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Automation and job loss: the Brazilian case

Automação e perda de empregos: o caso brasileiro

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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. We add to earlier research, that included the Brazilian case, as we consider the entire employment structure – including both formal and informal sectors – in order to estimate the proportion of jobs in the country that may be substituted by machines. Our results indicate that 58.1% of Brazilian jobs may disappear over the next 10 to 20 years due to automation. Moreover, we observe that jobs in the informal sector face higher probabilities of elimination by automation when compared to the formal sector.

Keywords

Automation, Technological change, Job Loss, Occupational Selection.

JEL Codes E24, J23, J24, O33.

Resumo

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. Ajudamos a incrementar as evidências existentes, para o caso brasileiro, dado que consideramos a estrutura do mercado de trabalho como um todo – incluindo os setores formal e informal – quando estimamos a proporção de empregos que podem ser substituídos por máquinas. Nossos resultados indicam que 58,1% dos empregos brasileiros podem desaparecer, nos próximos 10 ou 20 anos, em função da automação. Além disso, observamos que os trabalhadores ocupados no setor informal têm maior chance de ver seus empregos sendo substituídos por máquinas do que aqueles empregados no setor formal.

Palavras-chave

Automação, Mudanças Tecnológicas, Perda de Emprego, Escolha Ocupacional.

Códigos JEL *E24, J23, J24, O33.*

1 **Introduction**

We are experiencing a period 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 job loss. On the one hand, some studies confirm how automation has contributed to the elimination of jobs 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 job destruction 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 job loss 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 in 2013, within 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; Bowles, 2014; Pajarinen and Rouvinen, 2014).

For Brazil, we acknowledge two studies that estimated the probability of job automation following Frey and Osborne's study. The paper of Albuquerque *et al*. (2019) applied a methodology similar to Frey and Osborne's to calculate those probabilities. Using the textual descriptions of Brazilian occupations as an input for their algorithm, the authors estimated each occupation's automation risk. As a result, the authors calculated that 55% of formal Brazilian jobs may disappear in the next one or two decades. In turn, Lima *et al*. (2019) directly apply Frey and Osborne's (2017) probabilities to formal Brazilian occupations. Their conclusion pointed out that 60% of formal jobs in Brazil have a high risk of being automated in the near future.

Although Albuquerque *et al*. (2019) and Lima *et al*. (2019) provided a significant contribution to the discussion of the risks related to automation regarding the Brazilian formal labor market, neither study addressed the situation of the informal sector. It is important to consider that the informal sector employs a large proportion of Brazilian workers, comprising 43,9% of total jobs in 2017.[1] Therefore, this sector's exclusion in both studies represents a shortcoming with respect to the Brazilian case.

This research intends to fill the existing gap in the literature by applying Frey and Osborne (2017) automation probabilities to the entire Brazilian employment structure. Thus, we use employment data from the Continuous National Household Sample Survey (PNADC) that includes both formal and informal workers. To apply Frey and Osborne probabilities to Brazilian occupations, we develop a detailed compatibility process between the American Standard Occupational Classification (SOC 2010) and the Brazilian classification (COD 2010). 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. When comparing the formal and informal economies, we observe that the formal employees face less risk of being replaced by machines than their informal peers, although this difference is not large.

It is important to stress that this result actually represents a worst-case scenario, since it considers the proportion of jobs that technology will be capable of replacing in the near future. However, the actual implementation of new technologies will depend on numerous factors, such as favorable economic and political conditions. For instance, if these conditions delay the adoption of new technologies, then fewer jobs will be lost. Moreover, innovations themselves also help to create new jobs. Therefore, net job loss will likely be smaller than we estimate here, since technology will replace some jobs but create others.

The present 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 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. Finally, the fifth section contains our concluding remarks.

1 Data Source: Continuous National Household Sample Survey of 2017 (PNADC 2017) provided by the Brazilian Institute of Geography and Statistics (IBGE),

2 **Literature review**

The fear of technology and its effects on employment is not a new phenomenon in the history of modern societies.[2] 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 about 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 job loss has reemerged. In the scenario of economic crises in the late 2000s, the large job losses 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 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 ever. Therefore, the recently renewed fear of massive job destruction, due to automation, 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.[3] 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), leads to large job losses (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, future job loss that will take place due to technological innova-

2 Mokyr *et al.* (2015) provides a carefully look into the history of technological anxiety.

3 There is also a strand of literature discussing the possibility that automation could lead to job creation. Although we do not include this research line in this paper, we recommend the study of Autor *et al.* (2015) as a reference.

tions. Specifically, this literature examines the extent to which the data support the view that job loss 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 would 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 and 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". Furthermore, as these efforts tend to continue in the coming years, more and more tasks will become 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 method 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 routine and 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 that look at different countries (World Bank, 2016; Pajarinen and Rouvinen, 2014; Bowles, 2014). These articles use the same probabilities of automation that were estimated in Frey and Osborne (2017), facilitating cross-country analysis. Nevertheless, their methods and assumptions received some criticism. Regarding their methods, some studies pointed to an upward bias in the automation risks they estimated (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 their paper, even though the authors explicitly acknowledge this possibility.

For the Brazilian context, Albuquerque *et al*. (2019) used a methodology similar to Frey and Osborne's to estimate the risk of automation in the formal sector. Specifically, the authors gathered a rich set of information concerning the occupational characteristics of the jobs listed in the Brazilian Occupational Classification (CBO) in order to estimate their automation probabilities. We can summarize their methods as follows: a) the authors asked 69 specialists in machine learning to evaluate the likelihood of automation faced by occupations; b) the textual descriptions of jobs – including the listed tasks – was used as an input to train a Gaussian process to model and predict the probability of automation for each occupation. Finally, using employment data from the Annual Social Information Registry (RAIS), the authors estimated that approximately 55% of formal jobs have a high or very high probability of automation.

Lima *et al*. (2019) also investigated the risk of automation of formal Brazilian employment using RAIS data. The authors used the correspondence between CBO and SOC developed by Maciente (2014) to assign Frey and Osborne's probabilities to Brazilian occupations. Given that a small number of occupations remained unmatched after the crosswalk, the authors analyzed titles and tasks of occupations to link them with the most similar SOC occupations. After applying Frey and Osborne's automation probabilities to the Brazilian employment structure, the authors estimated that 60% of formal jobs are at high risk of automation in the following decades.

Therefore, both articles that analyze the Brazilian context – Albuquerque *et al*. (2019) and Lima *et al*. (2019) – find similar results: 55% in the former and 60% in the latter. However, these two studies limit the scope of their analysis and only consider formal employment.

In the present study, we contribute to the existing literature by also including informal employment in our estimates of the proportion of jobs that may be replaced by machines in the next couple of decades. We believe that incorporating the informal sector allows us to acknowledge the Brazilian employment structure as a whole. This broader view has significant importance in understanding of the overall Brazilian labor market, given the sizeable fraction of workers employed without formal ties in the country.[4] More precisely, in 2017 approximately 49,7% of Brazilian work-

4 See Ulyssea (2006) for a complete review on this topic.

ers were employed in informal jobs.[5]

It is important to mention that the inclusion of informal employment should affect our results. The question is how the incorporation of the informal sector might impact our numbers. Unfortunately, the answer is unclear. This is because, at least in theory, the resulting proportion of jobs at risk of being replaced by machines in the informal sector could be either larger or smaller. On the one hand, since informal workers are less qualified, and are therefore more likely to be employed in routine manual occupations, they tend to face higher risks of being replaced by machines. For instance, many of the least qualified workers are informally employed as sewing machine operators, a typical routine manual occupation, and are likely to have their jobs replaced by new technologies. On the other hand, because informal workers are also more likely to be employed in non-routine manual occupations, that involve highly sophisticated perception and manipulation tasks, they tend to be less vulnerable to automation. For example, many informally employed individuals are occupied as house-builders, and they need sophisticated perception because of the highly unstructured nature of their workplace, which makes them less likely to be replaced by machines.

Since the RAIS data does not include the informal sector, we adopted the PNADC, which covers the entire employed population.[6] However, this choice has implications for our work. This is because the classification of occupations used in this database, COD, is substantially more concise than CBO's and only lists occupational codes and names. Therefore, detailed descriptions of the tasks involved in each occupation are not provided. Given this insufficiency of information, we are unable to use the COD to estimate new automation probabilities. Consequently, our work has an important limitation, which is the fact that we are not able to estimate automation probabilities that are specific to the Brazilian occupations. To deal with this issue we adopt automation probabilities provided by Frey and Osborne (2017). However, since other studies also directly apply these same automation probabilities to different countries, we believe our work

5 Data Source: Continuous National Household Sample Survey of 2017 (PNADC 2017) provided by the Brazilian Institute of Geography and Statistics (IBGE).

6 It is fair to note that these databases have significant differences, but the discussion of these distinctions is outside the scope of the present article. For a detailed comparison among these databases see Negri *et al*., 2001.

at least has the advantage of being more comparable to the strand of the existing international literature that proceeds this way.

Moreover, because the automation probabilities used in this strand of the existing international literature are identical, it is possible to conclude that any difference in terms of the estimated proportion of jobs at risk of being replaced by machines stems solely from the distinct employment structures found in each country. In the case of Brazil, this implies that, if we estimate that a large proportion of this country´s jobs may be substituted by machines, it is because a substantial portion of its workforce is employed in occupations with a high risk of automation. Furthermore, while the direct association between occupations in different countries is open to criticism, we emphasize that, as argued by Dicarlo *et al*. 2016, the nature of occupations in most industrialized nations is quite similar.[7]

Finally, it is important to mention that our study adds 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, 2014; Santos *et al*., 2019).

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 ac-

7 Brazil Maia and Sakamoto (2015) argue: "Since these concepts are very similar to those used by the Brazilian CBO and the American OCS, the groups primarily reflect the structure proposed by these systems" (Maia and Sakamoto, 2015, p.5).

cording to the American Standard Occupational Classification (SOC 2010) – to the current standard of international databases (ISCO 2008). Although this stage involved some difficulties, BLS crosswalk from SOC to ISCO has been used in several international papers.[8]

In fact, 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 a 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.[9]

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

8 See, for example, World Bank (2016).

9 More precisely, we used information found in the following IBGE documents (last access on the 23rd of July of 2020):
1) https://www.ibge.gov.br/arquivo/projetos/sipd/oitavo_forum/COD.pdf.
2) ftp://ftp.ibge.gov.br/Censos/Censo_Demografico_2010/metodologia/anexos/anexo_7_ocupacao_cod.pdf.

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 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 vast majority of cases – 428 out of a total of 434 occupations – the third stage of our compatibility method worked properly.[10]

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.[11]

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 the automation probabilities assigned to each occupation. It is worth mentioning that in this fourth stage we use the PNADC 2017 information to help us choose, considering Brazilian labor market specificities, the one automation probability that we assign to each occupation.

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

10 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.

11 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%).

criteria to select the automation probability to be assigned to each occupation, such as the following: a) the maximum; b) the minimum; and c) the average. In order to verify how our results vary according to the adopted selection criteria, we compared our obtained estimates by using only two criteria: a) the maximum; and b) the minimum.

We focused only on these two selection criteria, 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 **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	4.2%	28,673	4.2%	3.5%	201
2651	3.5%				
2633	3.9%	44.0%	44.0%	3.9%	691
2633	4.0%				
2633	44.0%				
8322	89.0%	1,508,755	98.0%	2.9%	1,434,826
8322	25.0%				
8322	69.0%				
8322	98.0%				
8322	2.9%				

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.

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% = 1,478,580 jobs that can be automated).

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).

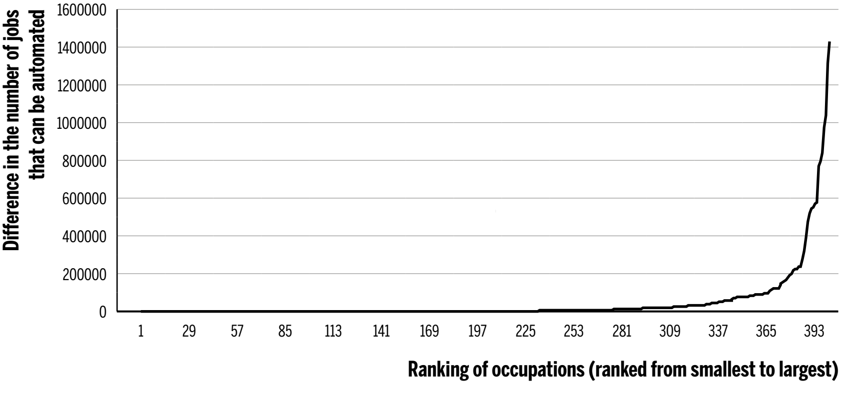
A brief way to compare the results obtained from the two chosen selection criteria, the maximum and the minimum, consists in directly analyzing the difference between the estimates of the number of jobs that can be automated in each case. Thus, according to Table 1, the difference found in occupation 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 far less in the case of both occupations 2651 and 2633. We reached the conclusion that the selection criterion matters far 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 greatly 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 Figure 1.

The numbers presented in Figure 1 are surprising. On the one hand, there is one positive conclusion represented by the fact that, in most occupations, the choice of selection criteria does not seem to matter much. This conclusion is reached 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 is also one negative conclusion, since, for some occupations, located in the extreme right of Figure 1, results may differ substantially depending on the chosen selection criteria.

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



Sources: Elaborated by the authors. 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).*

Due to the evidence presented in Figure 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 Figure 1, those for which the selection criteria seem to be very relevant.

We made another important decision, which is worth mentioning before moving on 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 Figure 1, only the 40 occupations that show the highest difference in terms of the number of jobs that can be automated. As a consequence, in this case, our first group becomes composed by the other 369 occupations (409 – 40 = 369).

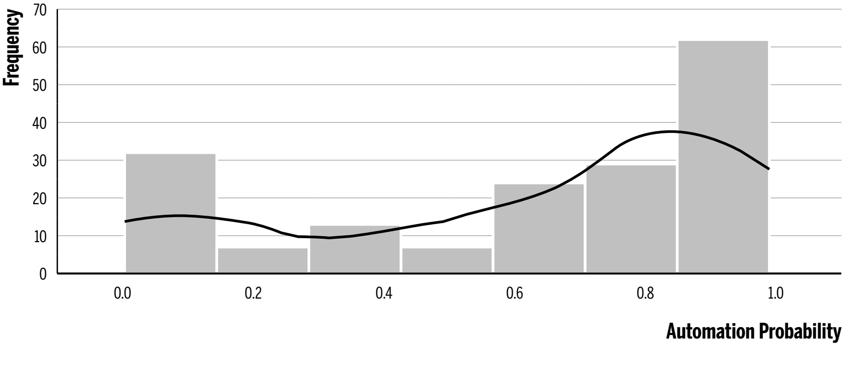
We are now left with explaining the selection criteria applied to each one of the two groups of occupations previously mentioned. For the first group – formed by the occupations in which the estimated number of jobs that can be automated almost did not depend on the selection criteria used – we decided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

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 very distinct automation probabilities for each occupation in the second group.

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 Figure 2, we can verify that the original data of the 40 occupations that form the second group already showed a large disparity in terms of their automation probabilities.

It is worth mentioning that Figure 2 shows a histogram of the automation probabilities originally associated to the 40 occupations in our second group. This means that the figure 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 Figure 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 Figure displays little mass. Therefore, Figure 2 makes it clear that the original data already had automation probabilities that were very different among themselves.

Figure 2 **Frequency of the automation probabilities associated to the fourty occupations that form our second group**



Sources: Elaborated by the authors. 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).

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 the one hand, we chose the maximum automation probability for the occupations of the Brazilian classification (COD 2010) that are coded as non-managerial.[12] 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.[13] On the other hand, we applied the minimum automation probability to the occupations of the Brazilian classification (COD 2010) coded as managerial.[14] We also chose this aiming to reproduce the behavior verified by the original Frey and Osborne (2017) data where low automation probabilities are usually associated to managerial occupations.[15]

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 the 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, we chose to calculate the automation probability using the average criteria, resulting in 52.0%.

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

13 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.

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

15 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.

On the other hand, the second occupation shown in the table, coded 1219, belongs to our second group. Besides, in this case we verified it is a managerial level-occupation.[16] Thus, as this occupation belongs to our second group and is also a managerial occupation, we chose to apply the automation probability of 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.[17] Therefore, we chose to apply the automation probability of 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%	1.5%
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 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.

16 Code begins with number 1.

17 Code does not begin with number 1.

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: a) apply the average criteria to all occupations in our first group; b) adopt the minimum criteria in the case of all managerial level occupations[18] belonging to our second group; and c) use the maximum criteria in the case of all non-managerial occupations[19] 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 likely 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: a) high automation probability (higher than 70%); b) mean automation probability (higher than 30% and equal to or lower than 70%); and c) 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%).

Following the method of applying the Frey and Osborne (2017) automation probabilities to the Brazilian context, we estimated that 58.1% of the country´s jobs are at risk of being replaced by machines in the next

18 Codes that begin with the number 1.

19 Codes that do not begin with the number 1.

10 to 20 years. Furthermore, our estimate for the formal sector is similar to Albuquerque *et al*. (2019) but differs from Lima *et al*. (2019). In fact, we calculated that 55.1% of the country´s formal jobs may be automated, while the numbers estimated by Albuquerque *et al*. (2019) and Lima *et al*. (2019) were 55.3% and 60.0%, respectively. Moreover, we estimated a higher risk of automation for the informal sector. In this case, we found that as much as 62% of the country´s informal jobs might vanish in the next two decades, because of automation.

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.

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 (World Bank Group, 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 (African Development Bank Group, 2018).

Consequently, we understand our result makes sense since it generates an estimated proportion of Brazilian jobs at risk of being replaced by machines, that lies within the range observed in other developing countries and is superior to those found in developed nations. More precisely, World Bank (2016) provides estimates on the proportion of jobs that can be automated for a selected group of developing countries, as shown in Table 3. It is clear from this table, that the result we found for Brazil lies within the range of estimates observed in other developing countries.[20]

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 – shown in Table 4 – include both developed and developing countries. We found the results in this research for the developed countries 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: a) 47.0% in the United Kingdom; b) 47.0% in Sweden; c) 49.0% in Ireland; d) 49.0% in the Netherlands; e) 50.0% in Belgium; f) 50.0% in Denmark; g) 50.0% in Luxemburg; h) 51.0% in Germany; i) 51.0% in Finland; and j) 54.0% in Austria (see Table 4).[21]

20 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.

21 Bowles (2014) uses a methodology similar to that implemented in our study. However, his 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 jobs that can be automated for 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.

5 Concluding remarks

In this paper, we investigated to what extent Brazilian jobs might be replaced by machines in the near future. We add to previous studies by including the informal economy in the investigation. Using the Frey and

Osborne (2017) automation probabilities, we estimate that machines may replace 58.1% of Brazilian jobs within 10 to 20 years. For the informal sector, we estimated a slightly larger automation risk of 62% compared to 55% in the formal sector. These findings underline a greater vulnerability of informal workers to automation.

It is important to emphasize that the net loss of Brazilian jobs should lie below our estimate. This is because the result we found, as well as the estimate provided by Frey and Osborne (2017), are based on the assumption that machines substitute all jobs that they are technically capable of replacing. However, the actual elimination of these jobs depends on other matters, such as economic conditions and political decisions. 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, we believe that our 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 a larger probability of being replaced by machines. This is a valuable knowledge as it creates a solid starting point for a discussion on how we can react in order to prevent severe job loss in the near future. Rather than creating a wave of panic about job losses in the next couple of decades, we believe that this approach can be understood as a warning, since it indicates that new technologies are technically capable of replacing an enormous part of Brazilian jobs. Thus, the automation issue must be handled immediately and with seriousness by policymakers, academics, and other institutions. It is mainly through the design and implementation of effective policies that these agents could help Brazil alleviate, or even avoid, massive job loss due to automation, in the next couple of decades.

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