies in which automation is an end activity have a large proportion of their employees allocated to information technology, even if they do not work for the automation of the company itself, but for the automation of other companies.

Table 1 – Professions used to create the variable ITU_f (4-digit CBO)

4-digit CBO	IT-related Occupation
2031	Researchers in exact and natural sciences
2122	Computer engineers
2123	Information Technology managers
2124	Information Technology Analysts
2341	Higher Education Teachers of mathematics, statistics and computer Science
3132	Electronic technicians
3171	Applications and systems development technicians
3172	Computer operations and monitoring technicians
4121	Data input and transmission equipment operators
7311	Electronic equipment assemblers

Source: Prepared by the authors

[12] The identified version of RAIS microdata allows the identification of firms and individuals by their names and ID number. While the unidentified RAIS microdata is available online, the identified version is restricted, and we only have access for these years.

2.3 Automatable occupations

To capture the essence of the study and focus on the wages of individuals in occupations that are currently highly likely to be automatable; adjustments had to be made in relation to the original research offered by Frey and Osborne (2013). By means of probabilistic classification, the authors determined the occupations at a high risk of being automated in the SOC-10 (Standard Occupational Classification of 2010). However, occupations in the data base used in this article (RAIS) are classified according to the CBO (2002), and there is no table of direct correspondence between the CBO and SOC-10. Chart 1 depicts the conversions used to analyze occupations.

Chart 1 – Steps of conversions used to elaborate occupational variables

CBO 2002	**ISCO 88**	**ISCO 08**	**SOC-10**
Brazilian Classification of Occupation from 2002	International Standard Classification of Occupations from 1988	International Standard Classification of Occupations from 2008	Standard Occupational Classification from 2010

Source: Prepared by the authors

During all the conversion steps, any instances of conversion problems were individually analyzed; where any divergence between the original occupation and the final occupation was large, it was considered 'non-automatable'. The complete list distinguishing automatable from non-automatable occupations in the supplementary online appendix. This table also reports the sample's distribution of individuals across CBO at 3-digit.

The conversion of the Frey and Osborne (2013) classification to the CBO is fundamental for this study, because it permits the inclusion of occupations that previously would not have been considered automatable, due to the technological context of the time. An emblematic example is the occupation CBO 782 (drivers of vehicles and operators of lifting and handling equipment).

In order not to make comparisons that reflect spurious results, such as comparing occupancy 411 (General Clerks), which is automatable, with occupation 121 (General Director), which is non-automatable, dummy variables were created for occupations in two digits CBO and they were interacted with ITU_f, which allows comparisons to be made only within each 2-digit group.

Considering the level of income, the 3-digit CBO occupations show some equivalence among themselves, when compared within the same occupation in two digits. Table 2 shows an example, occupation "42 - Workers attending the public". Except for sub-item 420, the other sub-items (421, 422, 423 and 424) are reasonably close in terms of wage level. Remembering that the econometric specification uses binary variables for 2-digit occupations as control, this proximity is important to ensure the comparison between an automatable occupation (in 3-digits) and a non-automatable occupation does not reflect other structural differences. However, sub-item 420 stands out from the others, because it presents hierarchically superior level to the other sub-items, which would also explain a difference in remuneration. To control this possible bias, the econometric specification includes a binary variable that separates supervisory occupations from the others, in addition to their interaction with the use of information technology. This interaction should present a positive coefficient, starting from the premise that skilled labor is '*complemented'* by capital (AUTOR *et al.*, 2003, ACEMOGLU, 1998 and 2002, FREY and OSBORNE, 2013, GOLDIN and KATZ, 1998).

Table 2 – Example of 2-digit and 3-digit CBO occupations

CBO - Description
42 – Workers attending the public
420 – Public attendance supervisors
421 – Checkout, ticket office clerks and alike
422 – Public information workers
423 - Dispatchers
424 - Interviewers, census takers and alike

Source: Prepared by the authors

The professions used to create the variable 'automatable occupation' were converted based on the American data (using O*NET[13], which has scales for a specific characteristic of each occupation). However, ideally, the CBO, in the same way, would have a certain degree of specification and characteristics necessary to perform a given function (i.e., desired manual dexterity, level of creativity required, level of personal interaction, etc.). If such clarity existed in the classification of professions, containing an objective degree of some of the inherent characteristics of the work performed, one might imagine an improvement in the parameters estimated in the model.

2.4 Descriptive Statistics

Table 3 presents the descriptive statistics summarizing some data by Brazilian state and federal district for the individual panel of four years (2010, 2011, 2012 and 2013). We report the number of observations we dropped from regressions due to missing data. In order to avoid outliers, individuals with a workload of less than 36 hours per week were excluded from the analysis and (their number is reported in line "Excluded Individuals"), leaving only individuals with loads between 36 and 44 hours per week. Besides, as we use many binary controls, groups formed by these controls with only one individual are automatically dropped, their number is reported in line "Dropped Singleton Obs.". The total excluded observations correspond to 16% of the initial sample, and their average by state is 19%.

Data from the formal sector blur the division that exists between north and south in Brazil, but distinguishes the less developed regions, the northeast and the north, from the more developed regions, the southeast and the south. The latter also concentrate population and the number of firms. The average hourly salary and high education in the Federal District (Distrito Federal) are striking, however, the extremely high salaries of the civil service in the federal capital Brasilia are computed in these figures.

On average, the value of the ITU_f is 0.0158 for the observed firms, what means that, on average, 1.58% of the occupations in firms are related to the information technology sector. The A_0 has an observed mean of 47.81%, which means that almost half of the workers perform functions susceptible to automation. This finding is similar to that reported by Frey and Osborne (2013), whose studies revealed that approximately 47% of North American occupations would be at high risk of being automated in the coming decades.

[13] O*NET (Occupational Information Network) is an online service developed under the auspices of the U.S. Department of Labor/Employment and Trading Administration. Its purpose is to measure changes in the nature of jobs, as well as their impact on the US economy. For this purpose, the service uses questionnaires answered by the workers themselves and, with this, evaluates and categorizes some specific attributes of the occupations, forming a graduation between variables, such as: manual dexterity, originality, social perception, persuasion, etc. (FREY and OSBORNE, 2013).

Table 3 – Summary of Descriptive Statistics

Regions	North							Northeast						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
States	Rondônia	Acre	Amazonas	Roraima	Pará	Amapá	Tocantins	Maranhão	Piauí	Ceará	Rio Grande do Norte	Paraíba	Pernambuco	Alagoas
Ln(*Houly Wage*)	1.899	1.835	1.852	1.942	1.878	2.113	1.91	1.757	1.719	1.639	1.697	1.708	1.811	1.699
	(0.002)	(0.004)	(0.002)	(0.005)	(0.001)	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Years of Schooling	10.859	10.938	11.369	11.499	10.53	11.42	11.343	10.955	10.859	10.988	10.834	10.666	10.617	9.084
	(0.002)	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)	(0.003)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
ITU_f	0.033	0.009	0.085	0.012	0.009	0.012	0.009	0.009	0.011	0.015	0.009	0.011	0.011	0.008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A_o	0.517	0.492	0.533	0.539	0.491	0.435	0.453	0.473	0.462	0.447	0.484	0.492	0.458	0.401
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Supervisor	0.024	0.023	0.023	0.013	0.023	0.16	0.016	0.023	0.024	0.029	0.021	0.021	0.026	0.018
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	33.677	34.054	33.34	34.903	33.992	35.841	34.42	34.156	36.419	34.589	35.766	35.812	35.2	34.881
	(0.008)	(0.015)	(0.006)	(0.019)	(0.005)	(0.015)	(0.010)	(0.006)	(0.008)	(0.004)	(0.007)	(0.007)	(0.004)	(0.007)
Tenure	48.293	55.746	34.05	58.198	39.061	66.133	49.168	43.671	72.275	44.839	63.626	61.455	48.61	51.845
	(0.060)	(0.129)	(0.035)	(0.147)	(0.031)	(0.124)	(0.069)	(0.041)	(0.076)	(0.028)	(0.058)	(0.058)	(0.028)	(0.055)
Number of Individuals	489985	135940	713385	99706	1200332	155171	312454	777268	476596	1744914	739268	648496	2076893	572118
Number of Firms	26006	6668	21671	4643	50446	6563	17803	37566	25199	85185	40772	36421	100484	28417
Missing Obs.	24498	6925	35418	5455	69561	4227	9904	48683	18659	93934	29762	25129	116569	48629
Excluded Individuals	101961	129904	646537	84433	981601	39687	97613	637211	186902	928677	275010	521463	745008	330881
Dropped Singleton Obs.	148842	44440	212112	32175	443466	51861	115720	294932	152713	492281	195311	196602	584332	162715
Actual Regression Obs	1831151	488790	2674715	355520	4188538	549672	1110079	2729121	1768973	6598565	2772268	2394087	7923470	2142121
Total Observations	2106452	670059	3568782	477583	5683166	645447	1333316	3709947	2127247	8113457	3272351	3137281	9369379	2684346

Standard errors in parenthesis. Missing observations are observations with missing values in one of variables of regression. Excluded individuals are those with workload of less than 36 hours per week. Singleton observations are dropped by Stata *reghdfe* command, as they refer to groups formed by binary controls with only one individual.

Table 3 – Summary of Descriptive Statistics, Continued

Regions	Northeast		Southeast				South			Centerwest			
	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
States	Sergipe	Bahia	São Paulo	Minas Gerais	Espírito Santo	Rio de Janeiro	Paraná	Santa Catarina	Rio Grande do Sul	Mato Grosso do Sul	Mato Grosso	Goiás	Distrito Federal
Ln(*Houly Wage*)	1.748	1.745	2.023	1.777	1.826	1.98	1.877	1.885	1.887	1.878	1.938	1.879	2.408
	[0.002]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
Years of Schooling	10.791	10.966	11.261	10.576	10.995	11.006	10.976	10.926	10.761	10.637	10.997	10.677	11.642
	[0.003]	[0.001]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]	[0.001]
ITU_f	0.01	0.012	0.022	0.016	0.011	0.017	0.015	0.017	0.014	0.008	0.01	0.008	0.023
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
A_o	0.428	0.481	0.506	0.489	0.479	0.494	0.484	0.491	0.485	0.453	0.468	0.485	0.49
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Supervisor	0.032	0.024	0.027	0.025	0.026	0.026	0.024	0.022	0.03	0.022	0.02	0.022	0.021
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age	35.478	35.05	33.979	33.962	34.214	35.861	33.765	32.898	34.122	33.893	33.223	33.725	35.086
	[0.008]	[0.003]	[0.001]	[0.002]	[0.005]	[0.002]	[0.003]	[0.003]	[0.003]	[0.007]	[0.006]	[0.004]	[0.005]
Tenure	61.533	46.253	39.458	37.12	35.408	45.73	37.332	35.83	40.085	33.325	32.425	38.689	64.404
	[0.071]	[0.023]	[0.007]	[0.013]	[0.028]	[0.016]	[0.016]	[0.018]	[0.017]	[0.032]	[0.030]	[0.025]	[0.042]
Number of Individuals	456366	2793237	17525440	6035077	1164868	5458940	3830726	2717829	3548627	766763	984211	1881349	1441276
Number of Firms	22371	160797	927094	392924	74556	265208	262871	192495	252773	45401	61652	117714	64989
Missing Obs.	21994	136236	1456292	430411	93990	538968	315495	347217	387382	55380	65700	109853	84422
Excluded Individuals	200023	1264324	5299646	3322929	577641	2235917	1469140	1073716	1916259	335033	279391	774089	418083
Dropped Singleton Obs.	139490	854136	3954538	1604739	301214	1496419	1008275	655214	780525	270130	331203	739280	539580
Actual Regression Obs	1708229	10316869	71727827	23716562	4611901	21374839	15423255	11276137	14611212	2899037	3806885	6925966	5311937
Total Observations	2069736	12571565	82438303	29074641	5584746	25646143	18216165	13352284	17695378	3559580	4483179	8549188	6354022

Standard errors in parenthesis. Missing observations are observations with missing values in one of variables of regression. Excluded individuals are those with workload of less than 36 hours per week. Singleton observations are dropped by Stata *reghdfe* command, as they refer to groups formed by binary controls with only one individual.

3. RESULTS

According to Bresnahan (2002), computer-based technologies are more effective at automating well-specified routine tasks. This automation allows the human work undertaken in such activities to be replaced. Hence, there is understood to be negative pressure on the wages of workers who perform intensive work in routine tasks which may vary according to the intensity of information technology use in the firm in which they are employed. With the reduction in the costs of computing power and, the consequent expansion in the Information Technology use, more and more activities could be 'routinized', for which it is necessary to be able to clearly describe the constituent steps.

Equation (2) was estimated for each Brazilian state and the coefficients of some variables of interest are reported in Table 4. The results show the robust standard errors clustered due to firm-specific variables. The dependent variable, hourly wage, is estimated at the individual level i; however, one of the explanatory variables used is ITU_f, which aggregated by firm. In this case, since our dependent variable is estimated at the individual level i, and clustering (ITU_f) at a higher level (group), it is also necessary to cluster the standard errors at this level, due to possible correlations within the cluster. We dropped all individuals with less than 36 worked hours per week.

We are interested in the coefficients of the two first variables, for studying the impact of automatable occupations, according to equation (3). We find positive and statistically significant coefficients α_1 of automatable status A_o, and the coefficients α_2 of the interaction $ITU \times A_o$ are negative and statistically significant in 20 over 27 geographical units. If we look at the average values of ITU_f from table 3, we conclude that the average impact of A_o on wages is positive; what does not support any substitution effect. While this result seems to be unexpected, it can be conceivably explained by the relative low costs of labor in a developing country like Brazil, comparing to computational costs. In this case, the substitution between *ITU* and labor would not be predominant.

Table 4 – Determinants of the individual wage

Regions	North							Northeast	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
States	Rondônia	Acre	Amazonas	Roraima	Pará	Amapá	Tocantins	Maranhão	Piauí
$ITU_f \times A_o$	-0.0727*	-0.180*	-0.0244	-0.00654	-0.0971*	0.126	-0.0667	-0.142***	-0.254***
	(0.039)	(0.0933)	(0.0186)	(0.0804)	(0.0579)	(0.161)	(0.0558)	(0.0427)	(0.096)
A_o	0.0333***	0.0590***	0.0152***	0.0634***	0.0405***	0.0472***	0.0425***	0.0499***	0.0776***
	(0.00758)	(0.00823)	(0.00468)	(0.0176)	(0.0056)	(0.0101)	(0.00596)	(0.00613)	(0.00872)
$ITU_f \times$ *Years of Schooling*	0.0261***	0.0155	0.0195***	-0.0105	0.0182***	-0.00508	-0.00058	0.0099	0.0259**
	(0.00329)	(0.0171)	(0.00475)	(0.0428)	(0.00667)	(0.0452)	(0.00861)	(0.00787)	(0.0116)
Years of Schooling	0.00338***	0.00222***	0.00473***	0.0163**	0.00215***	0.00556***	0.00869***	0.00288***	0.00257***
	(0.000603)	(0.000708)	(0.000446)	(0.00685)	(0.000558)	(0.00105)	(0.0014)	(0.000687)	(0.00078)
$ITU_f \times$ *Supervisor*	0.426	-0.166	-0.0821	-0.0363	-0.0811	0.806	0.156	0.00234	0.146
	(0.273)	(0.317)	(0.0781)	(0.112)	(0.0925)	(0.593)	(0.115)	(0.0896)	(0.178)
Supervisor	0.075	0.257***	0.183***	0.215***	0.185***	0.171***	0.187***	0.204***	0.108***
	(0.0478)	(0.025)	(0.00786)	(0.0253)	(0.00892)	(0.0147)	(0.0098)	(0.0156)	(0.0416)
Age	0.0312***	0.0269***	0.0260***	0.0338***	0.0322***	0.0316***	0.0344***	0.0226***	0.0168***
	(0.00208)	(0.00321)	(0.00191)	(0.00746)	(0.00217)	(0.00577)	(0.00657)	(0.00376)	(0.00516)
Age^2	-3.37E-04***	-0.000329***	-0.000325***	-0.000402***	-0.000386***	-0.000359***	-0.000418***	-0.000259***	-0.000195***
	(0.0000276)	(0.0000414)	(0.0000251)	(0.0000976)	(0.0000289)	(0.0000726)	(0.0000857)	(0.0000447)	(0.0000619)
Tenure	0.00072	0.000758***	0.00164***	9.61E-05	0.00118***	0.00151***	0.000590***	0.000635***	0.000935***
	(0.000818)	(0.000176)	(0.000143)	(0.000441)	(0.000115)	(0.000324)	(0.000184)	(0.000112)	(0.000272)
$Tenure^2$	-1.54E-06	-2.27E-06***	-4.17E-06***	1.12E-06	-2.52E-06***	-1.04E-06	2.93E-08	-8.87E-07**	2.85E-07
	(2.37E-06)	(4.66E-07)	(3.95E-07)	(1.27E-06)	(3.96E-07)	(1.69E-06)	(5.77E-07)	(3.57E-07)	(4.47E-07)
Constant	1.195***	1.263***	1.278***	1.057***	1.189***	1.281***	1.121***	1.234***	1.250***
	(0.0437)	(0.0619)	(0.0367)	(0.196)	(0.0404)	(0.103)	(0.119)	(0.0749)	(0.0889)
Observations	1831151	488790	2674715	355520	4188538	549672	1110079	2729121	1768973
R-squared	0.994	0.996	0.995	0.995	0.995	0.995	0.995	0.996	0.997

Individuals with less than 36 work hours per week were dropped. All regressions include individual, firm and year fixed effects, besides CBO 2-digit occupations interacted with ITU_f. Robust standard errors clustered by firm in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4 – Determinants of the individual wage, continued

Regions	Northeast							Southeast	
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
States	Ceará	Rio Grande do Norte	Paraíba	Pernambuco	Alagoas	Sergipe	Bahia	São Paulo	Minas Gerais
$ITU_f \times A_o$	-0.0229	-0.0835*	-0.0838**	-0.0945***	-0.0355	-0.109***	-0.0859***	-0.0405**	-0.0705***
	(0.0323)	(0.0432)	(0.0337)	(0.0218)	(0.0283)	(0.0276)	(0.0184)	(0.016)	(0.0124)
A_o	0.0381***	0.0349***	0.0240***	0.0251***	0.0346***	0.0320***	0.0386***	0.0124***	0.0273***
	(0.00307)	(0.00464)	(0.00445)	(0.00529)	(0.00556)	(0.00602)	(0.00348)	(0.00166)	(0.00201)
$ITU_f \times$ *Years of Schooling*	0.0223***	0.0102	-0.000419	0.00135	0.0714***	0.00891	0.00477	0.0140***	0.00332*
	(0.00495)	(0.00835)	(0.0054)	(0.0046)	(0.0103)	(0.00577)	(0.00309)	(0.00168)	(0.0018)
Years of Schooling	0.00472***	0.00300***	0.00211***	0.00326***	0.00312***	0.00376***	0.00306***	0.00459***	0.00349***
	(0.000599)	(0.000622)	(0.000737)	(0.00118)	(0.000488)	(0.000897)	(0.000281)	(0.000151)	(0.000141)
$ITU_f \times$ *Supervisor*	0.0438	-0.013	-0.0372	-0.0347	-0.0293	0.005	-0.0855***	0.0203	0.00851
	(0.0505)	(0.0668)	(0.0938)	(0.0445)	(0.094)	(0.0748)	(0.031)	(0.0221)	(0.0216)
Supervisor	0.130***	0.160***	0.148***	0.176***	0.178***	0.141***	0.178***	0.169***	0.182***
	(0.00645)	(0.00644)	(0.00856)	(0.00947)	(0.00929)	(0.0106)	(0.00498)	(0.0033)	(0.00336)
Age	0.0253***	0.0180***	0.0188***	0.0296***	0.0257***	0.0308***	0.0253***	0.0318***	0.0333***
	(0.00221)	(0.00512)	(0.00437)	(0.00251)	(0.00283)	(0.00364)	(0.00148)	(0.00195)	(0.00075)
Age^2	-0.000293***	-0.000210***	-0.000208***	-0.000366***	-0.000310***	-0.000368***	-0.000296***	-0.000386***	-0.000401***
	(0.0000284)	(0.0000658)	(0.0000526)	(0.0000313)	(0.0000362)	(0.0000476)	(0.0000187)	(0.0000256)	(0.00000981)
Tenure	0.000483***	0.000545***	0.000433***	0.000548***	0.000686***	0.000766***	0.00113***	0.00163***	0.00142***
	(0.0000892)	(0.000087)	(0.000119)	(0.000191)	(0.000145)	(0.000144)	(0.0000612)	(0.0000688)	(0.0000542)
Tenure^2	6.44E-07*	1.72E-06***	1.54E-07	1.02E-06**	1.43E-07	1.26E-07	-9.27E-07***	-2.64E-06***	-2.60E-06***
	(3.40E-07)	(5.20E-07)	(3.17E-07)	(4.34E-07)	(3.74E-07)	(4.85E-07)	(2.81E-07)	(4.84E-07)	(1.88E-07)
Constant	1.052***	1.235***	1.262***	1.181***	1.135***	1.056***	1.154***	1.320***	1.064***
	(0.0414)	(0.0856)	(0.0845)	(0.0397)	(0.0538)	(0.0682)	(0.0276)	(0.033)	(0.0133)
Observations	6598565	2772268	2394087	7923470	2142121	1708229	10316869	71727827	23716562
R-squared	0.996	0.996	0.996	0.995	0.996	0.996	0.996	0.995	0.996

Individuals with less than 36 work hours per week were dropped. All regressions include individual, firm and year fixed effects, besides CBO 2-digit occupations interact with ITU_f. Robust standard errors clustered by firm in parentheses, *** p<0.01, ** p<0.05, * p<0.1

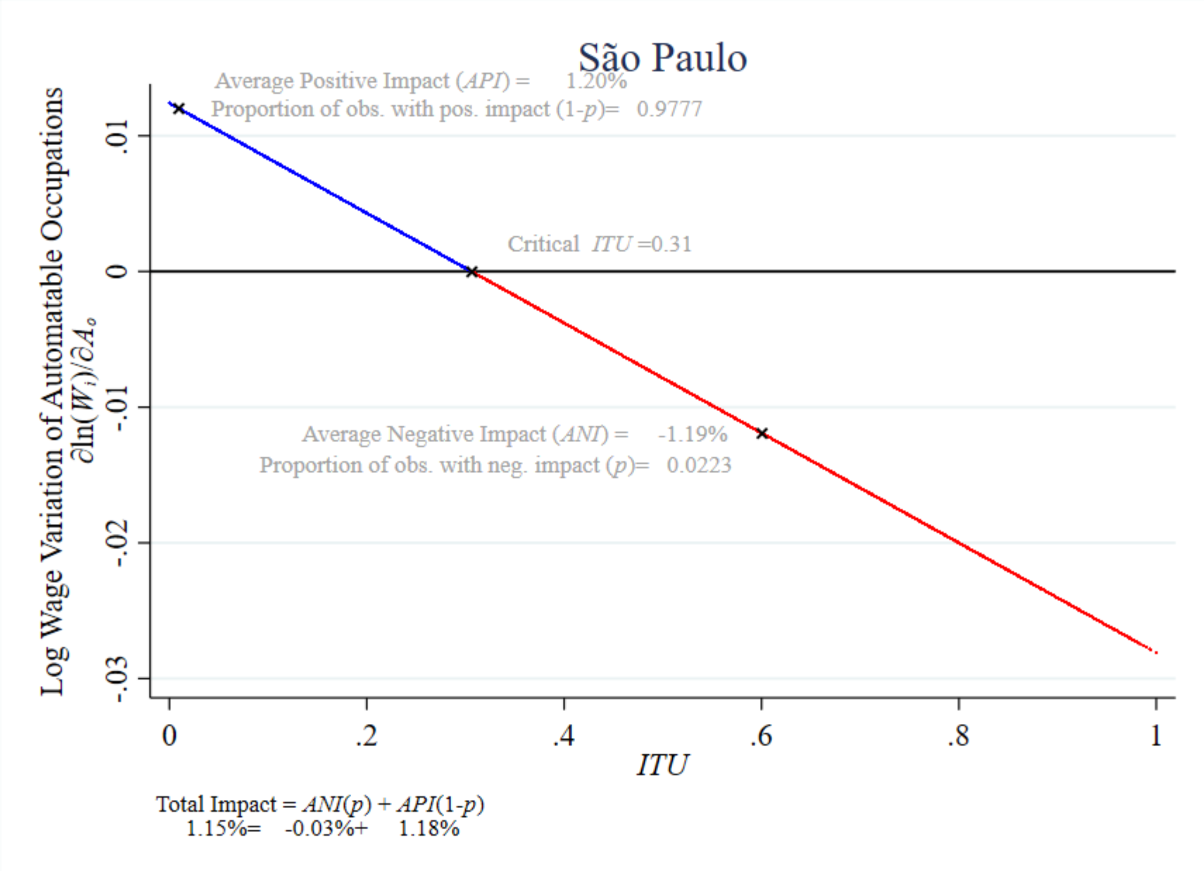
Table 4 – Determinants of the individual wage, continued

Regions	Southeast		South			Centerwest			
	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)
States	Espírito Santo	Rio de Janeiro	Paraná	Santa Catarina	Rio Grande do Sul	Mato Grosso do Sul	Mato Grosso	Goiás	Distrito Federal
$ITU_f \times A_o$	-0.148***	-0.0671***	-0.0714***	-0.0626**	-0.103***	-0.018	-0.0691**	-0.103***	-0.172***
	(0.0305)	(0.0169)	(0.0134)	(0.026)	(0.015)	(0.0284)	(0.0275)	(0.0255)	(0.0238)
A_o	0.0437***	0.0225***	0.0208***	0.00953***	0.00731***	0.0217***	0.0259***	0.0307***	0.0598***
	(0.00425)	(0.0025)	(0.00277)	(0.00188)	(0.00194)	(0.00356)	(0.00374)	(0.00444)	(0.00464)
ITU_f × *Years of Schooling*	0.00827*	0.0121***	0.0123***	0.0107***	0.00555**	-0.000328	0.00746	0.0102**	0.00618
	(0.00497)	(0.00304)	(0.0028)	(0.0021)	(0.00231)	(0.00462)	(0.00552)	(0.0043)	(0.00725)
Years of Schooling	0.00476***	0.00472***	0.00427***	0.00425***	0.00393***	0.00378***	0.00329***	0.00331***	0.00965***
	(0.000603)	(0.000622)	(0.000295)	(0.000162)	(0.00026)	(0.00043)	(0.00106)	(0.000564)	(0.00264)
ITU_f × *Supervisor*	-0.0434	0.0753**	0.0114	0.033	-0.0238	0.137**	0.112	-0.0757	-0.202***
	(0.0894)	(0.0375)	(0.028)	(0.0321)	(0.0398)	(0.0665)	(0.0828)	(0.0658)	(0.078)
Supervisor	0.187***	0.167***	0.169***	0.167***	0.156***	0.187***	0.140***	0.159***	0.216***
	(0.00775)	(0.00743)	(0.00421)	(0.00463)	(0.00929)	(0.00674)	(0.00707)	(0.00724)	(0.0161)
Age	0.0290***	0.0315***	0.0280***	0.0277***	0.0301***	0.0290***	0.0327***	0.0299***	0.0524***
	(0.00172)	(0.00141)	(0.00143)	(0.00272)	(0.00126)	(0.00192)	(0.0023)	(0.00168)	(0.0071)
Age^2	-0.000350***	-0.000376***	-0.000339***	-0.000338***	-0.000358***	-0.000342***	-0.000400***	-0.000361***	-0.000678***
	(0.0000224)	(0.0000178)	(0.000019)	(0.0000359)	(0.0000164)	(0.0000236)	(0.0000298)	(0.0000221)	(0.0000964)
Tenure	0.00159***	0.00103***	0.00149***	0.00183***	0.00195***	0.00140***	0.00164***	0.00158***	0.00193***
	(0.000193)	(0.0000736)	(0.0000723)	(0.000083)	(0.000062)	(0.0000888)	(0.000194)	(0.000095)	(0.000196)
$Tenure^2$	-3.14E-06***	-4.82E-07	-1.16E-06**	-3.38E-06***	-3.52E-06***	-2.89E-06***	-5.56E-08	-1.85E-06***	-1.07E-06
	(4.14E-07)	(5.56E-07)	(5.38E-07)	(6.06E-07)	(4.09E-07)	(4.17E-07)	(4.71E-07)	(2.82E-07)	(1.67E-06)
Constant	1.167***	1.271***	1.250***	1.275***	1.215***	1.240***	1.235***	1.220***	1.231***
	(0.0241)	(0.028)	(0.0227)	(0.0467)	(0.0215)	(0.0379)	(0.0339)	(0.0334)	(0.145)
Observations	4611901	21374839	15423255	11276137	14611212	2899037	3806885	6925966	5311937
R-squared	0.995	0.995	0.996	0.996	0.995	0.995	0.993	0.994	0.995

Individuals with less than 36 work hours per week were dropped. All regressions include individual, firm and year fixed effects, besides CBO 2-digit occupations interacted with ITU_f. Robust standard errors clustered by firm in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Nonetheless, some few individuals do experience a negative impact of A_o on wage. How to identify those? Recalling the linear parametrization $\frac{\partial \ln Wage}{\partial A_0} = \alpha_1 + \alpha_2 ITU_f$, the impact of automatable occupations on wage is positive for individuals working on firms presenting low values of *ITU* and may be negative for individuals working on firms with high values of *ITU*. Among the former ones, we may calculate the Average Positive Impact (*API*) of A_o on wages and the proportion of these individuals in the population (1-*p*). Analogously, we may calculate for the latter ones the Average Negative Impact (*ANI*) of A_o on wages and the proportion these individuals represent in the population (*p*). Therefore, we can express $\frac{\partial \ln Wage}{\partial A_0} = API(1-p) + ANI(p)$. We call the first right-hand side term "Positive Component" and the second right-hand side term "Negative Component". We are primarily interested in the second term.

Figure 2 – Individual Impact of Automatable Occupations on Wages in São Paulo.



Source: Prepared by the authors

To illustrate, Figure 2 plots the impact of A_o on wages for every individual in the sample of São Paulo. Focusing on the Negative Component, only a small proportion (*p*=0.0223) of those individuals would experience a reduction in their wages, as they work in a firm with *ITU* higher than 0.31. They would face an average negative impact (*ANI*) of -1.23%. The multiplication of *p* and *ANI* gives the "Negative Component", which contributes to the average impact of A_o on wage with -0.03%. This is relatively small compared to the Total Impact of A_o on wage, which is 1.15%,[14] however it gives a measure of substitution of labor due to automation.

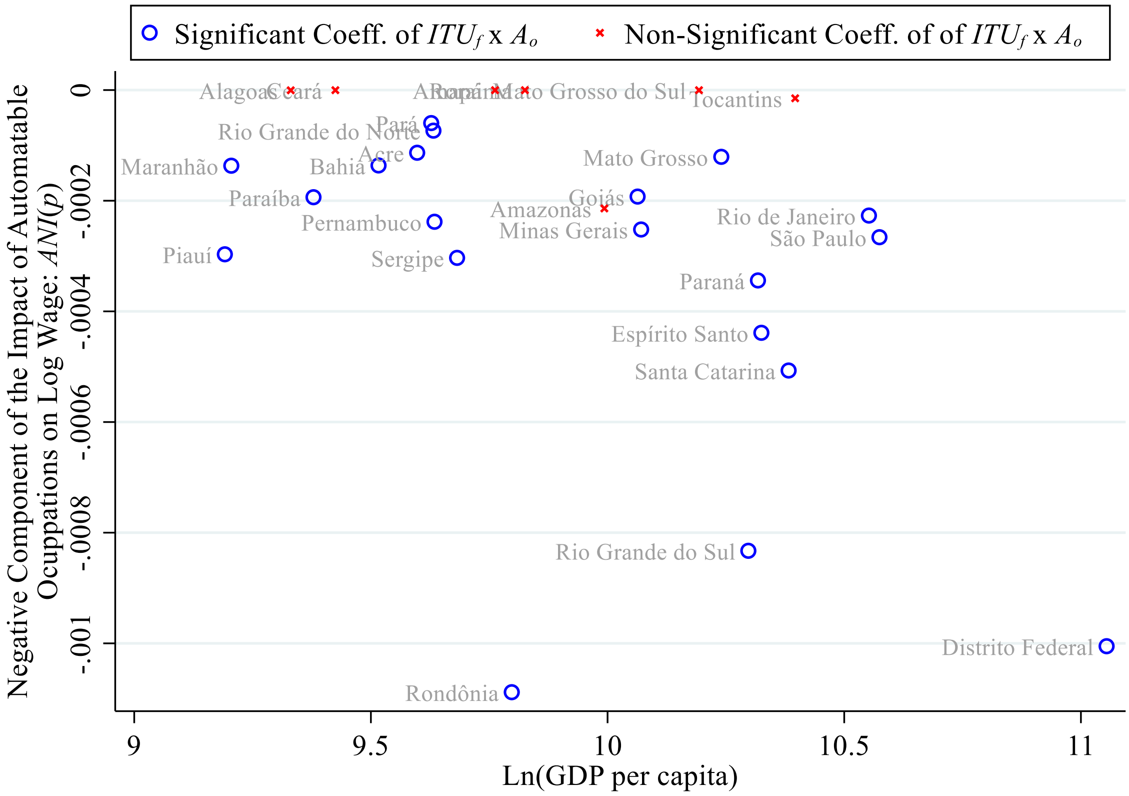
The more the firm uses information technology, the more likely it is to substitute workers in automatable activities, which reduces the firm's demand for occupations requiring routine work. Labor

[14] The "positive component" may be analogously calculated, as a proportion of 0.9777 (1-*p*) presents an average positive impact (*API*) equals to 1.20%, resulting in a "positive component" equals to 1.18%. The sum of the positive and negative components gives the total impact of A_o on wages, 1.15%.

supply at the individual level is inelastic in the short term. That is, the endowment of skills that a worker can offer to the productive process is fixed in the short term and depends, among other things, on his or her occupation. Employees need time to respond to changes in relative wages and earnings, notably if they need to be trained to enter a new occupation, possibly in a new job. Hence, if there is a reduction in the demand for automatable occupations, given an inelastic supply in the short term, the wages of such will tend to reduce. These results are in line with Bresnahan (1999) and Acemoglu and Restrepo (2018) that find that, in equilibrium, the tasks will be allocated according to the lowest effective cost of production - which, in turn, reduces the salary of the group of workers that will be replaced by machines. This phenomenon, known as 'displacement,' occurs when automation directly affects a type of skill required in production.

Although we should not lose sight that the Negative Component is relatively small, it is worth to compare it across states. Figure 3 plots the Negative Component in the vertical axis and the log of GDP per capita in the horizontal axis. We distinguish between states with significant coefficient α_2 of the interaction $ITU_f \times A_0$ from those states with non-significant coefficient, as the latter does not present Negative Component at all. We choose the logarithm of GDP per capita for this graphic representation as it provides a measure of development level, what could proxy for the costs of labor relative to the costs of computational capital.[15] We do not have the pretention to econometric identify the role of this relative cost, but we expect to find higher reduction in automatable occupations' wages if computational capital is relatively cheaper. Although the states of Rondônia and Rio Grande do Sul present a disproportionate wage reduction, the Negative Component is higher in more developed states, indicating that the substitution between labor and computational capital occurs more intensively in these states.

Figure 3 – Negative Component and Log of *per Capita* GDP by State.



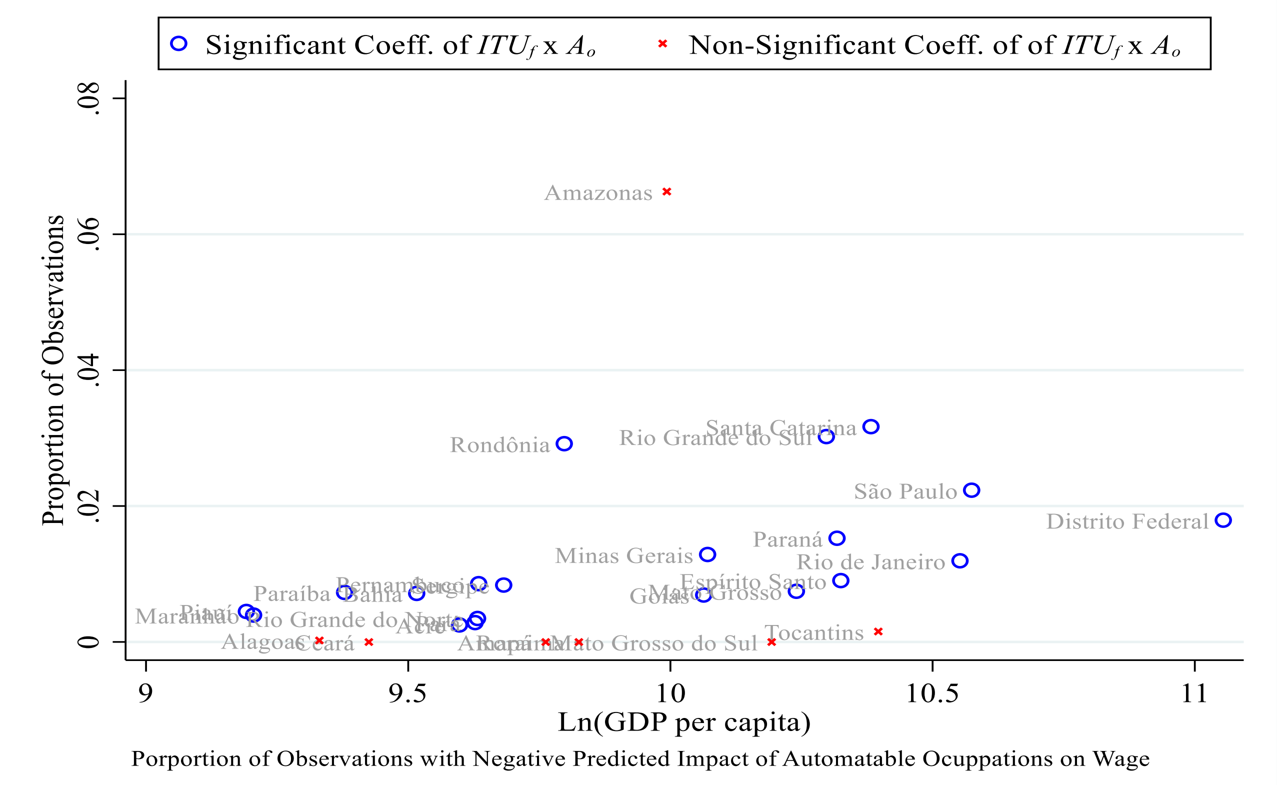
Source: Prepared by the authors

[15] The correlation of the Negative Component with the logarithm of the GDP per capita is -0.4358 with p-value=0.0231. We also tested the correlations with the Negative Component with the logarithm of GDP (correlation= -0.2677, p-valor=0.1770) and with the logarithm of population (correlation= -0.1201, p-valor=0.5508).

The proportion of individuals that suffer a reduction in wage if they assume automatable occupations also gives a measure of the substitution effect we are studying. Figure 4 shows their distribution over the log of GDP per capita, also distinguishing between states with significant coefficient α_2 of the interaction $ITU_f \times A_0$ from those states with non-significant coefficient. The proportion of individuals with wage reduction due to A_0 increases with the log of GDP per capita[16].

We may underscore an important outcome from this analysis. Although the average impact of A_0 on wages is positive, the underlying mechanism of labor substitution by automation is verified. As the coefficient α_2 of the interaction $ITU_f \times A_0$ is mostly negative and statistically significant, wages of automatable occupations suffer a pressure to reduce in firms where the Information Technology Use is intense. Brazil, as a developing country, does not seem to present all conditions for an extensive process of automation of jobs, instead, only firms ahead in the use of information technology are able to make that substitution.

Figure 4 – Proportion of Individuals in the Negative Component and Log of *per Capita* GDP by State.



Source: Prepared by the authors

4 CONCLUSION

In this research, we have sought to demonstrate how the current technological progress, symbolically represented by in the creation of disruptive technologies such as Artificial Intelligence, Robotics and Big Data, is part of this same process that began approximately two centuries ago. A common element in the subsequent stages of development and technological progress lies the intrinsic goal of promoting the replacement of labor by machines.

In order to interpret the impact new technological advances are having within the Brazilian labor market, the occupations most susceptible to substitution were defined as those with a high risk of automation according to Frey and Osborne (2013).

[16] The correlation is equal to 0.3545, with p-value=0.0696

The results of the present study point to the existence of a negative impact of the use of information technology on wages of workers performing functions susceptible to automation. In other words, individuals who perform automatable functions, whether manual or cognitive, are more likely to be replaced by information technology the more the firm they work in uses such technology. This competition between machine or software and human labor causes a notable negative pressure on the incomes of those workers, even in a developing country with relative low wages and high costs of information technology use.

The conclusions presented so far raise some issues for consideration about the limitations of this research. Some differences and limitations involving the data used in the research need to be weighed. Likewise, it is necessary to point out the limitations regarding the results found in comparison to the international literature used: many of the disruptive technologies (for example, autonomous vehicles), although they may be widely introduced in the United States or Europe, their introduction in Brazil is likely to face great difficulty due to the high cost of importing vehicles, as well as the poor quality of the road infrastructure.

Finally, according to data, about 45% of Brazilian workers are susceptible to be replaced. Assuming that the costs of technologies are sufficiently reduced, and their capacity increased over the coming decades, would it be reasonable to worry about the future of these workers? In the United States, interest is growing in the concept of a Universal Basic Income (UBI), a figure paid by the government as compensation to the population that may suffer forced displacement from the labor market due to the automation of jobs (YANG, 2018).

REFERENCES

ACEMOGLU, D. Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. **The Quarterly Journal of Economics**. vol. 113, no. 4, pp. 1055-1089. 1998.

ACEMOGLU, D. Technical change, inequality, and the labor market. **Journal of Economic Literature**, vol. 40, no. 1, pp. 7–72. 2002.

ACEMOGLU, D. Labor- and capital-augmenting technical change. **Journal of the European Economic Association,** vol. 1, no. 1, pp. 1–37. 2003.

ACEMOGLU, D; AUTOR, D. Skills, Tasks and Technologies: Implications for Employment and Earnings. **MIT Department of Economics Working Paper** No. 16082. 2011.

ACEMOGLU, D.; RESTREPO, P. Low-Skill and High-Skill Automation. **Journal of Human Capital,** vol. 12, No. 2, pp. 204-232. 2018.

AUTOR, D., KATZ, L.F. AND KRUEGER, A.B. Computing inequality: have computers changed the labor market? **The Quarterly Journal of Economics**, vol. 113, no. 4, pp. 1169–1213. 1998.

AUTOR, D., LEVY, F. AND MURNANE, R.J. Upstairs, Downstairs: Computer and Skills on Two Floors of a Large Bank. **Industrial and Labor Relations Review**, vol. 55, no. 3, pp. 432–447. 2002.

AUTOR, D., LEVY, F; MURNANE, R.J. The skill content of recent technological change: An empirical exploration. **The Quarterly Journal of Economics**, vol. 118, no. 4, pp. 1279–1333. 2003.

AUTOR, D. Why is There Still So Many Jobs? The History and Future of Workplace Automation. **Journal of Economic Perspectives,** vol. 29, no. 3, pp. 3-30. 2015.

BAER, W., GALVÃO, A. F. Tax burden, government expenditures and income distribution in Brazil. **The Quarterly Review of Economics and Finance.** Vol. 48, issue 2, pp. 345-358. 2008.

BOUND, J; JOHNSON, G. Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations. **The American Economic Review**, vol. 82, no. 3, pp. 371-392. 1992.

BRESNAHAN, T.F. Computerization and wage dispersion: an analytical reinterpretation. **The Economic Journal**, vol. 109, no. 456, pp. 390–415. 1999.

BRESNAHAN, T.F., BRYNJOLFSSON, E. AND HITT, L.M. 2002. Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. **The Quarterly Journal of Economics,** vol. 117, no. 1, pp. 339–376. 2002.

BRYNJOLFSSON, E. E MCAFEE, A. **Novas Tecnologias *versus* Empregabilidade: Como a Revolução Digital acelera a Inovação, desenvolve Produtividade e transforma de modo irreversível os Empregos e a Economia**. São Paulo. M.Books do Brasil Editora Ltda. 2014.

BRYNJOLFSSON, E. E MCAFEE, A. **A Segunda era das máquinas: trabalho, progresso e prosperidade em uma época de tecnologias brilhantes**. Rio de Janeiro. Altas Books. 2015.

FORD, M. **Rise of the robots: technology and the threat of a jobless future**. New York. Basic Books. 2015.

FREY, C.B. AND M.A. OSBORNE. **The Future of Employment: How Susceptible are Jobs to Computerization?** University of Oxford. 2013.

GOLDIN, C AND KATZ, L.F. Technology, Skill, and the Wage Structure: Insights from the Past. **The American Economic Review**, vol. 86, no. 2, pp. 252-257. 1996.

GOLDIN, C. AND KATZ, L.F. The origins of technology-skill complementarity. **The quarterly journal of economics,** vol. 113, no. 3, pp. 693–732. 1998.

GOODMAN-BACON, A. Difference-in-differences with variation in treatment timing. No 25018**, NBER Working Papers, National Bureau of Economic Researh,** Inc. 2018

IBGE. **Classificação nacional de atividades econômicas -** CNAE : versão 1.0 / Comissão Nacional de Classificação [e] IBGE. Available at https://biblioteca.ibge.gov.br/visualizacao/livros/liv2314.pdf. Accessed in 16 September 2019.

KRUEGER, A.B. How computers have changed the wage structure: evidence from microdata, 1984–1989. **The Quarterly Journal of Economics**, vol. 108, no. 1, pp. 33–60. 1993.

LEONTIEF, W. Technological Advances, Economic Growth, and the Distribution of Income. **Population and Development Review**, vol. 9, no. 3, pp. 403-410. 1983.

LEVY, F., MURNANE, R.J. With What Skills Are Computers a Complement? **The American Economic Review**, vol. 86, no. 2, pp 258-262. 1996.

MAZUMDER, S. iPad Purchasing Parity: Farewell to the Big Mac Index. **Economics Bulletin**, vol. 36, no. 4, pp. 2128-2136. 2016

MORAVEC, H. When will computer hardware match the human brain? **Journal of Evolution and Technology,** vol. 1, pp. 1-12. 1998.

NORDHAUS, W.D. Two centuries of productivity growth in computing. **The Journal of Economic History**, vol. 67, no. 1, p. 128. 2007.

RUSSELL, S E NORVIG, P. **Artificial Intelligence: A modern Approach**. 2nd Edition. 2002

SILVER, D., T. HUBERT, J. SCHRITTWIESER, I. ANTONOGLOU, M., A. GUEZ, M. LANCTOT, L. SIFRE, D. KUMARAN, T. GRAEPEL, T. LILLICRAP, K. SIMONYAN, D. HASSABIS. A General Reinforcement Learning Algorithm that Masters Chess, Shogi and Go Through Self-Play. **Science**. Vol. 362, Issue 6419, pp. 1140-1144. 2018

Turing, A.M. On computable numbers, with an application to the Entscheidungsproblem. **Proceedings of the London Mathematical Society**. Series 2, no. 42, pp. 230-265. 1936.

TURING, A. M. Computing Machinery and Intelligence. **Mind**, vol. 59, no. 236, pp. 433-460. 1950.

ULYSSEA, G. Regulation of entry, labor market institutions and the informal sector, **Journal of Development Economics**, vol., issue 1, pp. 87-99. 2010.

WOOLDRIDGE, J. **Introdução a Econometria uma Abordagem Moderna**, 2ª Ed., Thomson-Pioneira. 2006.

YANG, A. The War on Normal People: The Truth About America's Disappearing Jobs and Why Universal Basic Income is Our Future. **Hachette Books**. 2018.

ZEIRA, J. Workers, Machines, and Economic Growth. **The Quarterly Journal of Economics**, vol. 113, no. 4, pp. 1091-1117. 1998.