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Troca de trabalhadores por robôs: os impactos da automação no Paraná

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Paulo Henrique de Cezaro Eberhardt[1]

Abstract: The replacement of people by machines is not a recent concern. Common occupations may cease to exist due to recent advances in artificial intelligence, robotics, algorithms, and mechanization. This article aims to identify the regional impacts of replacing humans with machines, i.e., which municipalities will be most vulnerable. Using data from the research by Frey and Osborne (2017), the study analyzed and identified through geographically weighted regression that, in Paraná State, municipalities with a larger rural population should be the most affected by automation.

Keywords: *Automation; regional economy; economy of Paraná State; geographically weighted regression.*

Resumo: A troca de pessoas por máquinas não é uma preocupação recente. Com os recentes avanços em inteligência artificial, robótica, algoritmos e mecanização, ocupações comuns atualmente poderão deixar de existir. O objetivo desse artigo é identificar quais os impactos regionais da substituição de humanos por máquinas, ou seja, quais municípios estarão mais vulneráveis. Com os dados da pesquisa de Frey e Osborne (2017), foi identificado e analisado através de regressão geograficamente ponderada que no Paraná os municípios com população rural maior deverão ser os mais afetados pela automação.

Palavras-chave: *Automação. economia regional. economia paranaense. regressão geograficamente ponderada.*

Resumen: El intercambio de personas por máquinas no es una preocupación reciente. Con los recientes avances en inteligencia artificial, robótica, algoritmos y mecanización, las ocupaciones comunes actualmente pueden dejar de existir. El objetivo de este artículo es identificar los impactos regionales de reemplazar humanos por máquinas, es decir, qué municipios serán más vulnerables. Con datos de la investigación de Frey y Osborne (2017), se identificó y analizó mediante regresión ponderada geográficamente que en Paraná los municipios con mayor población rural deberían ser los más afectados por la automatización.

Palabras clave: *Automatización. economía regional. Economía de Paraná. regresión ponderada geográficamente.*

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INTRODUCTION

Concern over technological unemployment is not recent. In the industrial revolution, the replacement of workers by machines intensified (BRUE, 2006). This replacement is a form of innovation that currently has several names. Among them is automation, which is the replacement of workers by algorithms, robots, artificial intelligence, and machines operated by computers (CROWLEY, DORAN, AND MCCANN, 2021). In the United States, 47% of jobs have a high risk of being automated (FREY and OSBORNE, 2017). In Brazil, in turn, the estimate for 2018 shows that 3.57 million workers with formal jobs are in occupations with a high propensity for automation, while 10.5 million workers are in occupations with a medium-high propensity (ADAMCZYK, 2021).

The occupations most likely to be automated are those that require little creativity, little social interaction, low levels of cognitive activity, and routine activities. On the other hand, occupations with a low probability of being automated require higher cognitive and social skills, as well as rely more on decision-making (AUTOR, 2015).

Automation will become a major issue for regions and countries, along with environmental issues and climate change. Thus, studying its effects on society and its various elements (such as income inequality, the labor market, and regional and demographic effects) can help improve the welfare of everyone.

The regions that will be most influenced by automation may experience severe negative shocks in their labor markets, both due to the reduction in the overall number of workers and the change in their production structure. In this regard, research on regional resilience can provide important contributions as to how regions react to a negative shock, particularly caused by automation (JOYAL and BESSA, 2012; VIEIRA et al, 2012; MARTIN and SUNLEY, 2015; JOYAL, 2019; EBERHARDT and TUPY, 2022).

Bearing the above in mind e, this article aims to identify how the occupations most likely to be automated in the future are distributed in municipalities in the state of Paraná- BR. Concerning this issue, some questions arise: are the occupations most likely to be automated located in the smallest cities? Or in the most urbanized cities? Or in the poorest cities?

Thus, the contribution of this paper to the literature is to provide a regional perspective on the effects of automation in the municipalities of Paraná. The present study identifies which ones have the most jobs in occupations that will be most affected by automation and what the characteristics of these municipalities are, similar to the study by Crowley, Doran, and McCann (2021).

Considering the evidence found on the impacts of automation, is there a need for government intervention in the most affected sectors? Should the market economy define which sectors will be automated? What will happen to the people who lose their jobs to robots, since research demonstrates that the most affected ones will be those already most vulnerable?

This paper consists of this introduction, a literature review presenting some characteristics of automation, and the main conclusions of the research on the subject. In the following section, the occupations most likely to be automated and their distribution among the municipalities of Paraná are analyzed. The methodology outlines the empirical strategy used to identify the characteristics of the cities most vulnerable to automation. The article concludes with some final considerations.

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1. Literature review

Automation has led to a wide variety of research on its impacts on employment, wages, and income inequality, as well as regional and demographic impacts. Schumpeter (1942) demonstrated that the stimulus for economic growth was innovation, i.e. creating a new product, a new way of producing, and conquering new markets. Since then, innovation and technical progress have become one of the pillars of economic growth theories.

Regarding employment, research suggests that each robot introduced into the production process will replace 3.3 workers. Thus, replacing workers with robots will also reduce wages. Concerning inequality, if automation reduces the labor income share in relation to national income, capital owners will have their income increased in proportion to it, widening the gap between them and workers. Automation trends tend to aggravate the effects of income disparity and inequality (ACEMOGLU; RESTREPO, 2017, 2020a).

As for regional impacts, regions with a higher population density are less vulnerable to automation, and so are places with more creative activities (RIPPEL et al, 2007; CROWLEY; DORAN; MCCANN, 2021). Population density is relevant for explaining the externalities created by urban agglomerations, where the speed at which ideas spread is faster and the reduction in transportation costs helps generate income and employment.

In the context of increased automation, the poorest cities and those furthest away from major urban centers tend to have the strongest negative shocks and the worst economic performance. This happens because such cities rely more on occupations that do not require much cognitive skills and have a higher proportion of jobs in routine occupations (CROWLEY; DORAN, 2022).

Staduto et al (2009) observed the situation of workers' informality. In some cases, automation removed jobs occupied by workers with low education, which increased informality in Paraná State. Staduto and Kreter (2014) noticed a similar situation in rural areas of Brazil.

Regarding demographic aspects, countries with an older population tend to automate more. The same applies to industries with employees with a higher average age (ACEMOGLU; RESTREPO, 2018). As for education, workers at all levels of education are likely to lose jobs, even those with higher education (ACEMOGLU; RESTREPO, 2019).

2. Methodology

This study aims to identify the regions that will be most vulnerable to automation. To this end, an indicator that shows the proportion of workers in occupations that are more likely to be automated compared to the total number of jobs in the municipality was calculated. Such indicator was named "most likely" and was calculated for the 399 municipalities of Paraná.

The municipalities with the highest number of workers in these occupations were classified as "vulnerable". According to Frey and Osborne (2017), the occupations most likely to be automated are: livestock producers; agricultural producers; mineral processing workers; multipurpose agricultural producers; workers who assemble structures in civil construction; construction supervisors; insulation workers; ornamental stone processing workers; earthmoving machinery operators; and ceramic tiles, glass tiles, and stone setters.

In general, these occupations are related to rural activities and construction, in which the level of education corresponds to elementary school and wages are low.

Table 1 - Occupations most likely to be automated

Position	Occupation	CBO* code	Propensity for Automation	Quantity**	Schooling Years**	Average wage**
1	Livestock producers	6131	0,9969	1.260	7,07	1.503
2	Agricultural producers	6110	0,9565	2.650	7,26	1.377
3	Mineral processing workers	7121	0,9505	6.976	7,97	2.280
4	Multipurpose agricultural producers	6120	0,9499	2.619	6,69	1.499
5	Workers who assemble structures in civil construction	7155	0,9497	98.309	7,35	2.002
6	Construction supervisors	7102	0,9495	85.677	8,67	3.614
7	Insulation workers	7157	0,949	12.236	8,89	2.036
8	Ornamental stone processing workers	7122	0,9487	21.429	8,53	1.825
9	Earthmoving machinery operators	7151	0,9487	113.151	8,02	2.475
10	Ceramic tiles, glass tiles, and stone setters	7165	0,9486	20.293	8,68	1.880

Source: Adamczyk, 2021, p. 82.
*Classificação Brasileira de Ocupações (Brazilian Classification of Occupations)
**Data regarding the state of São Paulo for 2018

Some variables were selected to identify the characteristics of the cities most "vulnerable" to automation. Table 2 presents the descriptive statistics for such variables.

Table 2 - Descriptive statistics of the variables

	Description	Minimum	Maximum	Mean	Median	Source
Urbanization	Total number of people living in the urban area of the municipality (in %)	9,35	100	68,39	71,9	IBGE
Density	Number of people per km2	2,52	4515,65	69,08	26,2	IPARDES
Gini index	Index of income inequality	0,33	0,66	0,46	0,47	IBGE
GDP per capita	Production of goods and services divided by population	12,145	134.901	38.885	34.628	IBGE
Poverty	Poverty rate	0,84	38,11	10,27	8,43	IPARDES
Population	No. of inhabitants	1,309	1.963,726	29.066	9,573	IBGE
Most likely	Indicator of workers in occupations more likely to be automated (in %)	0	9,35	1,21	0,9	Authors' calculations

The employment data are from the 2021 Social Information Annual Report (RAIS). As for the other variables, the data used was from the most recent year available. The sources for the other variables are the Parana Institute for Economic and Social Development (Instituto Paranaense de Desenvolvimento Econômico e Social - IPARDES), the Institute for Applied Economic Research (Instituto de Pesquisa Econômica Aplicada - IPEADATA), and the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística - IBGE).

2.1 Global Model - Ordinary Least Squares (OLS)

Two strategies were used to determine the most vulnerable regions: linear regression based on ordinary least squares (OLS) and geographically weighted regression (GWR). For the OLS, the following equation was estimated:

$$y_i = \alpha_i + \beta_i\lambda_i + \varepsilon_i \quad \text{para } i= 1, 2, 3\ldots399 \qquad (1)$$

Where yi represents the dependent variable, α represents the intercept term, λ represents the set of independent variables presented in Table 2, β demonstrates the marginal effect of each independent variable, and ε are the residuals. One aspect of the OLS model is that all observations have equal weights, which correspond to a constant estimation of the parameters over space, i.e. representing a global regression model. Therefore, the OLS estimates that the effect of the independent variables on the dependent variable is the same for all observations.

2.2 Local Model - Geographically Weighted Regression (GWR)

Using the GWR model, the weight of each observation varies according to the distance between the municipalities. Geographically weighted regression (GWR) was first proposed by Brunsdon *et al.* (1996) as a method to explore spatial nonstationarity. GWR consists of a simple technique that allows the estimation of local parameters, rather than global ones.

According to the first law of geography, or Tobler's law, “everything is related to everything else, but near things are more related than distant things” (TOBLER, 1970). Therefore, to estimate the GWR model, bandwidth is defined in which the area of influence of the municipality i is configured. Geographically closer municipalities are assigned higher weights, which gradually decrease the farther the municipalities are from municipality i (PARTRIDGE *et al.*, 2008).

Charlton and Fotheringham (2009) demonstrate that it is necessary to include an indication of the location of each analyzed observation to estimate the GWR model, which results in the GWR version of the OLS with the following equation:

$$y_i(\mathbf{u}) = \beta_{oi}(\mathbf{u}) + \beta_{1i}(\mathbf{u})_{x1i} + \beta_{2i}(\mathbf{u})_{x2i} + \ldots \beta_{mi}(\mathbf{u})\, x_{mi} \qquad (2)$$

In which **u** is the weight of observation i in relation to its location. The optimal bandwidth selected for this study was determined by Akaike’s information criterion (AIC). The chosen one was a Gaussian function:

$$W_i(\mathbf{u}) = e^{-0,5(\frac{di(u)}{h})^2} \qquad (3)$$

In which $W_i(\mathbf{u})$ is the weight of observation i in relation to its location, $d_i(u)$ is the distance between the observations and h is the bandwidth. Nicholls and Kim (2019) and Partridge *et al.* (2008) also used the geographically weighted regression model in their studies. In Brazil, Silva (2017), and Gomes, Porsse, and Gonçalves (2019) also used such model.

3. Automation in Paraná and its regional effects

Automation will transform the labor market of countries, whether by destroying occupations that do not require many cognitive and social skills, or by creating new occupations that involve artificial intelligence, robotization, algorithms, and activities that rely heavily on decision-making.

Figure 1 presents the spatial distribution of the municipalities most likely to be automated. It also depicts the proportion of formal jobs listed in Table 1 compared to the total number of formal jobs in the municipality, and it was used as a proxy for the municipality's vulnerability to automation.

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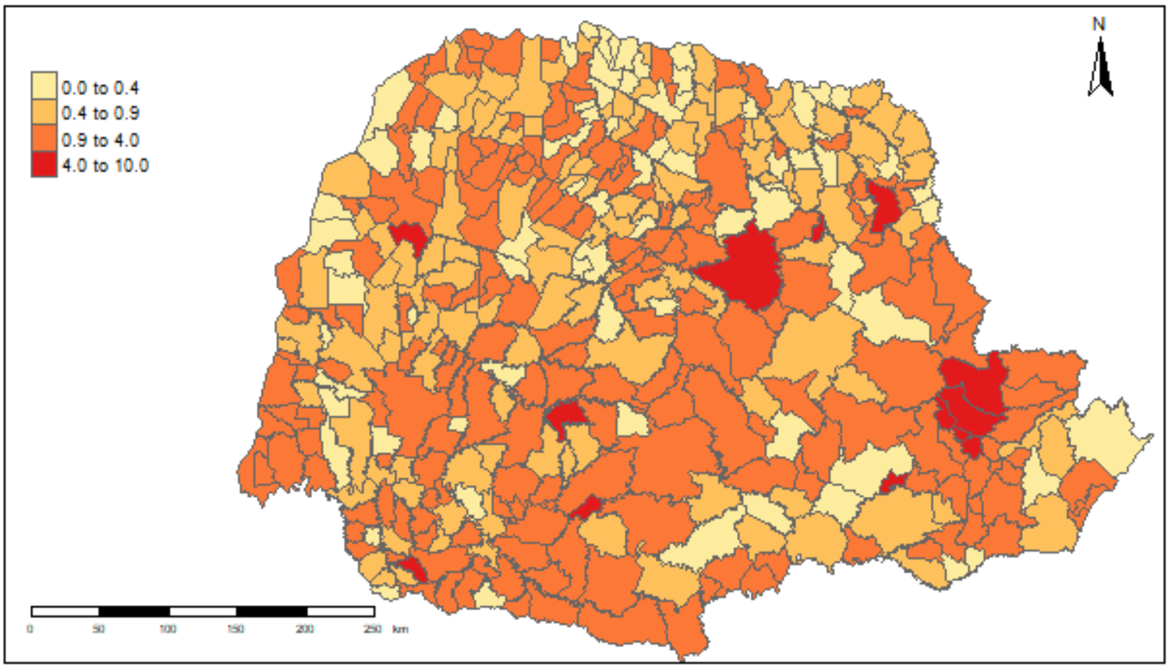
Figure 1 – Paraná State in Brazil: spatial distribution of occupations most likely to be automated - 2021



Source: results of the study

The results of the global and local models displayed in Table 3 suggest that municipalities with less urbanization will be the most affected, which has been identified in previous studies such as the ones mentioned in the literature review. In addition, Table 1 indicated that several occupations among the 10 most likely to be automated are predominantly rural.

The municipality of Marquinho ranks first among the municipalities with the highest number of jobs in occupations most likely to be replaced by artificial intelligence. In 2021, this municipality had 1 out of 10 jobs in occupations that are most likely to be automated, i.e., mostly workers operating machinery, earthmoving, and assembling wooden and metal structures in civil construction. The municipalities of Ortigueira and Cerro Azul comprise, along with Marquinho, the top three municipalities most vulnerable to automation.

Table 3 - Results of the global and local models

Variable	Min	Max	1º Quartile	Median	3º Quartile	OLS*
Intercept	3,59	3,71	3,61	3,65	3,70	3,62
Urbanization	-0,02	-0,02	-0,02	-0,02	-0,02	-0,02**
Gini Index	-1,34	-1,11	-1,25	-1,16	-1,13	-1,22
GDP per capita	0,00	0,00	0,00	0,00	0,00	0,00
Small municipality	-0,30	-0,24	-0,27	-0,26	-0,26	-0,27

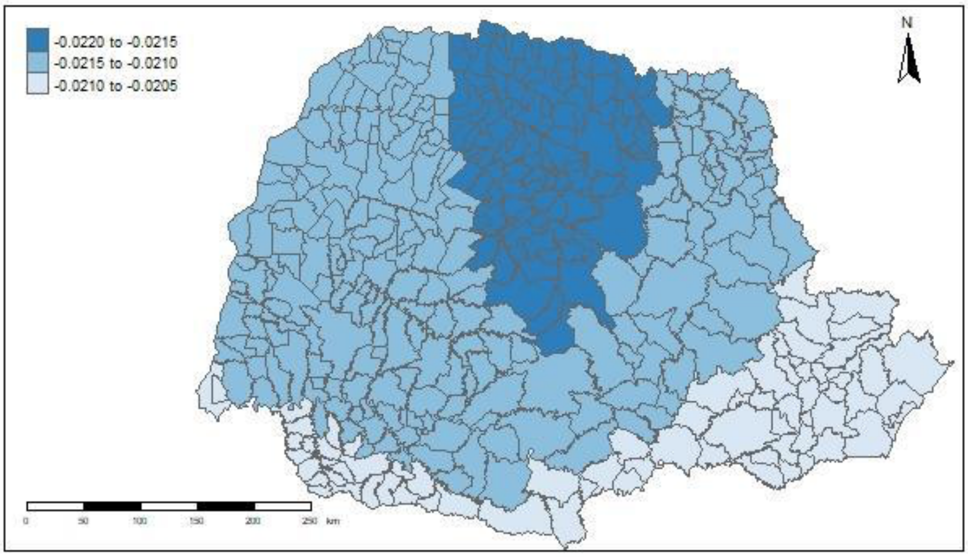
Source: research results

* Model with standard erros corrected for heteroskedasticity

**Statistically significant at 0,1%

The results of the local model (GWR) indicate that all the municipalities in Paraná have a negative correlation between the variable "most likely" and urbanization. It is possible to identify which regions will be the most affected considering their urbanization, as the local model estimates a parameter for each municipality. The most affected regions are presented in dark blue in Figure 2.

Figure 2 – Paraná State in Brazil: spatial distribution of the effects of urbanization on automation - 2021



Source: results of the study

Therefore, the global model indicates that municipalities with a more rural population will be more vulnerable to automation. Results from the local model, in turn, indicate that some municipalities will be more affected than others, considering their urbanization.

Final considerations

Algorithms are already present in everyday life, whether it is when we order something online, such as food or transportation, or when we are on social media, algorithms decide what we will see based on our previous behavior. These algorithms can provide benefits, such as the use of machine learning to analyze legislation on regional development (SILVA *et al*, 2010; RODRIGUES *et al*., 2022).

However, they can also have undesirable results. There are cases of algorithms predicting the performance of teachers, which can lead to dismissal if they do not meet the expected performance. There are also allegations of racism in facial recognition. Acemoglu and Restrepo (2020b) raised the question of whether the right type of artificial intelligence is being developed: one that will increase productivity, wages, and the welfare of everyone in society.

The literature demonstrates that the occupations that will be most automated are those that require less education, pay lower wages, and are located far from large urban centers. This process of job destruction by automation is irreversible. What will become of the less educated population who live far from urban centers?

Solutions are being proposed to mitigate this problem, such as universal basic income. However, the solution may not lie solely in economics. Automation also raises philosophical questions. For Harari (2015), people will have a worse fate than just being unemployed or exploited at their jobs: they will become useless citizens in an automated society.

Technological unemployment has existed and has been a threat for a long time, but innovations open up space for creating new occupations. We will have to wait and see what occupations artificial intelligence will create and what the future holds.

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