AUTOMATION AND UNEMPLOYMENT: THE BRAZILIAN CASE

Bruno Ottoni[1]
Paulo Rocha e Oliveira[2]
Lucas Estrela[3]
Ana Tereza[4]
Tiago Barreira[5,*]
Área ANPEC 9 – Economia Industrial e da Tecnologia

Sumário: Inovações tecnológicas estão ampliando a capacidade da máquina substituir o trabalho humano. Neste cenário, procuramos estimar – tomando como base o estudo de Frey e Osborne (2017), que utiliza dados americanos, e tem sido muito citado – quantos empregos brasileiros podem ser eliminados, em uma ou duas décadas, em virtude de tecnologias já existentes na atualidade. Nossos resultados indicam que 58,1% dos empregos brasileiros podem desaparecer, nos próximos 10 ou 20 anos, em função da automação.
Palavras-chave: Automação; Mudanças Tecnológicas; Desemprego; Escolha Ocupacional
Classificação JEL: E24; J23; J24; O33.

Abstract: Technological innovations are enabling machines to further replace human labor. In this context, we estimate – based on the Frey and Osborne (2017) study, which uses data from the United States of America (USA) – how many Brazilian jobs may be eliminated in one or two decades due to currently existing technologies. Our results indicate that 58.1% of Brazilian jobs may disappear in the next 10 to 20 years due to automation.
Keywords: Automation; Technological change; Unemployment; Occupational Choice
JEL Classification: E24; J23; J24; O33.

[1] IDados, FGV and UERJ.
[2] ISE, IESE Business School and IDados.
[3] UFRJ.
[4] IDados.
[5] IDados.
*Corresponding Author: tiago_cabral@idados.id or IDados, Rua Visconde de Piraja, 470, Ipanema, Rio de Janeiro, RJ, Brazil, ZIP: 22410-002.

1. INTRODUCTION

We are experiencing a moment of intense automation, in which new technologies have facilitated the replacement of human work by machines. Within this context, a growing number of studies are being written about the relationship between automation and unemployment. On one hand, some studies confirm how automation has contributed to increased unemployment in the past few decades (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Autor and Salomons, 2018; Dauth et al 2017). On the other, future-focused articles attempt to determine if automation may cause greater unemployment in the upcoming years (Frey and Osborne, 2017; Arntz et al 2017b).

One of the most cited studies, that attempts to determine if automation may cause greater unemployment in the near future, is Frey and Osborne (2017). This research begins by estimating the probabilities of machine substitution of various occupations in the United States of America (USA). Next, it uses these automation probabilities in an attempt to determine the proportion of American jobs that may disappear in the next few decades. According to the study, there already exists the technical capacity to automate 47.0% of American jobs within 10 to 20 years.

This result first appeared 2013, in a preliminary version of the Frey and Osborne study, which at the time generated great concern. Thus, new studies were conducted by applying to different countries the automation probabilities that Frey and Osborne estimated for the USA (see World Bank, 2016; Deloitte, 2015; Bowles, 2014; Pajarinen and Rouvinen, 2014). Although existing articles mention various countries, to the best of our knowledge no paper, analyzing the Brazilian scenario, has yet been published.

This research intends to fulfill the existing gap in the literature, considering that it develops a compatibility process that enables the application of the automation probabilities estimated by Frey and Osborne (2017) to Brazil. Our result suggests that 58.1% of Brazilian jobs may be substituted by machines – within a one-to-two-decade timeframe – due to already existing technologies. This means that 58.1% of Brazilian jobs can be automated within the next 10 to 20 years.

The article contains this introduction, in addition to five more sections. The second section presents a detailed literature review. The third section describes the compatibility method we have developed in order to apply the automation probabilities from Frey and Osborne (2017) to the Brazilian case. The third section also describes the databases used in the present study. Our main results are found in the fourth section. Additionally, in order to verify the consistency of our main results, we conducted a sensitivity analysis in the fifth section. Finally, the sixth, and last section, contains our conclusions.

2. LITERATURE REVIEW

The fear of technology and its effects on employment is not a new phenomenon in the history of modern societies.[6] The notorious Luddite movement in the 19th century is a major symbol of the type of reaction resulting from technological fear. In the 1930s, in the Great Depression context, Keynes (1933) emphasized the link between technology and job destruction. Still, the author also stressed that "technological unemployment' in the short run represented a "phase of maladjustment.". Later, Autor (2015) documented a strong concern on this topic in the 1950s and 1960s. Nevertheless, the employment to population ratio increased during the 20th century, reinforcing the idea that job losses represent a transitory phase after a technological innovation. Overall, previous technological advances had positive net effects on employment (Atkinson and Wu, 2017).

More recently, the debate regarding the relationship between automation and unemployment has reemerged. This reemergence is not surprising, given the ongoing computer revolution and the new advances in AI and robotics. As computer prices fell sharply during the 1980s, their adoption became

[6] Mokyr et al. (2015) provides a carefully look into the history of technological anxiety

widespread in North American workplaces. This new technology was pointed as one of the causes of the (concurrent) rise in inequality in the USA, as several authors documented a strong complementarity between investments in computer capital and higher demand for skilled workers (Autor et al., 1998; Levy and Murnane, 1996; Bound and Johnson, 1995), resulting in the enlarging of the wage gap between the skilled and the unskilled. Bresnahan et al. (1999) emphasized the substitution effect, as computers were able to do a limited set of repetitive work, previously done by humans.

The work of Autor et al. (2003) was the first to formally explain this relation of substitution and complementarity between humans and computers. Using a task-based approach, the authors identified that the fall in computer prices lowered the demand for human labor in routine tasks. Those tasks were labeled routine "because they can be fully codified and hence automated" (Autor, 2015, p.9). Also, the study shows that highly skilled workers experimented productivity gains with computerization, as abstract and complex tasks complement technology. In the light of the routinization hypothesis, several studies revealed job losses in middle-skill occupations (primarily linked to routine tasks), leading to a polarized workforce in the USA (David and Dorn, 2013; Autor et al., 2006); other developed economies (Antonczyk et al., 2018; Goos, et al., 2014; Michaels et al. 2014) and developing economies (Estevadeordal et al, 2017).

Although the skill-biased technological change framework was able to explain changes in the structure of employment related to computerization, the accelerated pace of innovation and adoption of AI and Robotics technology underlined a limitation of the model. In fact, Acemoglu and Autor (2011) clearly state that those new technologies cannot be used in their framework.

In the scenario of economic crises in the late 2000s, the higher unemployment rates were linked to the technological innovations that displaced labor (Brynjolfsson and McAfee, 2011). More critically, Brynjolfsson and McAfee (2014) alerted that the increasing pace of technological change quickly augmented in the range of human tasks that machines can do. Additionally, the authors called attention to the fact that new technologies are being adopted faster than in the past, which lowers the time available for labor markets to adjust before the next innovation is introduced. Therefore, the recent renewed fear of technological unemployment seems to be more reasonable than in the past.

As a matter of fact, there is a growing body of literature studying the relationship between these new technological advances and job loss. Here, we distinguish two different strands of this recent literature. The first one looks at the past and shows that the adoption, in the last few decades, of modern technologies (e.g., the dissemination of industrial robots), had a negative effect on employment (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Autor and Salomons, 2018; Dauth et al. 2017). The second strand of this recent literature is concerned with projecting, using econometric models, the future of technological unemployment. Specifically, this literature examines the extent to which the data support the view that unemployment tends to increase in the coming decades due to the intensification of human labor displacement by machines (Frey and Osborne, 2017; Arntz et al., 2017b).

The work of Frey and Osborne, first released in 2013 but only published in 2017, represented a breakthrough in the second strand of the literature mentioned above, for at least two reasons. First, they not only took the new technologies into account, but also considered that the potential for these innovations to displace labor will continue to increase in the next decades due to the recent advances in the fields of robotics, machine learning, and big data. As they state, their analysis considers the framework of Autor, Levy, e Murnane (2003), but they insert a broader look into what computers can do. To illustrate this increased capability of computers, the authors highlight that "Recent technological breakthroughs are largely due to efforts to turn non-routine tasks into well-defined problems”. Therefore, as those efforts tend to continue in the coming years, more and more tasks will be codifiable.

The methodology developed in Frey and Osborne (2017) is the second reason for the prominence of their study. This is because they developed a way to estimate, for most USA occupations, the risk of being replaced by machines in the next ten to twenty years. Specifically, they identified occupational characteristics in non-routine work that had the potential to be done by machines in the next two decades, counting with the collaboration of Engineers from Oxford. Then using a Gaussian process, they estimated the probabilities of automation for most USA occupations in the next ten to twenty years.

Moreover, Frey and Osborne's (2017) work served as a basis for many other studies which look at different countries (World Bank, 2016; Deloitte, 2015; Pajarinen and Rouvinen, 2014; Bowles, 2014).

These articles use the same probabilities of automation that were estimated in Frey and Orborne (2017), facilitating cross-country analysis since the same method was used for all countries. Nevertheless, their methods and assumptions received some criticism in the sequent years after. Regarding their methods, most studies point to an upward bias in the automation risk (Arntz et al., 2017a ; Autor, 2015). Additionally, the fact that Frey and Osborne (2017) do not address the potential for job creation enhanced by technology was also mentioned as a drawback of the paper, even though the authors explicitly acknowledge this possibility.

The absence of a consensus on how labor markets will look like in the future is not surprising, as our current ability to predict such a scenario is limited. Nevertheless, we believe that the attempt to measure the risk of automation directly, as first presented in Frey and Osborne (2017), is a powerful tool to highlight which jobs have more prospect of being replaced by machines. This is a valuable knowledge as it creates a solid point to discuss how we can react in other to prevent higher unemployment rates. Rather than creating a wave of panic about job losses in the future, we understand that this approach can be understood as a warning to policymakers, academics, and other institutions. Their policies to enforce a labor force more skilled to complement machines might alleviate massive technological unemployment.

To the best of our knowledge, there are no published articles that apply Frey and Osborne (2017) probabilities to the Brazilian case. However, we are aware of two other working papers, none of them published in academic journals, with the same goal as ours: the technical reports of Albuquerque et al. (2019) and Lima et al. (2019). Albuquerque et al. (2019) consulted specialists in the machine learning field to calculate the risk of automation for Brazil while Lima et al. (2019) directly applied the Frey and Osborne (2017) probabilities. Both studies adopted the Annual Report of Social Information (RAIS) dataset which only contains information on formal employment.

Our paper, differentiates from the two technical reports mentioned above since we use employment data from the Continuous National Household Sample Survey (PNADC). We chose to use the PNADC data because it provides a representative sample of the Brazilian labor market, including both the formal and the informal sector. As this latter sector represents more than 41% of Brazilian jobs, we believe that PNADC is best suited to study the Brazilian job market.

Considering these differences and given the large numbers of studies that adopted Frey and Osborne (2017) probabilities, we believe that our work has an important contribution as we dialogue directly with the international literature and consider the entire labor market by using the PNADC database. Moreover, we add to a small and growing strand of Brazilian literature that documents other impacts of technology on labor markets (e.g., Adamczyk et al, 2019; Gonzaga and Guanziroli 2019; Maciente, 2012 e 2016; Funchal and Soares 2013; Bressan and Hermeto, 2009).

3. COMPATIBILITY METHOD

The compatibility method that we developed to apply the Frey and Osborne (2017) automation probabilities to the Brazilian case consists of four stages, outlined below in greater detail.

3.1. Transitioning from U.S. to International classification

In the first stage, we used a crosswalk – provided by the Bureau of Labor Statistics (BLS) of the United States of America (USA) – which enabled transitioning from the American Standard Occupational Classification (SOC 2010) to the International Standard Classification of Occupations (ISCO 2008). Thus, this crosswalk enables the application of the automation probabilities estimated by Frey and Osborne (2017) – classified according to the American Standard Occupational Classification (SOC 2010) – to the current standard of International databases (ISCO 2008).

This first stage was the study's biggest challenge, as there is a significantly larger number of occupations in the American classification, which has approximately 802 different codes, as compared to the International classification, which has 438 different codes. Therefore, numerous automation probabilities are assigned to each occupation. This creates a problem that consists in the need to select only one, among all available automation probabilities assigned to each occupation. This issue was dealt with only in the fourth and final stage of our compatibility process.

3.2. Transitioning from International to Brazilian classification

In the second stage of our compatibility process, we used a self-developed crosswalk that enabled to transition from the International Standard Classification of Occupations (ISCO 2008) to the Brazilian classification (COD 2010). To develop this, we followed guidelines provided by the Brazilian Institute of Geography and Statistics (IBGE), which is the body responsible for producing and disclosing Brazil's employment data.[7]

We were then able to apply the automation probabilities estimated by Frey and Osborne (2017) – already translated to the International classification (ISCO 2008) – to the Brazilian standard (COD 2010). There were almost no challenges in this second stage. More precisely, in most cases – 434 out of a total of 438 occupations – our compatibility process worked properly.

3.3. Applying the automation probabilities to Brazilian data

Next, we executed the third stage of our compatibility method. This stage consists only of applying the automation probabilities of Frey and Osborne (2017) – already translated into the Brazilian occupational classification (COD 2010) – to Brazilian employment data. More precisely, we use the employment data available in the 2017 Continuous National Household Sample Survey (PNADC 2017), released by IBGE, which also adopts the Brazilian occupational classification (COD 2010).

As the occupational classification is identical in both bases that are paired in this third stage, there are practically no complications. Specifically, in the great majority of cases – 428 out of a total of 434 occupations – the third stage of our compatibility method worked properly.[8]

Before continuing, it is worth mentioning that we were able to assign at least one automation probability to 409 of the 428 occupations we successfully matched. The other 19 (428 – 409 = 19) were also successfully matched, but to occupations with no automation probability in the original Frey and Osborne (2017) study. Therefore, these 19 occupations were assigned no automation probability.[9]

3.4. Selecting only one automation probability for each occupation

We now reach the fourth and final stage of our compatibility method. As stated previously, at this stage we need to choose only one among all of the automation probabilities assigned to each occupation. It is worth mentioning that we use the PNADC 2017 information to help us choose, in this fourth stage, the one automation probability that we assign to each occupation.

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[7] More precisely, we used information found in the following IBGE documents:

1) https://ww2.ibge.gov.br/home/estatistica/indicadores/sipd/oitavo_forum/COD.pdf

2) ftp://ftp.ibge.gov.br/Censos/Censo_Demografico_2010/metodologia/anexos/anexo_7_ocupacao_cod.pdf

[8] Here we lost 6 occupations (considering that we made 428 out of 434 compatible) which exist in the Brazilian classification (COD 2010), but that are not present in the PNADC 2017.

[9] This means that we were unable to assign an automation probability to a very small proportion of 4.4% of the 428 occupations that we were able to make compatible ([19 ÷ 428] x 100 = 4.4%). In terms of employment, our compatibility method seems to obtain an even higher degree of success. Specifically, the compatibility process we have developed enabled us to assign some automation probability to 90.1 million jobs, a number that represents almost all 91.4 million jobs that we successfully matched. Therefore, we were unable to assign an automation probability to a very small proportion of 1.4% of the 91.4 million jobs we were able to make compatible ([1.3 ÷ 91.4] x 100 = 1.4%).

We begin by taking advantage of the fact that PNADC 2017 data provides information on the total number of people employed in each occupation in order to determine which is the only probability of automation that we choose to keep in each case. Note that we can adopt different criteria to select the automation probability to be assigned to each occupation as, for example, the following: (i) the maximum; (ii) the minimum; and (iii) the average. In order to verify how our results vary due to the adopted selection criteria, we compared our estimates obtained by using only two criteria, which are: (i) the maximum; and (ii) the minimum.

We focused only on the two selection criteria mentioned, the maximum and the minimum, since they produce the most extreme results. This option seems favorable considering that if the choice of selection criteria matters to our results, then differences tend to become more evident in this extreme comparison. Alternatively, the comparison between more similar selection criteria may lead to the false conclusion that the choice of the mentioned criteria does not matter to the estimates on the number of jobs that may be substituted by machines within one or two decades, based on already existing technologies.

Table 1 helps to illustrate how the chosen selection criteria, maximum and minimum, produce very different estimates of the number of jobs that can be automated. More precisely, the table shows that there are 1,508,755 employed people in occupation code 8322 (note that this code already consists of the one found in the Brazilian occupation classification, known as COD 2010). The automation probability of this occupation, according to the maximum criteria, is of 98.00%. This means that a total of 1,478,580 jobs in occupation code 8322 can be automated according to the maximum criteria (1,508,755 people working in occupation 8322 X automation probability of 98.00% = 1,476,580 jobs that can be automated).

Table 1: Illustration on how the maximum and minimum selection criteria were used to calculate the difference in the number of jobs that can be automated in each occupation

Occupation Code	Original Frey and Osborne (2017) Probabilities	Number of Jobs in the Occupation	Automation Probability of the Occupation According to the Maximum Criteria	Automation Probability of the Occupation According to the Minimum Criteria	Difference
2651 2651	4.2% 3.5%	28,673	4.2%	3.5%	201
2633 2633 2633	3.9% 4.0% 44.0%	1,723	44.0%	3.9%	691
8322 8322 8322 8322 8322	89.0% 25.0% 69.0% 98.0% 2.9%	1,508,755	98.0%	2.9%	1,434,826

Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO 2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Table

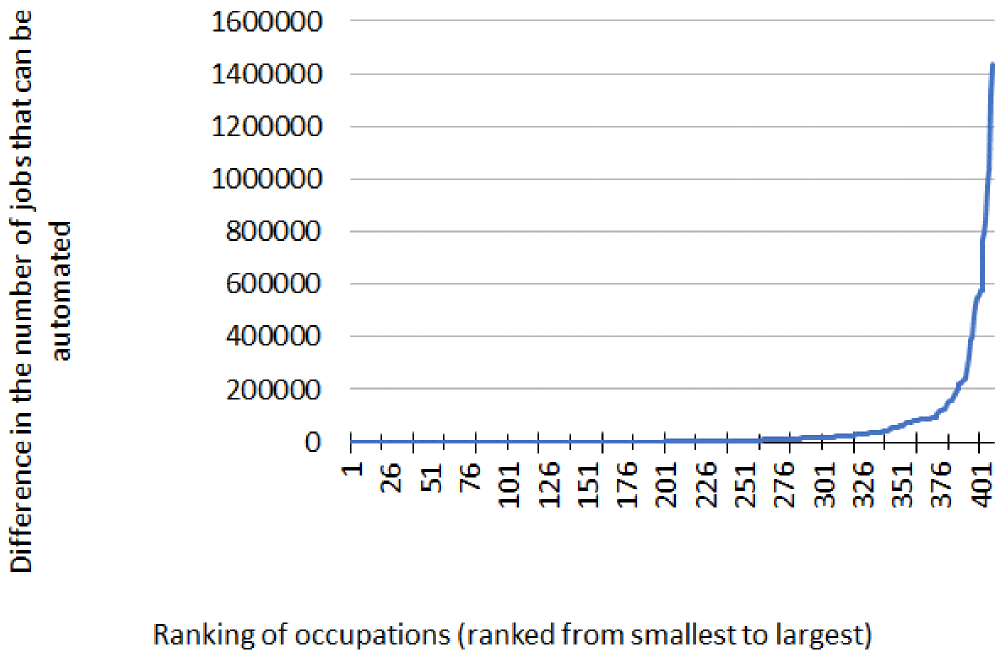
However, the estimated number of jobs that can be automated in occupation 8322 is way smaller when we apply the minimum criteria. Specifically, Table 1 shows that, according to the minimum criteria, only 43,754 jobs in occupation code 8322 can be automated (1,508,755 people working in occupation 8322 X automation probability of 2.90% = 43.754 jobs that can be automated).

A brief way to compare the results obtained from the two chosen selection criteria, the maximum and the minimum, consists in directly analyzing the difference between the estimates of the number of jobs that can be automated in each case. Thus, according to Table 1, the difference found in occupation 8322 reaches the expressive value of 1,434,826 jobs. This means that, in occupation 8322, the estimated number of jobs that can be automated when adopting the maximum criteria surpasses the value calculated when using the minimum criteria by 1,434,826 jobs.

Also, in Table 1 we can see that the difference calculated using the same method described above is of 201 jobs in occupation 2651 and of 691 jobs in occupation 2633. Therefore, the choice of selection criteria seems to matter way less in the case of both occupations 2651 and 2633. We reached the conclusion that the selection criteria matters way less for occupations 2651 and 2633 since, in both cases, the difference is relatively small when compared to the total of 91,4 million employed people in Brazil (data from PNADC 2017). The calculated differences for codes 2651 and 2633 also seem less relevant, even when compared to the smaller number of 90,1 million people who are employed in the more restrictive universe that considers only the 409 occupations to which we were able to apply the automation probabilities of Frey and Osborne (2017).

Considering the advantage shown by the analysis of the difference – which allows us to more directly compare the maximum and minimum estimated number of jobs that can be automated – we proceed with the calculation of the referred disparity for all of the 409 occupations with an automation probability. Next, we ordered those differences from lower to higher, seeking therefore to separate occupations with automation probabilities between those in which the number of jobs that can be automated highly depends on the chosen selection criteria and those in which the number of jobs that can be automated depends little on the chosen selection criteria. Results of this ordination of differences, from low to high, are shown in Graph 1.

Graph 1: Difference in the number of jobs that can be automated (maximum minus minimum criteria)



Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO

2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Image

The numbers presented in Graph 1 are surprising. On one hand, there is one positive conclusion represented by the fact that, in most occupations, the choice of selection criteria doesn't seem to matter much. This conclusion is made from observing that, in almost all occupations, the difference in number of jobs that can be automated obtained by the subtraction of the minimum from the maximum shows quite small values. On the other hand, there´s also one negative conclusion, since for some occupations, located in the extreme right of Graph 1, results may differ substantially depending on the chosen selection criteria.

Due to the evidence presented in Graph 1, we chose to split occupations into two distinct groups. The first group is formed by most occupations, those for which the choice of the selection criteria does not seem to matter much when calculating the number of jobs that can be automated. The second group is formed by the occupations located in the extreme right of Graph 1, those for which the selection criteria seems to be very relevant.

The advantage of separating the occupations into two distinct groups is the possibility of using different selection criteria in each one. However, before we proceed with the discussion on the selection criteria used in each group, it is worth mentioning that we verify, in a section bellow that aims to analyze the sensitivity of our results, how our estimates on the number of jobs that can be automated depend on this decision to split occupations into two distinct groups.

We made another important decision, which is worth mentioning before moving to the discussion about the selection criteria used in each group. More precisely, we decided to include in the second group, the one formed by the occupations located in the extreme right of Graph 1, only the 40 occupations that show the highest difference in terms of number of jobs that can be automated. Therefore, in this case, our first group is formed by the other 369 occupations (409 – 40 = 369). Note that, we also verify, in the sensitivity analysis section bellow, how this decision – to include in the second group only the 40 occupations with the highest difference in terms of number of jobs that can be automated – affects our results.

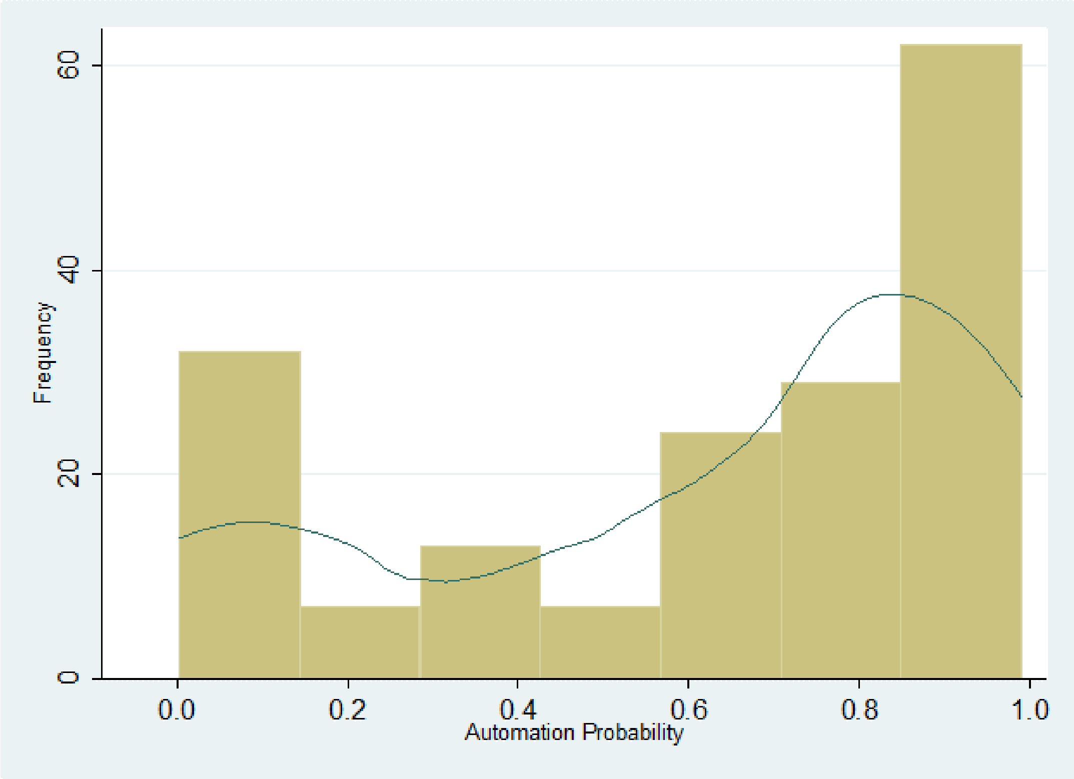
We are now left with explaining the selection criteria applied to each one of the two groups of occupations previously mentioned. For the first group – formed by the occupations in which the estimated number of jobs that can be automated almost did not depend on the selection criteria used – we decided to apply the average criteria. We made this choice since the average criteria has the advantage of being simpler. Moreover, we favored the average because other articles already adopted this same selection criteria. More precisely, we know of at least two studies, Pajarinen and Rouvinen (2014) and Bowles (2014), that used the average selection criteria as a way to apply – the automation probabilities that Frey and Osborne (2017) estimated for the Unites States of America (USA) – to other countries.

For the second group – formed by those occupations for which the choice of selection criteria is very relevant, since it substantially alters the estimates of how many jobs can be automated – we were forced to adopt a different procedure. In reality, we ended up choosing two different automation probabilities in this case, one calculated from the maximum criteria and one obtained from the minimum criteria. We made this choice with the intent of generating two automation probabilities for each occupation in the second group, not only distinct among themselves, but mainly characterized by being substantially different. It is worth mentioning that the sensitivity analysis section bellow also verifies how our main estimates, of jobs that can be automated, change when we apply criteria, other than the maximum and the minimum, to the occupations included in our second group. However, all of the alternatives considered in our sensitivity analysis bellow still only apply criteria, to our second group, that generate extreme probabilities. Next, we explain why we restrict our focus only to alternatives that generate these extreme probabilities.

We decided to select two quite different automation probabilities for all occupations in the second group since the original numbers of these professions already show great disparity among themselves. Thus, we find that the option of generating two quite different automation probabilities for each occupation enables the preservation of a characteristic that is present in the original data. In Graph 2, we can verify that the original data of the 40 occupations that form the second group already showed great disparity in terms of their automation probabilities.

It is worth mentioning that Graph 2 shows a histogram of the automation probabilities originally associated to the 40 occupations in our second group. This means that the graph presents not only the automation probabilities obtained from the maximum and minimum criteria, but also all other probabilities that were originally associated to the 40 occupations in the second group. Therefore, the graph shows that there is a great mass of probabilities both in its extreme left as in its extreme right. However, the center part of the graph displays little mass. Therefore, Graph 2 makes it clear that the original data already had automation probabilities that were very different among themselves.

Graph 2: Frequency of the automation probabilities associated to the fourty occupations that form our second group



Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO 2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Image

Now, we have to explain how we deal with the fact that we are left not only with one, but two automation probabilities for each of the 40 occupations that are included in our second group (one calculated from the maximum criteria and the other obtained from the minimum criteria). Thus, we need to explain how we selected only one among the two automation probabilities associated with each of the 40 occupations in our second group.

On one hand, we chose the maximum automation probability for the occupations of the Brazilian classification (COD 2010) understood as non-managerial.[10] We chose this aiming to reproduce the fact, verified in the original Frey and Osborne (2017) data, that high automation probabilities are usually associated to non-managerial occupations.[11] On the other hand, we applied the minimum automation probability to the occupations of the Brazilian classification (COD 2010) understood as managerial.[12] We

[10] Non-managerial occupations according to PNADC 2017 are all occupations with codes that begin with any number different than 1.

[11] In this case, we consider non-managerial occupations in the original Frey and Osborne (2017) study as those that do not have the word “supervisor” in their title.

[12] Managerial occupations according to PNADC 2017 are all occupations with codes that begin with the number 1.

also chose this aiming to reproduce the behavior verified by the original Frey and Osborne (2017) data that low automation probabilities are usually associated to managerial occupations.[13]

We view the strategy presented in the previous paragraph as reasonable, since it enables us to make an association among equals. More precisely, this strategy enables us, on one hand, to connect low automation probabilities, from Frey and Osborne (2017), to occupations that are harder for machines to replace, since they are classified as managerial in PNADC 2017. On the other hand, it enables us to link high automation probabilities, from Frey and Osborne (2017), to occupations that are easier for machines to replace, since they are classified as non-managerial in PNADC 2017.

Table 2 helps to illustrate how we choose only one automation probability for each occupation. Note that our choice will depend on the group to which each occupation belongs. Moreover, for occupations belonging to the second group our choice will also depend on whether the position is managerial or non-managerial.

The first occupation shown in the table, coded 2612, belongs to our first group. Thus, as this occupation belongs to our first group, we chose to calculate the automation probability using the average criteria, resulting in 52.0%.

On the other hand, the second occupation shown in the table, coded 1219, belongs to our second group. In addition, in this case we verified it is a managerial level-occupation.[14] Thus, as this occupation belongs to our second group and is also a managerial occupation, we chose to calculate the automation probability using the minimum criteria, resulting in 1.5%.

This table also contains a third occupation, coded 3334, which belongs to our second group. However, this occupation is non-managerial.[15] Therefore, we chose to calculate the automation probability using the maximum criteria, resulting in 97.0%.

Table 2: Illustration of how automation probabilities were chosen in the Brazilian case

Occupation Code	Occupation Group	Original Frey e Osborne (2017) Probabilities	Automation Probability of the Occupation According to the Maximum Criteria	Automation Probability of the Occupation According to the Minimum Criteria	Automation Probability of the Occupation According to the Average Criteria	Chosen Probability
2612	1	64.0%	64.0%	40.0%	52.0%	52.0%
2612	1	40.0%				
1219	2	25.0%	75.0%	1.5%	35.5%	0.0%
1219	2	73.0%				
1219	2	3.0%				
1219	2	1.5%				
1219	2	75.0%				
3334	2	97.0%	97.0%	7.5%	67.8%	97.0%
3334	2	7.5%				
3334	2	86.0%				

Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables

[13] In this case, we consider managerial occupations in the original Frey and Osborne (2017) study as those that have the word “supervisor” in their title.

[14] Code begins with number 1.

[15] Code does not begin with number 1.

transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO 2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Table

This completes the fourth, and final, stage of our compatibility process. In short, our choices, made in this fourth stage, allow us to generate an automation probability vector in the following manner: (i) apply the average criteria to all occupations in our first group; (ii) adopt the minimum criteria in the case of all managerial level occupations[16] belonging to our second group; and (iii) use the maximum criteria in the case of all non-managerial occupations[17] that belong to our second group.

4. RESULTS

Having concluded our compatibility process, which enables the association of only one automation probability to each occupation, we move on to calculate the proportion of Brazilian jobs which, based on currently existing technologies, will be substituted by machines in the next one or two decades. To produce results – on the proportion of Brazilian jobs that can be automated – comparable to those found by Frey and Osborne (2017), we separated the occupations between those with: (i) high automation probability (higher than 70%); (ii) mean automaton probability (higher than 30% and equal to or lower than 70%); and (iii) low automation probability (equal to or lower than 30%).

Thus, based on the described subdivision and following Frey and Osborne (2017), we calculated the proportion of Brazilian jobs subject to being substituted by machines from the ratio between a numerator, represented by the number of workers in all of the occupations with high automation probability, and a denominator, equal to the total number of workers in the economy. Using this ratio, we estimated for the Brazilian case – considering that 52.4 million people work in occupations with high automation probability and that there are 90.1 million workers in the overall economy – a proportion of jobs that can be automated equal to 58.1% ([52.4 ÷ 90.1] X [100] = 58.1%).

We understand our estimate, of 58.1% of Brazilian jobs that can be automated, to be in line with what would be expected for the country. We have the perception that our result makes sense from an empirical point-of-view, since specialists argue that the proportion of jobs that can be automated tends to be higher in developing countries than in developed countries (Peña-López 2016). This conclusion that the proportion of jobs that can be automated tends to be higher in developing countries than in developed countries is justified by the specialization of these countries in occupations that require little qualification and that are, therefore, more easily substituted by machines (AFDB et al 2018).

Therefore, we understand our result makes sense since it generates an estimated proportion of Brazilian jobs that can be automated similar to the ones observed in other developing countries and superior to those found in developed countries. More precisely, World Bank (2016) provide estimates on the proportion of jobs that can be automated for a selected group of developing countries, as shown in Table 3. In general, the estimates shown in this table are similar to the result we found for the Brazilian case, which makes us more confident of our estimate. For example, when focusing in the developing countries of Latin America, we can observe the following estimated proportions of jobs that can be automated: (i) 62.2% for the Dominican Republic; (ii) 63.1 for Uruguay; (iii) 63.7% for Paraguay; (iv) 64.6% for Argentina); and (v) 65.0% for Panama (see Table 3).[18]

[16] Codes that begin with the number 1.
[17] Codes that do not begin with the number 1.
[18] World Bank (2016) conduct a procedure similar to that adopted in this article. However, these authors apply the automation probabilities estimated by Frey and Osborne (2017), not just to one, but to several developing countries, in order to estimate the proportion of jobs, from these nations, that can be replaced by machines. Surprisingly, despite World Bank (2016) calculating the proportion of automated jobs in several developing countries, the authors in question do not consider Brazil.

Table 3: Comparison between the proportion of jobs that can be automated in developing countries

Country	Proportion of jobs that can be automated	Country	Proportion of jobs that can be automated
Uzbekistan	55.2%	Serbia	65.8%
Lithuania	56.2%	South Africa	66.5%
Malta	56.3%	Bolivia	66.8%
Latvia	57.0%	Mauritius	67.0%
Kyrgyzstan	57.8%	Malaysia	67.8%
Mongolia	59.9%	Macedonia	68.0%
Cyprus	60.9%	Costa Rica	68.4%
Seychelles	61.5%	Ecuador	68.6%
Tajikistan	61.6%	Romania	68.7%
Bulgaria	61.7%	India	68.9%
Dominican Republic	62.2%	Thailand	72.1%
Georgia	62.5%	Albania	72.7%
Uruguay	63.1%	Angola	73.8%
Croatia	63.1%	El Salvador	75.1%
Paraguay	63.7%	Guatemala	75.3%
West Bank and Gaza Strip	63.8%	Bangladesh	76.5%
Ukraine	64.0%	China	77.1%
Argentina	64.6%	Cambodia	78.5%
Nigeria	65.0%	Nepal	79.9%
Panama	65.0%	Ethiopia	84.9%
Nicaragua	65.5%		

Source: Monroy-Taborda et al (2016)
Note: Self-developed Table

Alternatively, Bowles (2014) calculates the proportion of jobs that can be automated for every country in the European Union. Thus, the results of that study include both developed and developing countries. We found the results in this research for the developed countries – which are shown in Table 4 – to be encouraging, since the values are, in great majority, lower than our estimate for the Brazilian case. For example, when focusing only on the ten countries with the highest per capita income of the European Union, the proportion of jobs that can be automated are as follows: (i) 47.0% in the United Kingdom; (ii) 47.0% in Sweden; (iii) 49.0% in Ireland; (iv) 49.0% in the Netherlands; (v) 50.0% in Belgium; (vi) 50.0% in Denmark; (vii) 50.0% in Luxemburg; (viii) 51.0% in Germany; (ix) 51.0% in Finland; and (x) 54.0% in Austria (see Table 4).[19]

[19] Bowles (2014) utilizes a methodology similar to that implemented in our study. However, this research applies the automation probabilities estimated by Frey and Osborne (2017), not to Brazil, but to all countries belonging to the European Union. In doing so Bowles (2014) is able to calculate the proportion of automated jobs from all nations covered in his analysis.

Table 4: Comparison between the proportion of jobs that can be automated in countries of the European Union

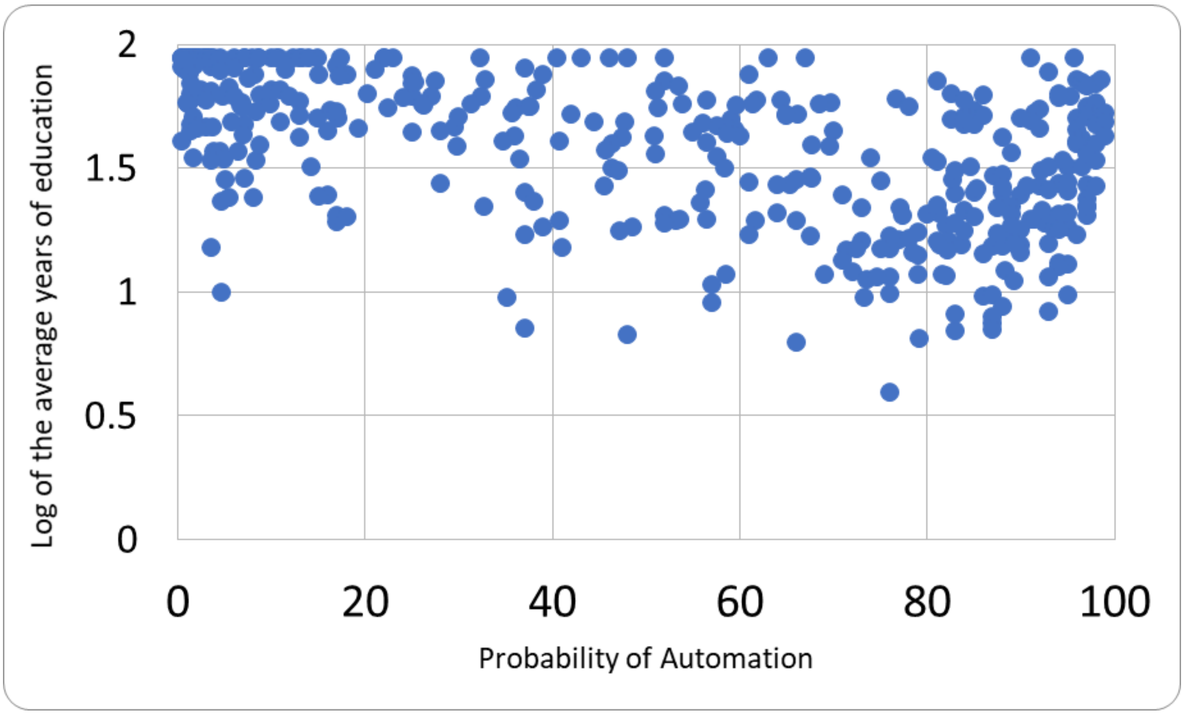
Country	Proportion of jobs that can be automated	Country	Proportion of jobs that can be automated
Sweden	47.0%	Austria	54.0%
UK	47.0%	Czech Republic	54.0%
Ireland	49.0%	Estonia	54.0%
Netherlands	49.0%	Hungary	55.0%
Belgium	50.0%	Slovakia	55.0%
Denmark	50.0%	Spain	55.0%
France	50.0%	Greece	56.0%
Luxembourg	50.0%	Italy	56.0%
Finland	51.0%	Poland	56.0%
Germany	51.0%	Bulgaria	57.0%
Latvia	51.0%	Croatia	58.0%
Malta	51.0%	Portugal	59.0%
Lithuania	52.0%	Romania	62.0%
Slovenia	53.0%		

Source: Bowles (2014)
Note: Self-developed Table

Even in comparison to the seminal Frey and Osborne (2017) study, which estimates that 47.0% of jobs can be automated in the United States of America (USA), our result also seems to make sense. More precisely, we understand that our estimate seems coherent since the USA is a developed country and Brazil is a developing country. Therefore, according to forecasts made by specialists, the proportion of jobs at risk of automation should be higher in the Brazilian case when compared to the American one. Fortunately, our number is in the expected direction, given that we have estimated that 58.1% of jobs can be automated in the Brazilian case, a projection that is higher than the 47.0% forecasted by Frey and Osborne (2017) for the USA.

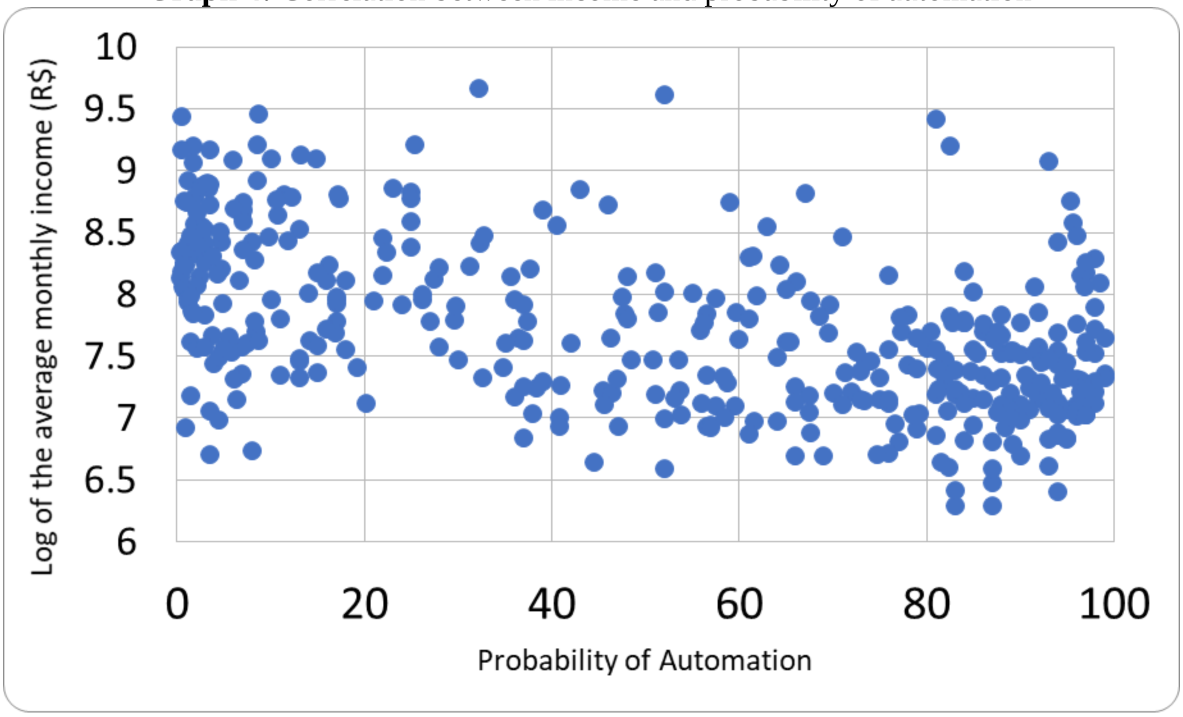
Before moving to the sensitivity analysis section, we replicated two correlation analysis executed by Frey and Osborne (2017) in order to determine if our results are comparable to theirs. Both analyses are executed at the level of the occupation. The first analysis calculates the correlation between educational attainment (mean) and our estimates of automation probability. The second analysis determines the correlation between the income (mean) and our estimates of automation probability. These two analyses are presented, separately, in Graphs 3 and 4.

Graph 3: Correlation between educational attainment and probability of automation



Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO 2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Image

Graph 4: Correlation between income and probability of automation



Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO 2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Image

The graphs (3 and 4), show that our estimates of automation probability are negatively correlated with both educational attainment and income. Thus, the numbers shown in these two graphs (3 and 4) confirm that our results are comparable to those of Frey and Osborne (2017), given that they also found their estimates of automation probability to be negatively correlated with both educational attainment and income.

5. SENSITIVITY ANALYSIS OF OUR RESULTS

Our estimated proportion of Brazilian jobs that can be automated, which is 58.1%, stems from three choices we made. Firstly, our estimate is a result of our choice to separate the occupations into two groups (the first one formed by occupations for which the adopted selection criteria did not seem very relevant and the second one formed by occupations for which the selection criteria was quite relevant). Secondly, our estimate stems from our choice in relation to the size of the second group (as we decided to allocate to this group a total of 40 occupations). Finally, our estimate is also a result of our choice over which selection criteria we found more adequate to be applied to our second group (being that we applied the maximum criteria for occupations classified as non-managerial and the minimum criteria for occupations classified as managerial).

Given that our estimate of the proportion of Brazilian jobs that can be automated depends on the three mentioned choices, we aimed to execute, in this section, a sensitivity analysis of our results. We particularly aimed to determine how much our result depend on the three choices we made. To simplify the discussion, we separated our sensitivity analysis – of the estimated proportion of Brazilian jobs that can be automated – into two parts. In the first part, we focused on the decisions that seem to be **very relevant** for our result. In the second part, we focused on decisions that seem to be **almost irrelevant** for our estimate.

5.1. Very relevant choices

Only one of the three choices we made has great relevance for our result. More precisely, we verified that our first choice, which was to separate occupations into two distinct groups, is very relevant to our study's result. The relevance of this particular choice is evidenced by the numbers shown in Table 5.

In Table 5, we provide both our main result and an alternative estimate calculated without dividing occupations into two distinct groups. More precisely, we actually proceeded in the opposite way in this alternative case, as we placed all occupations in one group and applied the average selection criteria to all of them. Our choice to consider this specific alternative scenario, which always uses the average selection criteria, comes from other studies that are similar to ours, such as Bowles (2014) and Pajarinen and Rouvinen (2014), both having proceeded in exactly this way. Thus, this alternative case enables us to identify how our result changes when we apply the same selection criteria as the one adopted in articles that are similar to ours.

Table 5: Proportion of jobs that can be automated per number of groups considered

Number of groups	Proportion of jobs that can be automated
Occupations separated into two groups	58.1%
Occupations united in one group	44.3%

Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO 2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Table

In the table we find that, when we apply the average criteria to all occupations and therefore replicate the exact process adopted in similar articles, we reach a result of 44.3% of Brazilian jobs that can be substituted by machines with currently existing technologies. Given all that has been discussed this far in our study, it seems clear that the estimate of 44.3% Brazilian jobs possibly automated does not make much sense. Actually, we see at least two reasons to believe that this result makes little sense in the Brazilian case.

Firstly, these 44.3% represent a number that is quite close to the 47.0% estimated for the United States of America (USA) and much lower than what is typically calculated for developing countries. In addition, this criterion also makes little sense from the statistical point-of-view, since it applies the average criteria not only to the occupations in our first group, but also to those in our second group. However, the occupations in our second group are exactly those that present, at the same time, very high automation probabilities (near the unit) and very low ones (close to zero). Thus, the application of the average criteria does not seem proper to the occupations in our second group, given that it creates an intermediate automation probability with little similarity to the original data marked by the concomitant presence of values located in the opposite extremities of the distribution.

This discussion corroborates even more with our choice to divide the occupations into two distinct groups, adopting different selection criteria for each one. We consider that our choice to separate the occupations into two distinct groups enables the generation of an automation probability vector that is capable of better reflecting the characteristics of the original Frey and Osborne (2017) data.

5.2. Almost irrelevant choices

Our two last decisions apply only to our second group and, fortunately, are nearly irrelevant for the estimate we found for the proportion of Brazilian jobs that can be automated. Our second choice, previously described, is about the size of our second group. Our third one relates to the selection criteria applied to our second group.

Our finding that the last two choices we made in this study are not very relevant to our result can be verified from the numbers shown in Table 6.[20] More precisely, the table shows that our result of the

[20] There is actually another decision we made in the present study and which is also nearly irrelevant to our main result of 58.1% of Brazilian jobs possibly being automated. This consists in ordering occupations according to the difference in jobs that can be automated, calculated using the maximum criteria and the minimum criteria. Thus, we are always separating our two groups

proportion of Brazilian jobs that can be automated is nearly unchanged when we consider either different sizes or different selection criteria for our second group.

In the first case, referring to the possibility of choosing different sizes for our second group, Table 6 considers two alternatives: (i) restricting the analysis to 30 occupations; or (ii) expanding the analysis to 50 occupations. In the second case, referring to the possibility of applying different selection criteria to our second group, the table considers the two following alternatives: (i) adopting the 90th percentile for non-managerial occupations and the 10th percentile for managerial occupations; and (ii) adopting the 75th percentile for non-managerial occupations and the 25th percentile for managerial occupations.

Table 6: Proportion of jobs that can be automated according to two characteristics of the second group (chosen size and selection criteria)

	Size chosen for the second group		
Selection criteria applied to the second group	30 occupations	40 occupations	50 occupations
90th percentile for non-managerial occupations and 10th percentile for managerial occupations	57.2%	58.1%	58.8%
Maximum criteria for non-managerial occupations and minimum criteria for managerial occupations	57.2%	58.1%	58.8%
75th percentile for non-managerial occupations and 25th percentile for managerial occupations	57.2%	57.9%	58.5%

Sources: Automation probabilities estimated by Frey and Osborne (2017), crosswalk - developed by the Bureau of Labor and Statistics (BLS) - which enables transitioning from the American Standard Occupation Classification (SOC 2010) to the International one (ISCO 2008), self-developed crosswalk - which enables transitioning from the International Standard of Classification of Occupations (ISCO 2008) to the Brazilian one (COD 2010) and the Continuous National Household Sample Survey of 2017 (PNADC 2017).
Note: Self-developed Table

Let's analyze the numbers shown in Table 6. On one hand, we observe that the lowest proportion of Brazilian jobs that can be automated is 57.2%. This number is obtained when: (i) we choose to allocate

based on this order that considers the calculation criteria of maximum and minimum. Fortunately, in results not shown here, we found that the choice of separating our groups based on this order is not very relevant to our main result. More precisely, we verified that this choice is irrelevant to our main estimate, since we executed the sensitivity analysis separating our groups based on orderings defined by the following alternatives: (i) between the 90th and the 10th percentiles; and (ii) between the 75th and the 25th percentiles. It is encouraging to say that our main result almost does not change when we create our groups based on these alternative orderings.

only 30 occupations in our second group; (ii) we apply the 75th percentile to the non-managerial occupations in the second group; and (iii) we apply the 25th percentile to the managerial occupations in the second group.

On the other hand, we notice that a higher proportion of Brazilian jobs that can be automated is 58.8%. This number is obtained when: (i) we choose to allocate 50 occupations in our second group; (ii) we apply the maximum criteria to the non-managerial occupations in the second group; and (iii) we apply the minimum criteria to the managerial occupations in the second group.

In short, we see the results shown in Table 6 as encouraging, since they are generally very similar to our preferred estimate of 58.1% Brazilian jobs that can me automated. Thus, the numbers contained in the table confirm that our estimate barely changes when we consider either different sizes or different selection criteria for our second group.

6. CONCLUSION

Using the Frey and Osborne (2017) automation probabilities, we estimate that 58.1% of Brazilian jobs can be replaced by machines in the next 10 to 20 years. In practice, the net loss of Brazilian jobs should lie bellow our estimate. This is because, the result we found, as well as the estimate provided by Frey and Osborne (2017), is based on the assumption that machines substitute all jobs that can be replaced. However, actual elimination of these jobs depends on other matters, such as economic and political issues. In addition, the possibility of job generation does exist, considering that some occupations are complementary to, instead of replaceable by, new technologies. Even if the net result of automation is not the effective elimination of 58.1% of Brazilian jobs, our study still serves as a warning, as it indicates that new technologies are technically capable of replacing an enormous part of the jobs in Brazil. Thus, the automation issue must be handled immediately and with seriousness by society.

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