Advances of robotization: Are safe jobs critically endangered?

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Abstract

Automation has spread rapidly in most developed countries, triggering a "wave of technology anxiety" in the job market. Concerns are being raised, fearing that these advances could significantly replace "safe" jobs in the foreseeable future, arousing the interest of policymakers and turning political interventions crucial. To shed light on these debates, a Fractional Logit Model was addressed to estimate the probability of automation risk faced by workers and the consequent shifts in employment in the United States. To evaluate changes in occupational patterns from technological innovations, we used unique data from the newly created Occupational Requirements Survey, gathering independent variables divided into cognitive, environmental, and physical requirements. We found that automation benefits jobs needing communication, problem-solving, and speed but risks those with supervisory roles. Physical tasks near machines, involving finger work or heavy lifting, are more vulnerable, while low-posture jobs are favored. Repetitive tasks and basic cognitive skills face the highest risk of automation-driven replacement. Contrarily, low posture duties are favored by automation, boosting demand for occupations that require them. Lastly, we confirm that occupations most exposed to tasks entailing basic cognitive skills and repetitive movements, such as administrative and office support positions, face the highest potential for substitution. Instead, occupations that require cognitive skills, including healthcare practitioners and information technology jobs, are far from being overtaken by automation. This disruption renders government interventions in active and passive labor market policies crucial to enable workers to adapt smoothly to technological changes.

Keywords: Industrial Robots; Labor Market; Employment; Risk of Automation; Occupational Tasks; Future of Work.

1 Introduction

Automation, such as industrial robots, has spread rapidly in many leading nations and is becoming prominent in today's economy. Their uptake has been particularly marked in economies with a strong manufacturing sector, aging populations, and labor shortages to fill gaps in the workforce, such as the United States (US), Japan, and some European countries (Acemoglu, Koster and Ozgen, 2023; Sun, Zhang, Cgen and Luan, 2023). In 2022, the US considered the dominant market on the American continent, was responsible for 71% of all

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installations. In particular, the country reported a 10% increase in robot installations, with a total of 39,576 units, close to the peak of 40,373 units achieved in 2018 (IFR, 2023). This phenomenon can be attributed to the robots' ability to enable the production and commercialization of goods and services without or with minimal human dependence, as well as their capability to carry out a widening range of tasks, thus arousing growing interest from firms' entities (Graetz and Michaels, 2018; Sun, Zhang, Cgen and Luan, 2023). Encouraged by the search for greater productivity and efficiency (Egana-delSol, Bustelo, Ripani, Soler and Viollaz, 2022), regarding repetitive tasks that require precision and speed, as well as greater flexibility and adaptability, since numerous robots are designed to be reprogrammed easily for a wide range of production processes, firms tend to invest heavily in automation. This trend is also fueled by the imperative reduction of costs (Adachi, Kawaguchi and Saito, 2024), leading firms to become more competitive and profitable in their operations (Ivanov, Kuyumdzhiev and Webster, 2020). However, simultaneously, concerns are being raised regarding its potential adverse impact on employment opportunities (Autor, 2015; Dengler and Matthes, 2018), contributing to a "wave of technology anxiety", fearing that automation could significantly substitute jobs in the foreseeable future (Arntz, Gregory and Zierahn, 2017; Ivanov, Kuyumdzhiev and Webster, 2020).

Notwithstanding, in recent years, the impact of these technologies on the labor market has been widely debated among academic researchers, policymakers, and business leaders (e.g., Brynjolfssonand McAfee, 2014; Acemoglu and Restrepo, 2020; Deschacht, 2021). Amidst these discussions, a central question arises: How many jobs will automation displace and which employees will be most affected? Furthermore, what are the possible implications for labor market policies? Our investigation seeks to address this issue by examining how automation reshapes the economy.

Lately, a large amount of empirical evidence, aroused by Autor, Levy and Murnane (2003), supports the idea that the "hollowing out" of middle-skilled workers is linked to the automation of routine tasks – activities that follow a clearly defined set of procedures and, hence, can be fully encoded and executed by machines (e.g., Autor, Katz and Kearney, 2006; Acemoglu and Autor, 2011; Cortes, Jaimovich, Nekarda and Siu, 2014; Goos, Manning and Salomons, 2014). The same findings suggest, simultaneously, that workers with both high and low levels of education, often engaged in non-routine tasks – activities that require problem-solving capacities, creativity, communications abilities and in-person interactions, and, therefore, hardly automated – benefit due to a virtuous combination of powerful complementarities between their competence sets and computerization tools (Autor, 2015). Nonetheless, this discussion has become even more intense, as some suggest that the rapid technological advances could lead to the automation of tasks and jobs previously considered safe (McKinsey Global Institute, 2013; Christenko, 2022), proving that high- and low-skilled employees are not immune to occupational shift either (Hershbein e Kahn, 2018).

This labor market disruption has aroused policymakers' interest and made policy interventions crucial (Bruckner, LaFleur and Pitterle, 2017). Experts suggest that targeted policies can mitigate the adverse effects of automation, facilitating smoother job transitions and reducing mass unemployment risks (Casey, 2020). It often involves workers acquiring new skills and transitioning into different sectors (Bessen et al., 2020). Governments can support these transitions by investing in active labor market policies, such as upskilling and reskilling programs and improved access to education, to better align workforce competencies with new job requirements (Schmidpeter and Winter-Ebmer, 2021). Strengthening the education system is essential to help

workers adapt to rapid technological changes and secure more stable positions (van Doorn and van Vliet, 2022). Additionally, passive labor policies like extended unemployment benefits and early retirement schemes can support displaced employees during job transitions, although these are only short-term solutions (Bürgisser, 2023). Universal Basic Income (UBI) is also recommended as a policy to provide financial security, helping individuals cope with economic instability caused by automation (McManus, 2023). Furthermore, governments can influence the pace and impact of technology through incentives for entrepreneurship and innovation. Proposals for a "robot tax," not yet implemented but highly advocated by several authors, address the imbalance between labor and capital taxation (Acemoglu and Restrepo, 2020; Bürgisser, 2023). Thus, recently, a few researchers in this field have addressed this issue and attempted to estimate the probability of automation risk faced by workers (Filippi, Bannò and Trento, 2023), allowing improved conclusions regarding the policies that ought to be carried out.

The first debate on "how susceptible are jobs to computerization" was reignited in 2017 by Frey and Osborne, who developed a novel methodology, later acknowledged as the occupational-based approach, to assess the likelihood of an occupation disappearing within a few decades due to technological progress in the US. For this purpose, they drew on existing literature on Machine Learning (ML) and Mobile Robotics (MR) and insights from a workshop conducted with two technology experts at the Oxford University Engineering Sciences Department. Pointing out several "engineering bottlenecks" corresponding to three main job task categories shielded from automation – perception and manipulation, creative intelligence, and social intelligence – together with the group of researchers subjectively hand-labelled 70 occupations considering their susceptibility to automation. Given this information and using variables from O*NET corresponding to the defined "engineering bottlenecks", Frey and Osborne developed an algorithm to provide the probability of computerization for 702 occupations and, subsequently, estimate, carrying out a probabilistic classification model for the automation risk. They suggest that roughly 47% of US workers are at risk of a high probability of being displaced by technology ($> 70\%$) in the next 10 to 20 years, including employees linked to transportation and logistics, offices and administrative support functions and manufacturing processes.

Nevertheless, this measure has been criticized by others. One criticism focuses on automation's propensity to target individual tasks rather than entire occupations. A second critique concerns the potential misunderstanding between automation and actual job losses, pointing out that the ability to employ machines instead of humans does not guarantee this adequate replacement. Hence, Arntz, Gregory and Zierahn (2016), adopting a task-based approach, claimed that the risk of workers losing their jobs due to robotization is significantly lower. Based on the idea that the degree of automation depends on how easily machines can undertake the tasks performed, this methodology relies on individual survey data – Program for the International Assessment of Adult Competencies (PIAAC). It focuses on an extensive list of mostly cognitive tasks carried out by each employee in their workplace, showing that workers within the same job can perform distinct tasks. To assess the relationship between employees' tasks and occupation automation, Arntz et al., (2016), as well as most subsequent research based on this method, use the computerization risk measure developed by Frey and Osborne (2017) and follow multiple imputation approach, since as only 2-digit ISCO codes are displayed in the individual-level database. Overall, the results suggested that, in the US and for OECD countries, only 9% of jobs are at high risk of being automated.

Although the literature on the impacts of automation on employment is extensive, the vast majority focuses on household-based surveys or comprehensive databases gathered from multiple sources, including employees' surveys or expert assessments. Moreover, to the best of our knowledge, the relationship between the automation risk and the resulting impact on employability levels and variables linked to non-cognitive skills and tasks liable to be replaced by machines shortly are often not considered. Additionally, many estimates are based on the probability developed by Frey and Osborne (2017) of an occupation being automated. This method can lead to inaccurate assessments of the risk of automation, as it does not consider how the pace of technological advancement influences this outcome. Thus, this research aims to address and deepen these sorts of nuances that have not yet been covered and estimate the probability of occupations undergoing shifts in employment patterns due to the risk of automation in the US. To frame our analysis, we carried out a Fractional Logit Model can be viewed as an extension of the Generalized Linear Model (GLM) specifically tailored for cases where the dependent variable is continuous and bounded between zero and one, such as proportions or fractions, providing a more appropriate analytical tool than ordinary least squares (OLS) regression in such contexts (Papke and Wooldridge, 1996). Over the years, several researchers have been focusing on forecasting tasks that tend to be easily automated. The traditional way of approaching this question is to analyze developments in the recent past. However, they argue that the results are not static, and the future shifts will significantly differ from the recent past (Hensvik and Skans, 2023).

To this end, to measure the automation risk and the consequent changes in employment, we relied on the Employment Projections (EP) program from the US Bureau of Labor Statistics (BLS), which aims to provide projections of around 800 occupational employment growth, for ten years (BLS, 2021). These projections are based on experts' evaluations regarding expectations of the adoption of advanced technologies, such as the use of robots or artificial intelligence, inter-sectoral shifts in demand, reorganizations in business management practices and offshoring (Government Accountability Office (GAO), 2019; Hensvik and Skans, 2023). To critically evaluate the change in occupational patterns due to technological innovations, we combined the above database with the Occupational Requirements Survey (ORS) conducted by the BLS. The ORS is a nationally representative survey based on establishments in private industry as well as state administration that collects unique information on the education, training and experience – the required minimum level of formal education, on-the-job training and previous work experience –environmental conditions – the various hazards that are present in the vicinity of the location where the tasks are carried out, – physical demands, – the physical activities requested – and cognitive and mental requirements – the skills workers need to be able to use their judgment, take decisions and communicate with others – needed to perform each occupation in the US labor market. Due to the novelty of the database, two waves were exclusively developed, characterized as a combination of several samples used to generate final estimates. The public data used for this analysis concerned the second and recent wave. They were collected for approximately 60,000 establishments, representing about 145,866,200 civilian workers and more than 500 occupations, over five years (2018-2023), with the final estimate produced by aggregating all the wave samples. Although the estimates are reliable and can be used for many purposes, it is crucial to consider some survey limitations. First, estimates are susceptible to sampling errors since the occupation requirements are assessed based on a sample of establishments rather than considering all existing ones. Secondly, comparing both waves is highly inadvisable, leading to a considerable reduction in the scope of the study since each set of

statistics has a differing size and data collection process and reflects employment requests only for the period provided (BLS, 2024). Third, in ORS data for public access, in addition to the notorious lack of complete information for many variables, thus reducing the number of occupations available for analysis, the data is exclusively aggregated, which can limit its usefulness for analyzing factors at a detailed level. Our review contributes to the academic debate on several fronts. Applying the fractional model provides a more robust and nuanced view of automation risk compared to the commonly used logistic regression, particularly since the latter assumes a binary dependent variable. Moreover, in the first place, a large proportion of studies, in addition to accounting for data prior to 2020 for 2-digit occupations, often rely on the results obtained in previous studies (e.g., Frey and Osborne, 2017), where there is a certain level of subjectivity and room for criticism, to measure the automation risk. In the second place, authors use "engineering bottlenecks" or, exclusively, cognitive variables to assess this susceptibility. Combining the two databases mentioned above – EP and ORS – to the best of our knowledge is also seen as a novelty. As well as not having been used previously in this field, it incorporates non-cognitive tasks, often carried out by industrial robots, that have not been, so far, included. Additionally, it is worth noting that variables in both O*NET and PIAAC are generally measured using a proficiency scores scale that is judged based on participants' performance. This measure shows the relative competence levels of workers compared to the sample rather than percentages, as in the ORS, which can lead to biased results.

The paper is structured as follows. Section 2 describes the data. Section 3 presents the empirical methods, reports and interpretations of the results. Section 4 concludes.

2 Data sources and variables

2.1 Data sources

The EP program, developed by BLS, is one of the primary data sources in this research. The main objective is to release 10-year projections of US employment by occupation based on experts' evaluations regarding assessing historical and current labor market data and industrial activity. The latest version covers the decade 2022-2032 for approximately 832 detailed occupations, according to the 2018 Standard Occupational Classification (SOC). This non-survey program[1] provide, for all agricultural workers and workers employed by private households, statistics regarding the expected growth or decline for wage and salary jobs as well as variables linked to education, work experience and training across occupations (BLS, 2021). To describe the projected growth or change in employment between 2022 and 2032, the experts characterize the quantitative results into five categories such as "decline", – if occupations are predicted to experience a drop in the number of jobs available – "little or no change", – if the demand for these occupations is expected to increase at a slower pace than average – "average", – if suggest stable employment prospects – "faster than average", – if the demand is predicted to grow at a higher speed than average for all occupations – "much faster than average" – if a very significant rise in employment takes place. These demand shifts reflect advances in technological innovation, such as the use of robots or artificial intelligence, intersectoral changes in demand, reorganizations in business

[1]The EP program uses the Occupational Employment and Wage Statistics (OEWS) survey, the Current Employment Statistics (CES) survey and the Current Population Survey (CPS) as primary sources to develop projections.

management practices and offshoring (GAO, 2019; Hensvik and Skans, 2023).

To critically evaluate the change in occupational patterns due to technological advances, we combined the above database with the ORS conducted by the BLS. The ORS is a nationally representative survey based on establishments in private industry and state administration, where all 50 states and the District of Columbia are up for selection. This database was designed to become the primary source of information on job searches used by the Social Security Administration's (SSA) disability programs. In other words, the goal is to accurately assess the physical or mental limitations experienced in light of the availability of jobs (Handel, 2015; BLS, 2024). Nevertheless, the estimates obtained can also be used for other purposes and provide a broad spectrum of insights about the nature of work (Gittleman and Monaco, 2020). This establishment survey collects unique information on the education, training and experience – the required minimum level of formal education, on-the-job training and previous work experience —- environmental conditions[2], – assessing concrete risks that are encountered in the vicinity of the workplace – physical demands[3], – the level and/or duration of physical activities requested – and cognitive and mental requirements[4], – the skills workers need to use judgment, make decisions, and communicate with others – needed to perform each occupation in the US labor market. These data are collected approximately annually and began in 2015 for nine months. Subsequently, new samples were drawn between 2016 and 2018, culminating in the first wave, representing a collection period of different sample sets containing around 25,300 establishments, which accounts for about 140.8 million civilian workers. In a posterior stage, over five years, between 2018 and 2023, a second and more up-to-date wave was developed, covering almost 60,000 establishments, representing nearly 145,866,200 employees, for more than 500 detailed occupations. However, since comparing both waves is highly inadvisable, as each set of statistics has a differing size and data collection process and reflects employment requests only for the period provided (BLS, 2024), our investigation focuses exclusively on the public data for the most recent wave.

2.2 Variables

To measure our dependent variable – shifts in the employability of occupations due to the automation risk – we adopted the statistics on projected growth since it is considered a metric intrinsically linked to technological progress. Thus, bearing in mind the data available for the change in employment between 2022 and 2032, we normalize the distribution from 0 to 1 to attain a continuous explained variable.

The key independent variables are based on the job requirements. Firstly, the significant insights Autor et al. (2003) introduced regarding selecting of variables within the cognitive and mental demands group were followed. According to their findings, due to the complexity of automation, the set of non-routine tasks in which employees hold comparative advantage requires in-person interactions, problem-solving, leadership and fast-paced reasoning skills. Empirical research on these sorts of factors associated with cognitive and interpersonal skills have also been empirically tested by, e.g., Arntz et al. (2016, 2017), Nedelkoska and Quintini (2018) and

[2]Environmental conditions cover elements such as outdoors, temperatures, wetness, humidity, heavy vibration, hazardous contaminants, proximity to moving mechanical parts, heights, and noise intensity levels.

[3]Physical demands include elements such as sitting, standing, lifting/carrying, pushing/pulling, reaching, gross and fine manipulation, low postures (such as stopping, crouching, kneeling, and crawling), climbing, driving, vision, speaking, and hearing.

[4]Cognitive and mental requirements include variables related to the frequency with a supervisor or other element checks the tasks, the pace and control of the work, personal contacts such as verbal interactions and personal skills, the variability of working hours and the work settings.

Brussevich, Dabla-Norris and Khalid (2019), to assess recent impacts on susceptibility to automation. That said, and given their relevance in the literature, variables such as people skills, problem-solving, supervision and work pace were adopted throughout this investigation.

Nevertheless, although recent technological advances have enabled automation to now extend to domains defined as non-routine (Frey and Osborne, 2017), its most pronounced impacts are noticed in well-defined, routine high-volume repetitive operations (Acemoglu and Autor, 2011; Autor, 2013) and those that involve more significant threats to workers' health (Javaid, Haleem, Pratap, Stingh and Suman, 2021). This technology, such as industrial robots, has unparalleled advantages in terms of speed and precision, which increasingly allow the performance of repetitive and time-consuming tasks such as picking, packing, palletizing (Javaid et al., 2021) and activities that require hand and finger dexterity (Arntz, 2016; Nedelkoska and Quintini, 2018). In addition, these improvements are also crucial when they involve physical strength, such as moving, lifting, and weighting heavy packs (Özkiziltan and Hassel, 2020; Javaid et al., 2021). Therefore, we decided to include variables that address these domains, such as low postures: stooping, crouching, kneeling, and crawling, maximum weight lifted or carried, fine manipulation and reaching. Furthermore, as pointed out, automated systems can provide considerable security benefits for human workers, as they can prevent injuries from working in hazardous conditions[5] (Wang et al., 2023). In this sense, human personnel can use robotics to carry out activities that are too dangerous in harsh environments as extreme temperatures or pressures and levels of radiation (Wong, Yang, Yan and Gu, 2018), extended exposure to noisy noises, dangerous contaminants as chemical exposures or radioactive materials (Javaid et al., 2021; Wang et al., 2023) and machines collision when in contact with mechanical parts (Lee, Shin and Lim, 2021). Hence, along these lines, tasks carried out in extreme cold, heights, proximity to moving mechanical parts and hazardous contaminants were also considered in our analysis. Additionally, as control factors, we included the number of highly qualified employees, the workers' amount with previous experience, and the average salary in each occupation. Table 1 summarizes all the independent variables selected, their respective definitions and examples of jobs that require the use of the skills and/or are exposed to the atmospheres previously mentioned.

Furthermore, the descriptive statistics for all the variables are given in Table A.1. Regarding the variables in the cognitive and mental requirements category, a high proportion of workers performing these tasks are, on average, potentially in professions likely to remain or grow their demand in the future. On the other hand, activities undertaken in hazardous environments, apart from extreme cold, involve, on average, a more significant proportion of workers in jobs where employment is projected to decline or stagnate. In tasks requiring physical ability, the numbers mirror those observed in the environmental conditions category, presenting a similar pattern. Lastly, on average, there are more qualified workers with higher wages in occupations that are predicted to grow in the future, and, in turn, more employees where previous experience is required in jobs that are expected to maintain their employment rate.

[5] According to the BLS, more than 5,000 fatal work-related injuries and more than 2.6 million non-fatal work-related incidents in 2021 were notified by industry employers in the US. Based on the reports, these injuries are generally due to contact with objects, excessive physical strength and bodily movements, falls, slips, trips, and transport accidents (Wang et al., 2023).

Table 1: Description of the tasks carried out in occupations

Independent variables/Tasks		Estimate	Definition	ORS examples
Cognitive and Mental Requirements	**People skills**	Number of workers[6] with more than basic people skills	**People skills** measure the ability to listen and communicate verbally and written. Tasks that entail coaching, guidance, supervision of others and involvement in negotiation often require more than basic skills.	• A police officer must respond and give instructions in unpredictable circumstances. • Customer service professionals must be capable of dealing with problems that arise in different situations.
	Problem-solving	Number of workers problem-solving is required more than once per day	**Problem-solving** measures the level of judgment and adaptability in response to new events, leading the worker to reflect on what to do next.	• Engineers must deal with complex technical problems in several areas. • Lawyers who study and examine the laws to develop the most effective strategies for tackling their customers' legal issues.
	Supervising others	Number of workers supervisory duties are required	**Supervising others** is meant to capture the physical proximity of direct supervisors to their employees on the job. The aim is to ensure that workers carry out their tasks and have an immediate answer to their needs when required.	• Designers work in their offices with the principal designer in nearby offices. • A machinist who produces parts for subsequent commercialization is monitored by the production supervisor in the supervisor's office in the same factory.

[6]The number of workers in each variable is obtained by multiplying the estimated percentage of workers with specific occupational requirements, based on the ORS, with the estimated number of employees in each occupation, taken from the Occupational Employment and Wage Statistics (OEWS).

Cognitive and Mental Requirements	**Work Pace**	Number of workers with consistent, generally fast work pace	**Work pace** is related to the actual speed (cognitive and/or physical) required to perform tasks. The pace of work can be interpreted in terms of the speed demanded of workers to accomplish repetitive tasks or the readiness expected of workers to react to a range of assigned tasks.	• A security guard in a building is open to the public and monitors employees and guests as they enter, and the flow of people is continuous. • A customer service assistant answers incoming calls constantly.
Environmental conditions	**Extreme cold**	Number of workers exposed to extreme cold	**Extreme cold** refers to tasks executed in atmospheres with temperatures equal to or below 40 degrees F for 2/3 or more of the working day or in atmospheres with temperatures equal to or below 32 degrees F for less than 2/3. Workers' exposure is not linked to weather conditions.	• A meat cutter operates in a cold room at 40 F more than 3/4 of the day. • An operator working in freezing tunnels spends short periods at -34 F.
	Heights	Number of workers exposed to heights, fully mitigated[7]	**Heights** concerns tasks carried out when workers are performing activities more than five feet above the ground and are in danger of falling.	• A tree pruner cuts branches wearing appropriate PPE such as helmets, safety glasses, gloves and fall protection systems. • Construction workers who repair structures in high-rise buildings. They use aerial lifts or protective harnesses to mitigate the risk of falls.

[7]Mitigation occurs when the employer installs safety systems or requires the use of personal protective equipment (PPE) for the

Environmental conditions	**Proximity to moving mechanical parts**	Number of workers in proximity with moving mechanical parts, fully mitigated	**Proximity to moving mechanical parts** refers to mechanical objects that can cause bodily injury when used correctly.	• Mechanics work on running engines while conducting repairs but use appropriate PPE, such as shields and interlocks on machines, to prevent accidental exposure to moving pieces. • A carpenter uses power tools to carry out his activities on a working day, using guarding and safety features.
	Hazardous contaminants	Number of workers exposed to hazardous contaminants, fully mitigated	**Hazardous contaminants** are present when workers are exposed to harmful substances in their breath, eyes and skin. Exposure to these elements can be through inhalation, ingestion or through physical contact.	• Firefighters enter burning buildings to evacuate the inhabitants, wearing toxic fume inhalation protectors. • An industrial metal worker using a respiratory mask to mitigate adverse health effects.
Physical Demands	**Low postures**	Number of workers low postures are required	**Low postures** report on tasks requiring stooping, crouching, kneeling, and crawling.	• A cleaner stoop to empty trashcans or bends down to grab a product. • An electrician kneels to connect cables or appliances in narrow spaces.

performance of tasks in order to totally or partially eliminate potentially harmful exposures that could result in severe injuries and illnesses in the workplace. If the safety systems or PPE eliminate the exposure, the variable is coded as "fully mitigated".

Physical Demands	**Maximum weight lifted or carried**	Pounds maximum weight lifted or carried, mean	**Lifting/Carrying** is a measure of physical strength. Lifting means moving an object up or down from one place to another while carrying an object, often holding it in our hands or arms.	• Assembly line workers lift items onto a conveyor belt. • Construction workers use tool belts to carry the items they need to perform their activities in the workplace.
	Fine manipulation	Number of workers fine manipulation is required	**Fine manipulation**, unlike gross manipulation, fine manipulation involves working mainly with the fingers, not the entire hand or arm.	• A laborer who must place small pieces on a production line. • Box office attendants, responsible for selling tickets and receiving payments.
	Reaching	Number of workers reaching overhead is required	**Overhead reaching** is interpreted as extending the hand(s) and arm(s), in any direction, higher than the head.	• Warehouse workers often need to reach items from high shelves. • Carpenters installing frames or ceiling panels demand overhead reaching.

3 Methodology

3.1 Fractional Regression Model

As discussed previously, various cognitive and non-cognitive tasks may impact the risk of automation of an occupation, and ultimately, influence its employment levels. Therefore, in seeking to assess how the 12 suggested independent variables, presented in Table 1, might influence the probability of shifts in employment levels, an FRM was proposed. The model, developed as a seminal work by Papke and Wooldridge (1996), was mainly designed to address cases where the dependent variable is continuous and delimited to the interval $[0, 1]$. Thus, to scale the data, to ensure that the continuous dependent variable falls between the 0 and 1 range, we normalized the change in employment between 2022 and 2032[8], based on the projections developed by BLS, which is defined by,

$$\Delta Emp_{22-23} = \frac{\Delta Emp_{22-32} - Min\left(\Delta Emp_{22-32}\right)}{Max\left(\Delta Emp_{22-32}\right) - Min\left(\Delta Emp_{22-32}\right)}. \tag{1}$$

[8]The change in employment between 2022-2032 is given by, $\Delta Emp_{22-23} = 1 - \frac{Emp_{32} - Emp_{22}}{Emp_{22}}$.

Hence, the following model was adopted to deal with the fractional response variable, which merely entails the assumption of a functional shape for y_o that imposes the intended restriction on the conditional mean of the explained variable,

$$E\left(y_o \mid \boldsymbol{X}_o, y_o \in (0,1)\right) = G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right) \tag{2}$$

where $0 \leq y_o \leq 1$ denotes the dependent variable – that illustrates the probability of the automation risk of a particular occupation – $\boldsymbol{X}_o^{'}$ refers to the explanatory variables of observation o, – that comprises the set of cognitive and non-cognitive variables – and, lastly, $G\left(.\right)$ is known as a non-linear cumulative distribution function satisfying $0 < G\left(.\right) < 1$. Hence, the choice applied in our research for $G\left(.\right)$ is the logistic transformation, $G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right) = \frac{e^{\boldsymbol{X}_o^{'}\boldsymbol{\beta}}}{1+\boldsymbol{X}_o^{'}\boldsymbol{\beta}}$, which is, indeed, a natural option for modeling proportions, since it maps $\boldsymbol{X}_o^{'}\boldsymbol{\beta}$ to the $(0,1)$ interval.

Notwithstanding, as in the empirical implementation of Hermalin and Wallace (1994), the model defined by 2 can be estimated consistently by non-linear least squares (NLS); it is more efficient to estimate by quasi-maximum likelihood (QML) method. Thus, Papke and Wooldridge (1996) suggested a particular QML estimator using Bernoulli's log-likelihood function, defined as,

$$LL_o\left(\boldsymbol{\beta}\right) = y_o log\left[G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right)\right] + \left(1-y_o\right) log\left[1 - G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right)\right]. \tag{3}$$

Following the research carried out by Gourieroux, Monfort and Trognon (1984), the resulting QML estimator for $\boldsymbol{\beta}$ is always consistent, if the model is correctly specified, regardless of the actual distribution of y_o conditional on $\boldsymbol{X}_o^{'}$, since the Bernoulli distribution is a member of the linear exponential family (Ramalho and Vidigal, 2006). Nevertheless, as observed, the crucial assumption of the FRM, which is the correct formalization of $E(y_o \mid \boldsymbol{X}_o^{'})$, must be satisfied to validate the findings. For this purpose, the extended Ramsey RESET test is computed, which allows the correct specification of the conditional mean to be assessed.

Nevertheless, the results obtained through the FRM merely indicate the signs (positive or negative) of each predictor variable on the predicted variable. Thus, in terms of economic interpretation, it is crucial to compute and interpret the regressors' marginal effects on the dependent variable's expected value. Hence, MEs of the k^{th} predictor x_k for the o^{th} observation can be derived by the partial derivative of the logisitic function with respect to x_k, which is given by,

$$ME_{ok} = \frac{\partial E\left(y_o \mid \boldsymbol{X}_o^{'}\right)}{\partial x_{ok}} = G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right)\left(1 - G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right)\right)\boldsymbol{\beta}_k. \tag{4}$$

In this sense, bearing in mind that the AME for the k^{th} predictor is the average of the marginal effects across all o^{th} observations, we attain,

$$AME_k = \frac{1}{o}\sum_{o=1}^{O} ME_{ok} = \frac{1}{o}\sum_{o=1}^{O} G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right)\left(1 - G\left(\boldsymbol{X}_o^{'}\boldsymbol{\beta}\right)\right)\boldsymbol{\beta}_k. \tag{5}$$

which is considered a powerful tool that provides a transparent and interpretable measure of assessing how changes in prediction factors influence the response variable, on average. Moreover, it enables us to compare

the relative importance of distinct explanatory variables on the outcome.

3.2 Econometric results

Obtained from the estimation implied by the FRM, we present the empirical results for Models A, B and C, in Table 2. However, Model A is limited to predictor variables related to "cognitive and mental requirements," while Model B expands the analysis by incorporating independent variables tied to "environmental conditions." Model C, which is the main focus of our analysis, encompasses both previous sets of predictors and adds those related to "physical demands." Moreover, we also assessed the goodness-of-fit. We carried out diagnostic tests that enabled us to verify whether there were any specification errors in the different regression models conducted. Furthermore, to compare the models' accuracy, the regressions above were re-estimated exclusively for 214 observations, as illustrated in Table 3.

Upon an initial examination of the empirical adequacy of the models, displayed in Table 2, we concluded that, based on the RESET test, there is exclusively evidence of functional form misspecification in Model A, suggesting that it may be necessary to revise the structural form or include other possible relevant variables. Turning now our focus to Table 3, since it is more appropriate to compare the model fit across regressions, we perceived that there is no evidence of functional form misspecification in Model B and C. Hence, to be assured of our findings, we visually assess the performance of the predictive model C by comparing the predicted probabilities produced by the FRM with the actual values observed, as illustrated in Figure 1. Therefore, considering the 45-degree dashed line reference, we gather that most of the points lie on or close to the line, suggesting a strong prediction accuracy, leading us to focus our investigation on this last model.

Regarding the impact of each of the predictive variables on the risk of automation, we found a negative and statistically significant relationship between tasks requiring people skills, problem-solving, work pace, extreme cold, hazardous contaminants, and low postures and the estimated mean probability of an occupation decreasing its employment levels. By contrast, we identified a positive and statistically significant relationship between supervising others, proximity to moving mechanical parts, fine manipulation, and reaching and the predicted mean likelihood of an occupation diminishing its employment levels. Additionally, the negative and positive estimated coefficients and statistically significant variables for lifting and carrying weight reflect the non-linear quadratic (concave) relationship, indicating an adverse – until the maximum weight value is reached – and favorable correlation in the estimated mean probability of jobs requiring these activities being automated and, consequently, suffer a decrease.

However, despite the insights concerning both the assessment of the model's fit and the relationship between the predicted and dependent variables, nothing is said about the magnitude of the average marginal effects, which are illustrated in Table 4, which, in turn, illustrates how independent variables influence the estimated probabilities. First, for the set of cognitive and mental variables, we perceived that an increase of one thousand workers in activities where people skills, problem-solving and work pace are required, leads to a decrease of 0.007 pp, 0.028 pp and 0.005 pp, respectively, in the predicted mean probability of a decline in employability due to a positive impact of automation in this sort of occupations, ceteribus paribus (cp). Contrarily, the same increment of employees in supervising others' tasks results in a rise of 0.014 pp in the estimated mean likelihood, cp.

According to Autor et al. (2003) and Goos et al. (2014), employees who undertake more analytical roles (e.g., problem-solving and planning), as well as activities that involve interpersonal communication (e.g., selling, negotiating, and advising), are less prone to be displaced. Subsequently, also studying the effects of automation on the expansion or decay of employment, Arntz et al. (2016), Frey and Osborne (2017), and Nedelkoska and Quintini (2018) obtained the same insights, which is in line with our evidence. Furthermore, supporting our vision, it is widely recognized that technological tools have increased the risk of dehumanization by minimizing the role of human supervisors in the workplace. These developments can be witnessed, for instance, through service robotics, computer visions (Tuomi, Tussyadiah, Ling, Miller and Lee, 2020), collaborative robots or wearables, transforming these activities into extenuating practices of endless surveillance, which sharply increases productivity (Stefano, 2019). Hence, one example that has received greater attention is the wearable work tools used by Amazon workers. These instruments automatically track their movements and location on a minute-by-minute basis, avoiding the intervention of human oversight, resulting in improved work speed and efficiency at lower costs (Marino and Monaca, 2020).

Second, by analyzing the section on environmental conditions, we noticed that an enhancement of one thousand employees in roles where they are exposed to extreme temperatures and hazardous contaminants – conducts to a decrease of 0.018 pp and 0.059 pp, according to the same order, on the predicted mean probability of an occupation suffering a decrease in its demand, cp. By contrast, an increase of one thousand workers necessary to be in proximity to moving mechanical parts leads to a boost of 0.071 pp in the predicted mean likelihood, cp.

Due to the lack of research into the relationship between environmental conditions and the projections of occupations being automated, no literature provides direct insights into the subject to the best of our knowledge. Nevertheless, jobs in extremely low-temperature environments in the US cover a wide range of industries, often encompassing refrigerated warehouses, food production installations, health and medical research jobs, and chemical and materials handling, among others. In this sense, this occupation does not necessarily involve routine activities and can often entail decision-making and, in some situations, communication and organizational skills. Additionally, the investment and ongoing maintenance expenses can outweigh the advantages due, for instance, to space limitations in cold rooms and refrigerated warehouses and the thoroughness of chemical treatment.

Robots are also frequently used to perform dangerous activities previously carried out by human workers (Javaid, Haleem, Singh and Suman, 2021). According to the BLS, in the US, among all civilian jobs, around 14.9% of workers faced hazardous contaminants in 2016 while undertaking their activities. In greater detail, large shares of these jobs include installation, maintenance, and repair occupations, buildings and grounds cleaning and maintenance, and occupational health and safety specialists and technicians (BLS, 2016). Hence, when the magnitudes of the hazards reach the point where human exposure poses a long-term health threat, robots can be utilized to prevent this issue. This phenomenon can result from individuals' limited endurance and dexterity in conducting activities when they must wear protective suits to protect themselves from hazards, which must be implemented as a necessity to manage risks so that work can be carried out safely (Siciliano and Khatib, 2016). Nevertheless, most of these occupations are in the non-routine field, which restricts their replacement. In this sense, humans remain indispensable for roles that require complex decision-making, versatility, and

practical knowledge in hazardous contaminant management. Several examples of professions can be cited as firefighters, where automation of duties is complex due to the unpredictable character of emergencies, and laboratory technicians, who handle chemicals and other hazardous materials where precise measurements and assessments are demanded to avoid possible risks of errors in sample processing.

By contrast, jobs that involve working in proximity with moving mechanical parts are, in most scenarios, routine – potentially in the manufacturing and production, construction and heavy equipment, and automotive and transportation industries – facilitating their progressive replacement. Additionally, the frequent accidents with operator injuries that occur mainly due to collisions during machines' operations also raise concerns (Lee, Shin and Lim, 2021). Most machines are unaware of their surroundings and can be hazardous to humans, for example, by not stopping or reaching a high, uncontrolled speed (Murashov, Hearl, and Howard, 2016). Thus, according to Matt and Rauch (2020), this interaction can lead, for instance, to trapped fingers, bruises, and errors due to multiple urgent stop buttons for different operations, fractures, or sprains. Hence, to minimize risks, implementing new automated systems can lead to replacing workers, resulting in the need for retraining to adjust to the new requirements of the labor market.

Lastly, turning our attention to the physical demands segment, a raise of one thousand employees where low postures tasks are required and a rise of 1 pound (lb) loaded leads, according to the same order, to a decline of 0.011 pp and 0.136 pp in the estimated mean probability of an occupation experiencing a drop in its employability levels, cp while the same tasks that demand fine manipulation and reaching results in an enhancement of 0.045 pp and 0.016 pp, respectively, cp.

Although studied distinctly, Frey and Osborne (2017), also analyzing the impact of tasks related to finger and manual dexterity and the capacity to work in cramped workspaces and awkward positions, similarly concluded that these variables had relatively high values in the risk of replacement. While human labor remains at a comparative advantage in activities that require more complex handling, technological developments suggest that these advantages may eventually diminish, requiring an innovative restructuring of tasks. Fernández-Macías, Klenert and Antón (2021) and Montobbio, Staccioli, Virgillito and Vivarelli (2023) underlined and deepened these findings. They concluded that the most exposed professions to automation involve dexterity, manipulation, loading objects into machines and equipment, heavy lifting, and moving cargo. Moreover, it is also important to highlight the notorious exposure of the manufacturing sector, followed by health services, which have been highly affected by a recent wave of automation (Montobbio et al., 2023). It allows surgeons to conduct delicate, complex procedures where precision is crucial, with high accuracy, minimized invasion, and superior dexterity. Notwithstanding that activities associated with fine manipulation agree with the statement above, tasks requiring awkward positions remain comparatively unaffected by automation, while roles demanding strength appear to be favorably affected by advances in machinery. Indeed, awkward postures lead to disorders that are often connected to physical risk factors, such as several inflammatory diseases and painful degenerative pathologies. Therefore, solutions to reduce the incidence of Musculoskeletal Disorders have been pursued (Cardoso, Colim, Bicho, Braga, Menozzi and Arezes, 2021). One possible way to alleviate employees from repetitive tasks and excessive effort is to introduce industrial robots (Gualtieri, Rauch and Vidoni,2021). However, not all the activities can be undertaken by robots alone. These machines are pre-programmed to operate in a particular position and, hence, cannot fit all workers. Humans have a significant number of redundant degrees of freedom

and the boundaries of the range of movement can differ from individual to individual (Xie, Lu, Wang, Su, Liu and Xu, 2024), which are complex to replicate with current robotic developments. Thus, despite significant efforts, even with the development of collaborative robots, humans continue to take the leading role.

Focusing on the maximum weight lifted and carried, the effect on the predicted likelihood was contrary to our original expectations. Nevertheless, it is worth noting that we are studying a non-linear concave quadratic relationship. Therefore, it is preferable to compute the marginal effects for values above the turning point of the quadratic function – given by 65.270 lbs – rather than the average pounds lifted or carried. Once computed, we find that for higher weights – over 162.800 lbs – an increase in the amount transported causes an upward shift in the expected probability of the occupation in concern being automated, which subsequently reduces its employability demand. Nevertheless, this shift has a considerably compelling justification. Even before the Industrial Revolution, mechanisms had been developed to replace human labor in tasks that implied physical strength, such as grinding or hammering. At the end of the 18th century and the beginning of the 19th century, mainly in the textile and manufacturing industries, a major leap forward was achieved, thus allowing the considerable replacement of labor-intensive activities by machines. Since the mid-20th century, with the improvement of machines' ability to perform heavy lifting roles and the introduction of the first industrial robots, it become feasible to start automating progressively more complex tasks in this field. Hence, it is tempting to believe that these machines had their strongest effect on employment some generations ago, suggesting that the impact of current industrial robots' technology on the economy is perhaps slight and far from destructive (Farnández-Macías, Klenert and Antón, 2021). Additionally, the room for substitution seems narrow since, according to Polanyi's paradox following Michael Polanyi's (1966), "we know more than we can tell." In other words, in line with Polanyi's observation, some tasks are not automatable as there are competencies that we exclusively understand tacitly, and the underlying "rules" are not known. Most labor processes, even in occupations that involve physical strength, are based on a wide array of contributions, not just of a routine nature. In particular, let us examine a concrete example of the role played by machines in construction. Although the amount of physical work needed to perform – such as laying bricks or lifting weights – is increasingly reduced due to the introduction of robotics, the number of employees in these occupations is not abruptly dropping. Construction laborers rely on a mixture of tacit know-how, such as the evaluation of materials, adjustments on the ground, and communication with co-workers in dynamic environments without automation. Hence, although many advances have been achieved in human strength replacement, the complexity of human adaptation and involvement remains crucial, limiting complete computerization and the subsequent sharp fall in employability (Autor, 2014).

3.3 Occupations with high and low chance of automation

Lastly, to identify which occupations are most and least affected by automation, we computed the mean predicted probabilities for shifts in employment, reflecting the implications of automation for each occupation, as illustrated in Table A.2. Not surprisingly, we find that occupations with a high chance of automation, which consequently experience a decline in employability, cover: Office clerks, general; Bookkeeping, accounting, and auditing clerks; Cashiers; Receptionists and information clerks; First-line supervisors of office and administrative support workers; Secretaries and administrative assistants, except legal, medical, and executive; Machinists;

Retail salespersons; among others. As mentioned by Frey and Osborne (2017), these positions are particularly prone to be performed by machines in the reasonably near future due to their routine characteristics, including basic cognitive skills, repetitive movements, and manual dexterity (Autor et al., 2003; Arntz et al., 2016; Caravella and Menghini, 2018). Although these professions involve interaction and communication skills, they do not necessarily demand high social intelligence (Frey and Osborne, 2017). For instance, nowadays, these professions are increasingly being replaced by robots in warehouses as well as overtaken by algorithms, which, in turn, alert shoppers to products they might wish to buy (Chui, Manyika and Miremadi, 2016). Thus, with the expansion of these AI product recommendations and as online purchasing escalates, retail workers face an insecure future. Moreover, big data algorithms are already quickly moving into the domains of integrated calendar and office management systems, as well as areas that depend on storing or accessing information. This implies that many occupations linked to office and administrative support will become vulnerable to automation (Frey and Osborne, 2017). Regarding the computerization of production occupations, the predicted probabilities reflect the tendency that has been visible in recent decades, with industrial robots occupying the routine roles of the majority of workers, mainly in the manufacturing sector (Frey and Osborne, 2017; Vermeulen, Kesselhut, Pyka and Saviotti, 2018). Therefore, our findings align with the conclusions reached by Frey and Osborne (2017) for the high probability of automation.

Instead, occupations with a low chance of automation, which consequently experience a growth in employability, encompass Medical and health services managers, Cooks of restaurants, Veterinarians, Physical therapists, Lawyers, Computer and information systems managers, Nurse practitioners, and Software developers, among others, as also observed in the findings produced by Frey and Osborne (2017) and Pouliakas (2018). Despite the growing use of artificial intelligence, the constant need to draw on cognitive skills, as well as the necessity to use creative thinking, effective communication, adapt to unique circumstances and human judgment and values-based decision-making, means that the above fields are still far from being overtaken by automation (Autor et al., 2003; Arntz et al., 2016; Caravella and Menghini, 2018). Thus, technological advances are viewed as a tool to boost human efficiency and productivity, not to supplant them.

Table 2: Results of the Fractional Regression Model

Independent variables		Model A - Cognitive tasks model	Model B - Cognitive and environmental tasks model	Model C - Cognitive, environmental and physical tasks model
Cognitive and Mental rquirements	**People skills**	0.00007 (0.00013)	0.00010 (0.00012)	-0.00030^{**} (0.00012)
	Problem-solving	-0.00111^{**} (0.00055)	-0.00113^{**} (0.00052)	-0.00112^{**} (0.00056)
	Supervising others	0.00032^{***} (0.00018)	0.00026^{***} (0.00016)	0.00056^{*} (0.00015)
	Work Pace	-0.00029^{**} (0.00014)	-0.00022^{**} (0.00011)	-0.00020^{***} (0.00012)
Environmental conditions	**Extreme cold**		-0.00053^{***} (0.00029)	-0.00073^{*} (0.00020)
	Heights		-0.00138 (0.00197)	-0.00156 (0.00222)
	Proximity to moving mechanical parts		0.00075 (0.00103)	0.00288^{**} (0.00118)
	Hazardous contaminants		-0.00217^{***} (0.00124)	-0.00239^{***} (0.00142)
Physical Demands	**Low postures**			-0.00045^{*} (0.00014)
	Maximum weight lifted or carried			-0.00872^{***} (0.00452)
	(Maximum weight lifted or carried)^2			0.00007^{***} (0.00004)
	Fine manipulation			0.00045^{*} (0.00014)
	Reaching			0.00016^{**} (0.00008)
Controls	**Education**	✓	✓	✓
	(Education)^2	✓	✓	✓
	Experience	✓	✓	✓
	(Experience)^2	✓	✓	✓
	Wages	✓	✓	✓
Pseudo R^2		0.0069	0.0056	0.0082
RESET test		8.33	4.05	3.92
(p-value)		(0.016)	(0.132)	(0.142)
Number of observations		256	243	214

Note: Supervising others is statistically significant at 0.107.

Table 3: Model Fit of Fractional Regression Model considering 214 observations for Model A, B and C.

	Model A - Cognitive tasks model	**Model B - Cognitive and environmental tasks model**	**Model C - Cognitive, environmental and physical tasks model**
Pseudo R^2	0.0055	0.0058	0.0082
RESET test	7.45	3.03	3.92
(p-value)	(0.024)	(0.220)	(0.142)
Number of observations	214	214	214

Figure 1: Predicted vs. observed values for the probability of an occupation being automated based on the Fractional Regression Model C

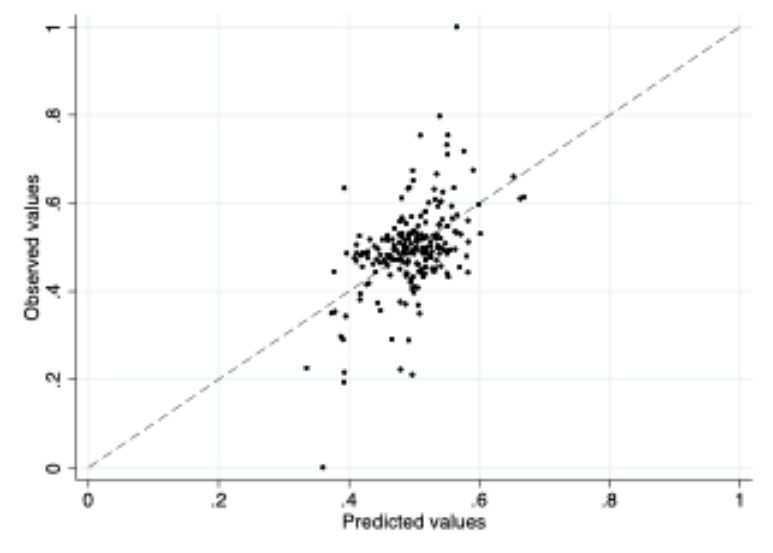


Table 4: The Marginal Effects of the Fractional Regression Model using AME approach

Independent variables		Model A - Cognitive tasks model	Model B - Cognitive and environmental tasks model	Model C - Cognitive, environmental and physical tasks model
Cognitive and Mental rquirements	**People skills**	0.00002	0.000024	-0.00007^{**}
		(0.00003)	(0.00003)	(0.00003)
	Problem-solving	0.00027^{**}	-0.00028^{**}	-0.00028^{**}
		(0.00013)	(0.00013)	(0.00014)
	Supervising others	0.00008^{***}	0.00007^{***}	0.00014^{*}
		(0.00005)	(0.00004)	(0.00004)
	Work Pace	-0.00007^{**}	-0.00006^{**}	-0.00005^{***}
		(0.00003)	(0.00003)	(0.00003)
Environmental conditions	**Extreme cold**		-0.00013^{***}	-0.00018^{*}
			(0.00007)	(0.00005)
	Heights		-0.00034	-0.00039
			(0.00049)	(0.00055)
	Proximity to moving mechanical parts		0.00019	0.00071^{**}
			(0.00025)	(0.00029)
	Hazardous contaminants		-0.00054^{***}	-0.00059^{***}
			(0.00031)	(0.00035)
Physical Demands	**Low postures**			-0.00011^{*}
				(0.00003)
	Maximum weight lifted or carried			-0.00136^{***}
				(0.00068)
	Fine manipulation			0.00011^{*}
				(0.00003)
	Reaching			0.00004^{**}
				(0.00002)
Controls	**Education**	✓	✓	✓
	(Education)^2	✓	✓	✓
	Experience	✓	✓	✓
	(Experience)^2	✓	✓	✓
	Wages	✓	✓	✓
Number of observations		256	243	214

Note1: Supervising others is statistically significant at 0.107.
Note2: The marginal effects of the maximum weight lifted or carried are estimated considering the average weight (in pounds) lifted or carried – given by 23.939 lbs. If estimated for the turning point of the quadratic relationship – 65.270 lbs by setting the derivative to zero – the effect on the predicted probability becomes positive, although not statistically significant. The marginal effect reaches statistical significance when weights greater than approximately 162.800 lbs are adopted.

4 Conclusion

Automation has been spreading rapidly in most developed countries, becoming prominent in today's economy and triggering a "wave of technology" anxiety in the job market (Arntz et al., 2017). Induced by the growing adoption of machines, the increase in productivity and efficiency (Egana-delSol et al., 2022), as well as greater

flexibility and adaptability, has been noticeable. This has resulted in firms lowering their costs and increasing their competitiveness and flexibility (Ivanov et al., 2020), leading to potential adverse impacts on employment opportunities and changing the nature of work across occupations (Autor, 2015; Dengler and Matthes, 2018). However, the concerns raised are different across all professions. A large body of evidence, elicited by Autor et al. (2003), supports the idea that occupations comprising activities that follow a set of routine and clearly defined procedures can be undertaken by machines and, consequently, result in the replacement of human beings.

Nevertheless, this debate became more intense when some authors pointed out that technological advances could lead to the automation of tasks and jobs that were previously taken for granted (McKinsey Global Institute, 2013; Christenko, 2022). Since then, much has been written recently regarding the danger machines pose to laborers. Frey and Osborne (2017) sparked the first public debate by stating that 47% of jobs in the US are at risk of being automated. One of their main constraints is that they are centered on occupations rather than individual tasks when assessing the threat of automation. Thus, Arntz et al. (2016), to overcome this limitation, based on the idea that the ease of automation depends on how effortless machines can carry out the tasks, concluded that, in OECD countries, only 9% of jobs are at high risk of being automated. Even to the best of our knowledge, the relationship between the replacement risk and non-cognitive tasks is often not considered, which limits the ability to explain differences in the future of employment.

In this sense, this research aims to examine the impact of the automation process on a range of tasks and the subsequent effect on the employment dynamics of the occupations. Hence, to frame our investigation, we developed a FRM where it was estimated the impact of a set of independent variables resulting from advances in automation, which fall into three distinct divisions – cognitive and mental requirements, environmental conditions and physical demands on the probability of a given occupation experiencing a decline in its employment levels.

Focusing on the set of cognitive and mental variables, we find that, on the one hand, an increment in the demand of tasks that require abilities to listen and communicate, a certain level of judgment and adaptability in response to new events, and a speed of execution, do not result in a dropped employment levels in their respective occupations. Since workers who perform analytical and interpersonal communication roles are less susceptible to being replaced, the findings aligned with the expectations. On the other hand, a rise in the demand for supervision activities leads to a decline in the recruitment of employees in occupations requiring these duties. Due to the improvement of service robotics, computer vision, and collaborative robots, which bring endless surveillance, individuals are no longer necessary, leading to dehumanization by technological tools. Regarding environmental conditions factors, we observed that the growth in activities carried out in environments that require extremely low temperatures causes an increase in the employability of these occupations since they do not necessarily involve routine activities.

By contrast, regarding the predictors linked to the environmental conditions, in the event of an expansion in services requiring proximity to mechanical objects, a rise in the decline of employability in professions handling these requisites is predicted. As a result of the increase in operator injuries due to collisions while operating machinery and the often-routine tasks carried out, it is notorious that replacing workers with some form of automation is becoming more accessible to minimize risks. Nevertheless, activities carried out in hostile environments, where workers are in contact with dangerous contaminants or exposed to extremely cold temper-

atures, do not suffer a negative impact from advances in automation, which translates into an increase in the employability of occupations.

Lastly, concerning the predictors linked to physical demands, a rise in the demand for roles that entail working mainly with fingers causes a drop in employability in these occupations. In contrast, an increment in tasks entailing low postures, such as stooping, squatting, kneeling, and crawling postures, results in an enhancement, as expected. Since machines are pre-programmed to operate in a particular position, it becomes complex to replicate the movements of employees. Hence, humans continue taking the lead. Regarding physical strength, exciting results were obtained. Conclusions from previous studies frequently indicate a positive relationship between the increase in weight lifted or carried and the trend toward task automation. However, we attained different findings. By considering a non-linear concave quadratic relationship among the dependent and independent variables, we noticed that an increase in the amount transported causes a decline in employment stability and an enhancement in employment growth in these occupations. From the late eighteenth and early nineteenth centuries, but especially in the mid-twentieth century, the development and subsequent improvement of machines' ability to perform heavy lifting roles have been remarkable. Thus, it is tempting to conclude that these machines had their most considerable impact on employment generations ago, suggesting that the impact of current industrial robots' technology on the economy is perhaps slight and far from destructive (Farnández-Macías, Klenert and Antón, 2021). We also found that Polanyi's paradox may partly justify the outcomes achieved. Although automation can significantly boost productivity in strength-related roles, the complexity of human judgment and adaptability, which cannot be automated, ensures that human involvement remains essential (Autor, 2015). Thus, at higher weight levels, there may be encouragement to increase the development and the posterior use of machines, consequently reducing employability in these occupations.

Therefore, we can confirm that the effect of automation on the employment dynamics of the occupations varies according to the tasks required in each job. Indeed, almost all occupations include roles that tend to be automated. Nevertheless, it is the routine ones – which include, for example, basic cognitive skills, repetitive movements and manual dexterity (Autor et al., 2003; Arntz et al., 2016; Caravella and Menghini, 2018) – that face the greatest potential for substitution and, consequently, the negative relationship between occupations' automation and positive changes in employment. Our model predicts that most workers employed, mostly in cashiers and retail salespeople jobs, along with specific office and administration support professions and a few production occupations, tend to be highly substituted by machines due to their redundant activities, which diminish their employment levels. Instead, the ones mainly linked to engineering and science occupations, management and sales, legal roles and healthcare practitioners, due to their complexity and non-routine characteristics, are at a low risk of being automated, reflected in an upward trend in demand for these positions. Thus, our findings closely follow the conclusions reached by Frey and Osborne (2017) and are consistent with recent technological progress documented in the literature.

This research has shed some light on the debates about the influence of automation on a wide range of tasks and its consequent impact on job growth in several occupations. As workers are forced to switch jobs, governments must invest in active labor market policies. Implementing upskilling, re-skilling programs, and improving access to tertiary education can mitigate the adverse effects of automation on employment, enabling workers to transition to safer roles. In addition, passive labor market policies, like extending unemployment

benefits or offering early retirement, provide temporary relief but are insufficient for long-term challenges. A more effective approach could be UBI, offering regular financial support to help individuals invest in education and adjust to new job opportunities. Moreover, governments should also consider regulating automation by introducing a "robot tax" to balance labor and capital taxation and address inefficiencies in resource allocation. Nevertheless, we firmly believe that more research is needed into the evolution of employment, particularly in mind various cognitive and non-cognitive factors, to continuously develop and implement policy measures that enable workers to adapt to technological changes.

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Appendix

Appendix A.1

Table A.1: Descriptive statistics for the explained and explanatory variables

Variables		Projected Employment Growth	Frequency	Percent	Mean	Standard Deviation	Minimum	Maximum
Employability of occupations		Total	457	-	0.50	0.10	0	1
Cognitive and metal requirements	**People skills**	Total	432	1	206.51	374.32	0.057	3490.44
		"Decline" and "little or no change"	144	0.33	204.44	404.07	0.060	2231.21
		"Average"	120	0.28	205.15	296.57	0.630	3490.44
		"Faster than average" and "much faster than average"	168	0.39	209.25	331.27	0.16	3156.80
	Problem-solving	Total	351	1	45.43	117.71	0.03	1582.02
		"Decline" and "little or no change"	131	0.37	27.38	64.67	0.031	396.50
		"Average"	94	0.27	56.51	172.70	0.069	1582.02
		"Faster than average" and "much faster than average"	126	0.36	55.93	108.22	0.03	918.43
	Supervising others	Total	436	1	64.63	228.55	0.02	3406.07

		"Decline" and "little or no change"	150	0.34	47.41	184.13	0.033	1559.44
Cognitive and metal requirements	**Supervising others**	"Average"	122	0.28	86.21	335.46	0.069	3406.07
		"Faster than average" and "much faster than average"	164	0.38	64.32	155.72	0.02	1251.65
	Work Pace	Total	335	1	113.93	201.14	1.139	1634.27
		"Decline" and "little or no change"	114	0.34	108.88	203.30	1.265	1517.68
		"Average"	93	0.28	125.50	210.74	1.139	1485.74
		"Faster than average" and "much faster than average"	129	0.39	122.57	239.46	1.16	1729.01
Environmental conditions	**Extreme cold**	Total	449	1	19.48	99.27	0.02	1360.63
		"Decline" and "little or no change"	151	0.34	16.70	60.97	0.027	508.27
		"Average"	126	0.28	21.54	124.12	0.026	1360.63
		"Faster than average" and "much faster than average"	172	0.38	20.42	106.22	0.02	929.70
	Heights	Total	433	1	3.37	9.385	0.017	117.55

		"Decline" and "little or no change"	144	0.33	2.73	6.30	0.031	57.38
		"Average"	121	0.28	5.20	14.92	0.026	117.55
	Heights	"Faster than average" and "much faster than average"	168	0.39	2.61	5.53	0.02	34.29
Environmental conditions	**Proximity to moving mechanical parts**	Total	424	1	6.11	16.60	0.02	202.29
		"Decline" and "little or no change"	140	0.33	8.22	17.15	0.036	57.38
		"Average"	116	0.27	7.13	22.54	0.026	202.29
		"Faster than average" and "much faster than average"	168	0.40	3.63	9.64	0.02	96.29
	Hazardous contaminants	Total	432	1	8.74	20.97	0.02	147.65
		"Decline" and "little or no change"	138	0.32	8.04	31.07	0.036	147.65
		"Average"	120	0.28	12.26	26.84	0.059	146.12
		"Faster than average" and "much faster than average"	165	0.38	6.78	15.00	0.02	123.73
Physical demands	**Low postures**	Total	402	1	187.93	422.38	0.04	3129.21

		"Decline" and "little or no change"	137	0.34	203.04	447.60	0.036	3129.21
		"Average"	113	0.28	211.21	411.98	0.073	2922.46
Physical demands	**Low postures**	"Faster than average" and "much faster than average"	152	0.38	157.01	407.27	0.05	2791.261
	Maximum weight lifted or carried	Total	386	1	24.82	20.52	1.86	126.42
		"Decline" and "little or no change"	135	0.35	26.68	19.61	2.47	117.13
		"Average"	108	0.28	25.99	21.98	2.87	126.42
		"Faster than average" and "much faster than average"	143	0.37	22.17	20.08	1.86	109.80
	Fine manipulation	Total	450	1	308.97	540.66	3.48	3746.96
		"Decline" and "little or no change"	150	0.33	350.93	641.46	4.125	3746.96
		"Average"	128	0.28	310.79	541.76	5.274	3490.44
		"Faster than average" and "much faster than average"	172	0.38	271.02	433.60	3.48	3156.80
	Reaching	Total	317	1	138.58	316.72	0.76	2799.20

		“Decline” and “little or no change”	121	0.38	169.28	387.61	0.109	1437.68
		“Average”	106	0.33	133.46	298.68	1.284	2457.21
Physical demands		“Faster than average” and “much faster than average”	145	0.46	157.01	407.27	0.05	2791.26
Controls	**Education**	Total	455	1	85.14	212.36	0.08	1928.94
		“Decline” and “little or no change”	153	0.34	51.53	162.74	0.109	1437.68
		“Average”	130	0.29	91.07	246.69	0.079	1928.94
		“Faster than average” and “much faster than average”	172	0.38	110.55	220.45	0.08	1627.18
	Experience	Total	391	1	179.14	323.81	0.31	3427.12
		“Decline” and “little or no change”	129	0.33	168.82	317.81	0.309	1622.70
		“Average”	109	0.28	202.83	419.62	0.466	3427.12
		“Faster than average” and “much faster than average”	153	0.39	170.97	241.44	2.49	1532.32
	Wages	Total	457	1	5728.8	2915.68	2326.67	23110

		"Decline" and "little or no change"	153	0.33	54773.53	25178.41	27920.00	246440.00
		"Average"	130	0.28	74653.31	41531.08	28130.00	277320.00
Controls		"Faster than average" and "much faster than average"	174	0.38	76617.59	33501.78	28370.00	173670.00

Appendix A.2

Table A.2: Predicted mean probability of an occupation being automated based on the Fractional Regression Model

Occupation	**Soc Codes**	**Predicted mean probablity**
Office clerks, general	43-9061	0.668
Bookkeeping, accounting, and auditing clerks	43-3031	0.663
Cashiers	41-2011	0.653
Receptionists and information clerks	43-4171	0.601
First-line supervisors of office and administrative support workers	43-1011	0.599
Secretaries and administrative assistants, except legal, medical, and executive	43-6014	0.590
Machinists	51-4041	0.583
Retail salespersons	41-2031	0.582
Hairdressers, hairstylists, and cosmetologists	39-5012	0.582
Packaging and filling machine operators and tenders	51-9111	0.580
Sewing machine operators	51-6031	0.576
Hosts and hostesses, restaurant, lounge, and coffee shop	35-9031	0.571
Medical secretaries and administrative assistants	43-6013	0.570
Waiters and waitresses	35-3031	0.566
Word processors and typists	43-9022	0.565
Maids and housekeeping cleaners	37-2012	0.565
Tutors	25-3041	0.563
Billing and posting clerks	43-3021	0.563
Office and administrative support workers, all other	43-9199	0.561
Hotel, motel, and resort desk clerks	43-4081	0.559
Human resources assistants, except payroll and timekeeping	43-4161	0.557
Public safety telecommunicators	43-5031	0.556
Medical records specialists	29-2072	0.552
Firefighters	33-2011	0.552
Order clerks	43-4151	0.552
Dispatchers, except police, fire, and ambulance	43-5032	0.552
Tellers	43-3071	0.551
Packers and packagers, hand	53-7064	0.551
Amusement and recreation attendants	39-3091	0.550

Food batchmakers	51-3092	0.550
Payroll and timekeeping clerks	43-3051	0.550
Eligibility interviewers, government programs	43-4061	0.548
Landscaping and groundskeeping workers	37-3011	0.545
Procurement clerks	43-3061	0.544
Dishwashers	35-9021	0.543
Court, municipal, and license clerks	43-4031	0.541
Community and social service specialists, all other	21-1099	0.541
Gambling cage workers	43-3041	0.541
Library assistants, clerical	43-4121	0.541
Janitors and cleaners, except maids and housekeeping cleaners	37-2011	0.541
Legal secretaries and administrative assistants	43-6012	0.539
Security guards	33-9032	0.538
Production, planning, and expediting clerks	43-5061	0.538
Laundry and dry-cleaning workers	51-6011	0.538
Food preparation workers	35-2021	0.537
Information and record clerks, all other	43-4199	0.536
Protective service workers, all other	33-9099	0.536
Architectural and civil drafters	17-3011	0.535
Cutting, punching, and press machine setters, operators, and tenders, metal and plastic	51-4031	0.534
Property, real estate, and community association managers	11-9141	0.534
Bus drivers, school	53-3051	0.534
Dental assistants	31-9091	0.533
Library technicians	25-4031	0.532
Sales representatives, wholesale and manufacturing, except technical and scientific products	41-4012	0.531
Computer numerically controlled tool operators	51-9161	0.531
First-line supervisors of entertainment and recreation workers, except gambling services	39-1014	0.530
Tax examiners and collectors, and revenue agents	13-2081	0.530
Locker room, coatroom, and dressing room attendants	39-3093	0.527
Cleaners of vehicles and equipment	53-7061	0.527
First-line supervisors of food preparation and serving workers	35-1012	0.526
Counter and rental clerks	41-2021	0.525
Recreation workers	39-9032	0.525

Rehabilitation counselors	21-1015	0.525
Customer service representatives	43-4051	0.522
Physical therapist aides	31-2022	0.520
Dining room and cafeteria attendants and bartender helpers	35-9011	0.519
Civil engineering technologists and technicians	17-3022	0.519
Industrial truck and tractor operators	53-7051	0.518
Machine feeders and offbearers	53-7063	0.518
Inspectors, testers, sorters, samplers, and weighers	51-9061	0.518
Lodging managers	11-9081	0.517
Adhesive bonding machine operators and tenders	51-9191	0.517
Bus drivers, transit and intercity	53-3052	0.517
Insurance sales agents	41-3021	0.517
Molding, coremaking, and casting machine setters, operators, and tenders, metal and plastic	51-4072	0.516
English language and literature teachers, postsecondary	25-1123	0.515
Paralegals and legal assistants	23-2011	0.514
Archivists	25-4011	0.514
Graphic designers	27-1024	0.514
First-line supervisors of personal service workers	39-1022	0.513
First-line supervisors of housekeeping and janitorial workers	37-1011	0.512
Compensation, benefits, and job analysis specialists	13-1141	0.512
Urban and regional planners	19-3051	0.512
Coating, painting, and spraying machine setters, operators, and tenders	51-9124	0.512
Dental hygienists	29-1292	0.511
Welders, cutters, solderers, and brazers	51-4121	0.510
Education and childcare administrators, preschool and daycare	11-9031	0.510
Drilling and boring machine tool setters, operators, and tenders, metal and plastic	51-4032	0.509
Animal caretakers	39-2021	0.508
Meeting, convention, and event planners	13-1121	0.507
Medical assistants	31-9092	0.506
Butchers and meat cutters	51-3021	0.506
Lifeguards, ski patrol, and other recreational protective service workers	33-9092	0.506
Mental health and substance abuse social workers	21-1023	0.505

Food service managers	11-9051	0.505
Bartenders	35-3011	0.504
Parts salespersons	41-2022	0.504
Teachers and instructors, all other	25-3099	0.504
Environmental science and protection technicians, including health	19-4042	0.504
Motorcycle mechanics	49-3052	0.503
Recreation and fitness studies teachers, postsecondary	25-1193	0.502
Furnace, kiln, oven, drier, and kettle operators and tenders	51-9051	0.501
Museum technicians and conservators	25-4013	0.500
Special education teachers, middle school	25-2057	0.500
Teaching assistants, postsecondary	25-9044	0.500
Light truck drivers	53-3033	0.499
Pourers and casters, metal	51-4052	0.498
Social and human service assistants	21-1093	0.498
Locksmiths and safe repairers	49-9094	0.498
Political science teachers, postsecondary	25-1065	0.497
Curators	25-4012	0.497
Epidemiologists	19-1041	0.497
Cost estimators	13-1051	0.496
Career/technical education teachers, secondary school	25-2032	0.495
Plumbers, pipefitters, and steamfitters	47-2152	0.495
Crane and tower operators	53-7021	0.495
Social and community service managers	11-9151	0.494
Recreational vehicle service technicians	49-3092	0.494
Shipping, receiving, and inventory clerks	43-5071	0.493
School psychologists	19-3034	0.492
Substitute teachers, short-term	25-3031	0.491
Veterinary technologists and technicians	29-2056	0.491
Clergy	21-2011	0.491
Maintenance workers, machinery	49-9043	0.491
Metal-refining furnace operators and tenders	51-4051	0.490
Pharmacy technicians	29-2052	0.490
Highway maintenance workers	47-4051	0.489
Loan officers	13-2072	0.489
Public relations specialists	27-3031	0.489
Construction and building inspectors	47-4011	0.488

Food scientists and technologists	19-1012	0.487
Entertainment and recreation managers, except gambling	11-9072	0.487
Automotive service technicians and mechanics	49-3023	0.487
Exercise trainers and group fitness instructors	39-9031	0.486
Librarians and media collections specialists	25-4022	0.486
General and operations managers	11-1021	0.485
First-line supervisors of construction trades and extraction workers	47-1011	0.485
Maintenance and repair workers, general	49-9071	0.484
Instructional coordinators	25-9031	0.483
Tapers	47-2082	0.482
Secondary school teachers, except special and career/technical education	25-2031	0.482
Administrative services managers	11-3012	0.482
First-line supervisors of production and operating workers	51-1011	0.482
Electro-mechanical and mechatronics technologists and technicians	17-3024	0.481
Carpenters	47-2031	0.481
Water and wastewater treatment plant and system operators	51-8031	0.481
Physical therapist assistants	31-2021	0.479
Fundraising managers	11-2033	0.479
Occupational health and safety specialists	19-5011	0.479
Computer network support specialists	15-1231	0.478
Childcare workers	39-9011	0.478
Cooks, institution and cafeteria	35-2012	0.477
Special education teachers, secondary school	25-2058	0.476
Heavy and tractor-trailer truck drivers	53-3032	0.476
Chefs and head cooks	35-1011	0.473
Managers, all other	11-9199	0.472
Laborers and freight, stock, and material movers, hand	53-7062	0.472
Control and valve installers and repairers, except mechanical door	49-9012	0.470
First-line supervisors of landscaping, lawn service, and groundskeeping workers	37-1012	0.469
Preschool teachers, except special education	25-2011	0.468
Educational, guidance, and career counselors and advisors	21-1012	0.468
Child, family, and school social workers	21-1021	0.468

Fast food and counter workers	35-3023	0.467
Software quality assurance analysts and testers	15-1253	0.465
Facilities managers	11-3013	0.464
Transportation, storage, and distribution managers	11-3071	0.463
Mobile heavy equipment mechanics, except engines	49-3042	0.462
Industrial production managers	11-3051	0.459
Electricians	47-2111	0.459
Elementary school teachers, except special education	25-2021	0.459
Purchasing managers	11-3061	0.459
Education administrators, kindergarten through secondary	11-9032	0.458
Environmental scientists and specialists, including health	19-2041	0.456
Licensed practical and licensed vocational nurses	29-2061	0.454
Installation, maintenance, and repair workers, all other	49-9099	0.451
Construction laborers	47-2061	0.449
Industrial machinery mechanics	49-9041	0.448
Human resources specialists	13-1071	0.447
Police and sheriff's patrol officers	33-3051	0.445
Market research analysts and marketing specialists	13-1161	0.444
Human resources managers	11-3121	0.442
Financial and investment analysts	13-2051	0.441
Electrical power-line installers and repairers	49-9051	0.439
Nurse midwives	29-1161	0.437
Painters, construction and maintenance	47-2141	0.432
Computer occupations, all other	15-1299	0.430
Sales representatives, wholesale and manufacturing, technical and scientific products	41-4011	0.429
Civil engineers	17-2051	0.429
Mechanical engineers	17-2141	0.427
Nursing assistants	31-1131	0.427
Electrical engineers	17-2071	0.422
Marketing managers	11-2021	0.420
Sales managers	11-2022	0.420
Construction managers	11-9021	0.418
Industrial engineers	17-2112	0.417
Personal financial advisors	13-2052	0.417
Middle school teachers, except special and career/technical education	25-2022	0.416

Architectural and engineering managers	11-9041	0.412
Network and computer systems administrators	15-1244	0.411
Heating, air conditioning, and refrigeration mechanics and installers	49-9021	0.411
Computer user support specialists	15-1232	0.408
Sales representatives of services, except advertising, insurance, financial services, and travel	41-3091	0.396
Financial managers	11-3031	0.395
Physician assistants	29-1071	0.393
Chief executives	11-1011	0.393
Medical and health services managers	11-9111	0.392
Cooks, restaurant	35-2014	0.391
Veterinarians	29-1131	0.387
Physical therapists	29-1123	0.378
Lawyers	23-1011	0.377
Computer and information systems managers	11-3021	0.373
Nurse practitioners	29-1171	0.360
Software developers	15-1252	0.335