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The Impact of Robotization on Productivity, Employment, and Wages: Evidence from Portuguese Firms

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Abstract

The rapid growth of robot adoption in firms all over the world has piqued the interest of many researchers, leading to the publishment of several pieces of literature regarding the effects of robotization. While some authors highlight the positive side of this new technology, such as higher wages (e.g., Compagnucci et al., 2019) and productivity (e.g., Graetz & Michaels, 2018), others focus on the negative issues, such as the possibility of the replacement of workers with robots (e.g., Arntz et al., 2016). There is, however, a gap in the literature regarding Portuguese firms. Studies like that of Amador and Silva (2023), Barbosa and Faria (2022), and Amador (2024) are fairly recent and focus more on the productivity side of the topic. Using microdata from *INE*'s *IUTICE, QP,* and *SCIE*, we aim to provide a worker and firm-level approach to the effects of robotization on productivity, employment, and wages in Portuguese firms, helping the general public, firms, and researchers interested in the topic understand how robotization is evolving in Portugal and how it may affect the levels of productivity and wages and even help understand if and which occupations are susceptible to automation. We find that both from a descriptive and econometric perspective, firms with robots tend to be more productive, engaged in higher value-added activities, and demand higher turnover values. These firms present a higher predominance of workers performing Routine Manual tasks and a lower prevalence of workers performing Non-Routine tasks, when compared with their counterparts that do not use robots. Lastly, workers in these firms are better paid and more qualified, across all types of tasks.

JEL Codes: D24; E24; J21; J24

Keywords: Robots, Total Factor Productivity, Labor Productivity, Wages, Employment

Resumo

O rápido crescimento da adoção de robôs em empresas de todo o mundo tem despertado o interesse de muitos investigadores, levando à publicação de vários artigos sobre os efeitos da robotização. Enquanto alguns autores destacam o lado positivo desta nova tecnologia, como o aumento dos salários (e.g., Compagnucci et al., 2019) e da produtividade (e.g., Graetz & Michaels, 2018), outros concentram-se nas questões negativas, como a possibilidade de substituição de trabalhadores por robôs (e.g., Arntz et al., 2016). Existe, no entanto, uma lacuna na literatura relativa às empresas portuguesas. Estudos como os de Amador e Silva (2023), Barbosa e Faria (2022), e Amador (2024) são bastante recentes e centram-se mais na vertente da produtividade. Utilizando microdados dos inquéritos IUTICE, QP e SCIE do INE, pretendemos fornecer uma abordagem ao nível do trabalhador e da empresa sobre os efeitos da robotização na produtividade, emprego e salários nas empresas portuguesas, ajudando o público em geral, as empresas e os investigadores interessados no tema a compreender como a robotização está a evoluir em Portugal e como pode afetar os níveis de produtividade e salários e até mesmo ajudar a compreender se e quais as profissões são suscetíveis à automação. Verificamos que, tanto de uma perspetiva descritiva como econométrica, as empresas com robôs tendem a ser mais produtivas, a envolver-se em atividades de maior valor acrescentado e a exigir valores de volume de negócios superiores. Estas empresas apresentam uma maior predominância de trabalhadores a desempenhar tarefas rotineiras manuais e uma menor prevalência de trabalhadores a desempenhar tarefas não rotineiras, quando comparadas com as suas congéneres que não usam robôs. Por último, os trabalhadores destas empresas são mais bem pagos e mais qualificados, em todos os tipos de tarefas.

Códigos JEL: D24; E24; J21; J24

Palavras-Chave: Robôs, Produtividade Total dos Fatores, Produtividade do Trabalho, Salários, Emprego

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1. Introduction

Over the past decade, the global robot stock has been rapidly increasing (Figure A1[1]), reaching almost 4 million operational industrial robots in 2022, due to the growing incorporation of robots in industries and services. While industrial robots are mostly concentrated in subsectors of manufacturing industries such as "Electronics, Automotive, and Metal and Machinery" (Figure A2[2]), service robots are most present in "Transportation and Logistics" and are making their way into the "Hospitality" sector (Figure A3[3]), either supporting or replacing employees in service encounters (Tuomi et al., 2020). Their importance is so significant that some authors consider it the "most important innovation that has impacted the production process in the past three decades" (Compagnucci et al., 2019, p. 6127).

Although there are many studies on automation and its consequences, the lack of literature on the Portuguese economy is evident. Mainly due to the lack of data, Portugal is only mentioned in OECD-level studies (OECD, 2019), at a national level (a firm-level approach might yield different results). Studies such as those of Amador and Silva (2023), Barbosa and Faria (2022), and Amador (2024), who use the same database as us, focus more on the productivity effect of Information and Communication Technologies (including automation). Thus, it seems valuable to perform a similar study using the most recent data available, while also extending it to assess the impact of automation on employment and wages.

Hence, this research aims to help fill the mentioned gap, by studying the impact of robotization on Portuguese companies' productivity, employment, and wages using microdata at the firm level, provided by *Instituto Nacional de Estatística* (*INE*). Therefore, the goals of this dissertation are to characterize the use of robots among Portuguese firms (by industry, size, age, and location) and to assess the correlation between robotization and productivity, employment, and wages.

This research holds relevance for a wide audience, including the general public, firms, and researchers interested in the subject, since it provides empirical evidence on the impact

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[1] Figure A1, in the annex, presents the Worldwide Operational Stock of Industrial Robots

[2] Figure A2, in the annex, presents the Worldwide Annual Installations of Industrial Robots by Consumer Industry

[3] Figure A3, in the annex, presents the Top 5 Application Areas for Service Robots in 2022

of automation on productivity (i.e. by assessing if firms with robots tend to have higher productivity than those without), employment (i.e. by examining the extent to which robots replace human workers) and wages (i.e. by assessing if firms with robots tend to pay higher wages than those without), while also addressing the gap in the existing literature, building upon the existing studies and providing a foundation for future research.

Therefore, the main research questions that we aim to answer are: "Are Portuguese firms that use robots more productive?", "Does the use of robots affect employment in Portuguese firms? How and to what extent is it affected?", and "Is there any correlation between robotization and wages in Portuguese firms?".

From our analysis, we show that firms only using industrial robots and firms using both types of robots[4] tend to be more productive than those that do not utilize robots, with special relevance to the latter. On the other hand, concerning the value added per worker of the activities in which these firms engage and their turnover (per worker), we show that only firms that employ both types of robots present significantly higher values. Regarding employment, we find that firms with robots have a higher predominance of workers performing Routine Manual tasks than firms that do not rely on robots, even though there appears to be a downward trend in this type of task. Perhaps we are dealing with a case of reverse causality: it is not because firms use robots that there is an increased need for Routine Manual tasks, but on the contrary, it is because firms have an above-average need for Routine Manual tasks that leads them to implement the usage of robots in their firms. On the other hand, despite an upward trend in workers performing mainly Non-Routine tasks, these seem to be more common in robot-free firms than in their robot-using counterparts. In terms of the workforce, companies with robots generally feature a greater share of men and more qualified workers. As for the wage analysis, we conclude that workers in firms equipped with robots tend to be paid higher monthly and hourly wages, especially when the firms employ both types of robots. This assessment remains true across the various types of tasks, even though we note a larger difference in Non-Routine Cognitive tasks.

This dissertation is structured as follows: after this introductory chapter, the second chapter presents a review of literature related to automation, covering key concepts (Automation, Industrial, and Service robots) and existing studies that analyze its impacts on

[4] (Industrial and Service Robots)

productivity, employment, and workers' wages. The third chapter describes the methodology. The fourth chapter presents the empirical results. The last chapter presents the main conclusions.

2. Literature review

2.1. Concepts: Automation, Industrial and Service Robots

Although the concepts of Automation and Robots are not new, they are still evolving, thus giving importance to first understanding how these terms appeared and only then to ascertain their impacts in today's lives.

The concept of Automation comprises several technologies and was present in all stages of the Industrial Revolution. From mechanical production based on steam and water to conveyor belts and mass production to digital automation of production (i.e. using IT technologies), and, finally, contemporary automation (i.e. based on Robots, Artificial Intelligence, etc.) (Kamarul Bahrin et al., 2016), the concept has constantly been evolving. This research will focus on the robotic side of the Fourth Industrial Revolution automation.

As stated before, the fourth stage of the Industrial Revolution introduced autonomous robots as one of its key drivers (Kamarul Bahrin et al., 2016). Ever since the last decades of the 20th century, they have evolved considerably, "becoming more productive, flexible, versatile, safer and collaborative" (Kamarul Bahrin et al., 2016, p.138).

However, not all robots are identical. It is important to distinguish between Industrial and Service robots[5].

According to *INE*, Industrial Robots are:

> "Automatically controlled, reprogrammable, multipurpose manipulators programmable in three or more axes, in a fixed or mobile location for use in industrial automation. Most industrial robots are based on a robotic arm with a solid base and a series of links and joints that end in an effector (finisher) that performs tasks". (e.g., cartesian robots, SCARA robots, articulated robots, polar robots, etc.).

On the other hand, according to *INE*, Service Robots are:

> "Machines that have a degree of autonomy capable of operating in a complex and dynamic environment, which may require interaction with people, objects, or other devices. They use wheels or legs to achieve mobility and are often used in

[5] In this research we will not take into account software robots (computer programs) due to the lack of data regarding the usage of those types of robots in Portuguese firms

inspection, transport, or maintenance tasks." (e.g., autonomous vehicles, robots' inspection and maintenance, cleaning robots, etc.).

2.2. Impact on Productivity

Having clearly defined the key concepts of this research, it is now useful to review some of the existing literature regarding the automation of tasks and jobs (Arntz et al., 2016) and its implications for productivity (Cette et al., 2021; Graetz & Michaels, 2018; etc.).

Cette et al. (2021) estimate robots' contribution to productivity growth, through capital deepening and Total Factor Productivity (TFP), using data from 30 countries from 1975 to 2019. According to the authors, in most OECD countries (including the USA) between 1975 and 2019, productivity growth due to robotization did not exceed 0.2 pp. per year, with Germany (from 1996 to 2005) and Japan (from 1976 to 1995) being outliers and experiencing the largest productivity growth due to robots (0.7 pp. and 0.87 pp., respectively) (Cette et al., 2021). At the same time, they conclude that this contribution seems more meaningful at a firm level rather than at a country level (Cette et al., 2021). Finally, the authors suggest that "robotization has not been the source of a significant revival in productivity" (Cette et al., 2021, p.4).

On the other hand, Graetz and Michaels (2018) estimate the effects of industrial robots on productivity, wages, employment, and output prices using panel data, at an industry-level, from 1993 to 2007 in 17 countries, making use of the IFR[6] for data on robot usage and EU KLEMS[7] for data on inputs, outputs, and prices. Using an econometric approach, they estimate that greater robot usage increased annual labor productivity by 0.36 pp., while also increasing TFP (Graetz & Michaels, 2018). Additionally, they find that each increase in robot density produced increasingly smaller productivity gains (diminishing marginal returns) (Graetz & Michaels, 2018).

Similarly, Acemoglu and Restrepo (2019, p.4) state that "by allowing a more flexible allocation of tasks to factors, automation technology also increases productivity", through a "productivity effect".

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[6] International Federation of Robotics

[7] EU-level analysis of capital (K), labor (L), energy (E), materials (M), and service (S) inputs

Gentili et al. (2020) point out that the debate regarding the impact of robotization on the labor market will be divided between optimists and pessimists, however "the two stances may not be contradictory" (Gentili et al., 2020, p.153). They perform a cross-country and cross-sector cluster analysis and conclude that the cluster with the highest robotization presents higher productivity and is composed of high-technology industries (Gentili et al., 2020). As concluded by the authors, "Overall, the results seem to be in line with the optimistic view" (Gentili et al., 2020, p.168) of the future of the labor market.

At this point, it seems rational to conclude that robotization tends to increase productivity. However, this effect is not linear across different industries and firm sizes. Corroborating this, Barbosa and Faria (2022) determine the impact of some digital technologies on the productivity of Portuguese firms, from 2014 to 2019. On the one hand, the authors find that robots positively impact productivity in high-tech firms (but only when used in conjunction with other ICT investments) and in Small and Medium Enterprises (SME) (limited to laggard firms and independent of other ICT investments) (Barbosa & Faria, 2022). On the other hand, their empirical results suggest that, overall, "Portuguese firms investing in robotic technologies are still not able to extract productivity gains, even when combined with different degrees of ICT intensity and sophistication" (Barbosa & Faria, 2022, p.13). Nevertheless, taking into account that there is more recent data available than that used in the literature, it is beneficial to assess whether or not Portuguese firms that use of robots tend to have higher productivity values than those that do not make use of them, using the most recent available data. It also seems valuable to distinguish the impact of robotization on productivity (and on employment and wages) according to the type of robot used in the firm (Only Industrial Robots vs Only Service Robots vs Both Types of Robots).

The differences in results from the studies referred to above can be explained by the contingency of the effect of robotization on productivity upon contextual factors, which differ across space and time, as is the case with many technological advancements. Truly, there is a sensitivity of robotization to the country and industry context (Gentili et al., 2020).

2.3. Impact on Employment

Unlike its effect on productivity, the impact of automation on employment seems straightforward, with low-skilled workers being prone to replacement by robots and high-skilled workers prone to have their jobs complemented and facilitated by robots.

According to Acemoglu and Restrepo (2019, p. 27), "Automation, by creating a displacement effect, shifts the task content of production against labor, while the introduction of new tasks in which labor has a comparative advantage improves it via the reinstatement effect". Contrary to popular belief, automation will not put workers instantly out of their job, much due to the fact that the adoption of new technologies (such as robots) is "a slow process, due to economic, legal and societal hurdles" (Arntz et al., 2016, p.4).

Therefore, workers can switch tasks to prevent unemployment, moving to jobs created due to the use of robots. However, not all workers will have to reskill or upskill. In fact, according to Arntz et al. (2016, p.4), "Low-qualified workers are likely to bear the brunt of the adjustment costs as the automability of their jobs is higher compared to highly qualified workers". Additionally, Arntz et al., (2016) find that, on average, across 21 OECD countries, only 9% of jobs are prone to automatization. Similarly, Vermeulen et al. (2018, p.19), state that "technology-affected occupations contained in the making and applying sectors is -roughly- at most 20% of the jobs".

Corroborating the conclusions above, OECD (2019), using IFR data, finds that robotization leads to an increase in the number of professionals (high-skilled workers), with an average change of nearly 21% in this category of workers, across the countries in the sample (Portugal presents one of the highest changes, with a 30% increase). On the other hand, the authors find that robotization leads to a decrease in elementary occupations (-5.1%) in terms of employment in the majority of the countries in the sample (Portugal presents a 9% decrease) (OECD, 2019), clearly showing that the Portuguese workforce has been more impacted by automation than most countries.

In the agricultural sector, Marinoudi et al. (2021) find that more than 80% of the agricultural workforce engages in manual tasks and that there is strong evidence that 70% of the agricultural domain is susceptible to robotization. Additionally, only 3% of the workforce engages in cognitive routine tasks (which can be partially robotized) and 9% engages in cognitive non-routine tasks (which have a low probability of robotization) (Marinoudi et al., 2021).

Thus, we can conclude that robotization induces a shift in the workers' qualifications required by companies. Routine manual tasks, which usually are performed by low-skilled workers, will be gradually automated and the new tasks created by the emergence of robots (mainly cognitive routine and non-routine tasks, performed by high-skilled workers) will be on demand. Contrary to most ICT technologies, robots do not polarize the labor market (Graetz & Michaels, 2018). Indeed, robot technology is skill-biased, hurting the "relative position of low-skilled workers rather than the middle-skilled ones" (Graetz & Michaels, 2018, p.755).

2.4. Impact on Wages

The impact of automation on wages, much like its impact on productivity, varies depending on the institutional environment of the countries and the period being studied. Thus, the conclusions and relationships established between robotization and wages, are diverse and sometimes ambiguous.

In the USA, a study by Acemoglu and Restrepo (2020) concludes that from 1990 to 2007, for every additional robot per thousand workers, wages decreased by 0.42%. However, this study is contradicted by that of Sequeira et al. (2021), in which the authors state that the relationship between automation and wages is, for the same period, U-shaped, meaning that automation leads to a decrease in wages and then an increase, "after a given level of robots' penetration within industries" (Sequeira et al., 2021, p.115).

Still in the USA, Chung and Lee (2022) examine the five-year intervals within the period from 2005 to 2016 and conclude that robots' exposure effect on local wages is initially negative but turns positive in the later intervals (which may not be conflicting with the U-shaped curve mentioned by Sequeira et al. (2021)).

On a more international scale, Graetz and Michaels (2018), in addition to the conclusions already discussed in chapter 2.2 of this research, state that robotization also leads to higher wages, although to a smaller extent than the estimated effect on productivity.

In the OECD, Compagnucci et al. (2019) find that, from 2011 to 2016, robotization growth led to an increase in hourly wages. Additionally, the authors conclude that the industries where robotization grows at a faster pace present a slower real wage growth, suggesting "that the substitution effect is larger than the complementary effect between robots and humans in these sectors" (Compagnucci et al., 2019, p.613).

Aksoy et al. (2021) also conclude that robotization leads to an increase in wages, in 20 European countries, from 2006 to 2014. However, they find that the wage increase is not the same for all workers. In fact, the gender pay gap is worsened due to robotization, with a 10% increase in robotization leading to a 1.8% increase in the gender pay gap (Aksoy et al., 2021). The authors explain the reasons for this effect, with it being mostly due to the countries that already had high inequality levels and due to men getting paid more than women in occupations that require higher skills.

The effect of automation on wage inequality is not new in the literature. In fact, it is discussed in studies like that of Acemoglu and Restrepo (2018), Lankisch et al. (2019), and Brezis and Rubin (2023). However, these studies present different perspectives on the subject.

Acemoglu and Restrepo (2018), unlike other studies that examine the effect of automation on wage inequality, and by taking a task-based approach, distinguish the impact of automation on wage inequality between low-skill automation and high-skill automation. According to the authors, while low-skill automation (i.e. automation of tasks previously performed by low-skill workers) leads to an increase in wage inequality, high-skill automation (i.e. automation of tasks previously performed by high-skill workers) leads to a decrease in wage inequality (Acemoglu & Restrepo, 2018).

Lankisch et al. (2019), relying on a model of economic growth, point out the importance of investments in higher education to mitigate the negative effects of automation. According to the authors, automation leads to a reduction of the wages of low-skill workers and may even reduce the wages of high-skill workers (in what Acemoglu and Restrepo (2018) call "ripple effects") (Lankisch et al., 2019). Additionally, automation raises the skill premium (raising wages for highly educated workers) (Lankisch et al., 2019), hence giving importance to investments in higher education as a mechanism to raise the share of high-skill workers in the economy (who are less prone to automation) and to help reduce, or at least mitigate, the effect of automation on wage inequality (Lankisch et al., 2019).

Furthermore, also regarding wage inequality due to automation, Brezis and Rubin (2023) provide an additional layer of complexity to the subject. According to the authors, there is not just a single type of skilled worker and education. Instead, there are two types of each: high-ability and low-ability skilled workers and elite and standard universities, with the difference between the two types of education being the "elitism gap", which allows the separation of high- and low-ability workers (Brezis & Rubin, 2023). Therefore, the students graduating from elite universities go on to become high-ability workers in the high-tech sector, while the students graduating from standard universities become low-ability workers in low-tech industries (Brezis & Rubin, 2023). Automation thus increases wage inequality due to affecting the "matching effect" between abilities and education (Brezis & Rubin, 2023). Finally, the authors conclude that "the narrative with robots is not about robotics but about the intelligence of human beings" (Brezis & Rubin, 2023, p.15) and that inequality is the cost of being at the frontier of technology.

3. Data Description

3.1. Databases

For this research, we use three annual inquiries provided by *INE*: *Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas* (*IUTICE*), *Quadros de Pessoal* (*QP*), and *Sistema de Contas Integradas das Empresas* (*SCIE*).

The *IUTICE* survey aims at providing information regarding ICT usage in a representative sample of Portuguese Firms. This survey is not a standardized administrative procedure, and thus, each year, the questions asked and the firms answering those questions vary, leaving us with an unbalanced panel data, meaning that some firms only appear in one year, others appear in two and some appear in all three. Considering this, we only make use of three spells of the survey (2018, 2020, and 2022 - the ones that contain questions regarding robot usage). The process of cleaning and preparing the data for the empirical analysis was demanding, mostly due to conflicting value labels. In fact, a downside to *IUTICE* not being a standardized inquiry was that merging data from different spells resulted in conflicting value labels, which required manual manipulation, in each spell, to allow for the correct merging.

Moving to the second database, *QP* is a survey collected by the Portuguese Ministry of Labor, resulting from an administrative procedure. The data refers to the month of October of each year and has the geographic scope of the country (Mainland and Autonomous Regions). The obligation to submit the "*Quadros de Pessoal*" concerns all entities with workers at their service (in the private sector), apart from central, regional, and local administration and public institutes (for these entities it only applies to workers under individual employment contracts) and domestic service workers. Thus, the data covers virtually the entire population of firms in the private sector and its workers, and it does not suffer from sample selection bias problems. This dataset includes information on firms (e.g., capital, ownership, economic activity, number of workers, the volume of sales, location, etc.), establishments (e.g., number of workers, location, nature of the economic activity, etc.), and workers (e.g., age, gender, wage, education level, tenure, type of contract, hours worked, etc.). For this research, we use six spells of *QP*, from 2016 to 2021 (the most recent available data), regarding firms and workers (we do not use the establishments database). The process of "cleaning" and preparing the data for analysis was relatively simple for this database, as *QP* results from an administrative procedure (as mentioned above), and therefore, is already well documented and presents few errors. Moreover, since the inquiry was standardized across the years, there were no problems regarding conflicting labels (contrary to what happened in the *IUTICE* database).

Regarding *SCIE*, its main objective, as stated before, is to characterize the economic-financial behavior of companies. This is made possible through variables with significant relevance to the business sector and financial ratios commonly used in corporate financial analysis. Additionally, based on demographic indicators about companies, the dataset contains information regarding the status of companies (i.e. active, inactive, etc.) and the number of people employed. The database comprises all companies (partnerships, sole proprietors, and independent workers) that carry out a production activity of goods and/or services during that period in the country, except for financial and insurance companies and entities that are not market-oriented (non-profit organizations), namely central and local public administration units, and various associative activities. For this study, we use seven spells of *SCIE*, from 2016 to 2022. Almost all the firms present in *QP* are present in *SCIE*, but unlike *QP*, the *SCIE* dataset has some missing values. After dropping them and keeping the relevant variables, we chose a few measures of performance (among the many that could be inferred from the data) that seemed most fit for the research we intend to conduct. Those measures are Total Production per Worker Employed (in Real Terms), Real Value Added per Worker (at Factor Costs), and Real Firm Turnover (all the values were discounted at the official Consumer Price Index[8], according to *INE*).

3.2. Sample

The sample we use is different for each analysis since the databases being used vary (e.g., to assess the impact of robots on wages, we use *QP* and *IUTICE*, but to assess the impact on productivity, we use *SCIE* and *IUTICE*). Instead of merging all three databases and performing the descriptive analysis with the same sample, we decided to maximize the number of observations in each analysis, by minimizing the number of databases being used (merging all databases meant losing more observations).

[8] Base year 2012 = 100

Our main database, the *IUTICE* inquiry, is composed of 6,375 firms for 2018, 6,141 firms for 2020, and 6,992 firms for 2022, making a total of 19,508 observations (see Table 1). In a given year, each observation corresponds to a different firm, and across the three years, there are 15,198 unique firms (see Table 2), with most of them (12,356 - 81.30%) only appearing once in the dataset and only 1,468 (9.66%) appearing in all three years (see Table 2), making it difficult to assess the impacts of robotization in the long term.

Table 1 – Number of Observations in *IUTICE* (Portugal - 2018, 2020 & 2022)

Year	N	Percent
2018	6,375	32.68
2020	6,141	31.48
2022	6,992	35.84
Total	**19,508**	**100.00**

Source: *IUTICE* and Own Calculation

Table 2 – Number of Times a Firm Appears in *IUTICE* (Portugal - 2018, 2020 & 2022)

Number of Times	N	Percent
1	12,356	81.30
2	1,374	9.04
3	1,468	9.66
Total	**15,198**	**100.00**

Source: *IUTICE* and Own Calculations

Finally, Table 3 shows how the sample is reduced when merging *IUTICE* with the other databases we use. As we can verify, when merging *IUTICE* with *SCIE*, the number of firms drops to 15,013. On the other hand, when merging it with *QP*, the number of unique firms drops to 9,288.

Table 3 – Matched Observations and Firms across Databases

Database	***IUTICE*** 2018, 2020 & 2022	***IUTICE + SCIE*** 2018, 2020 & 2022	***IUTICE + QP*** 2018 & 2020
Matched Observations*	19,508	19,291	1,694,520
Matched Unique Firms	15,198	15,013	9,288

Note: * In the case of *IUTICE + SCIE*, each observation corresponds to a firm that appeared in both databases. In the case of *IUTICE + QP*, each observation corresponds to a worker that appeared in both databases.
Source: *IUTICE*, *QP*, and *SCIE* and Own Calculations

4. Robots and Firms Characteristics

We are, at this point, able to present and discuss the main findings of this study. As stated before, the descriptive analysis is divided into four subchapters and is followed by the econometric analysis.

4.1. Robots Usage

Table 4 presents the distribution of firms in terms of Robot Usage. We can see that there are 1,070 firms that use industrial robots, 382 that use service robots, and 372 that use both types, across the three spells, meaning that observations of firms with at least one kind of robot represent only 9.35% of the sample. Since a firm can appear more than once in the dataset (Table 2), these numbers of Robot Usage might be lower when considering unique firms.

Table 4 – Distribution of Firms by Robot Usage (Portugal - 2018, 2020 & 2022)

Industrial Robots	**Service Robots**		**Total**
	YES	**NO**	
2018			
YES	94	337	431
%	21.81	78.19	100.00
NO	104	5,840	5,944
%	1.75	98.25	100.00
Total	**198**	**6,177**	**6,375**
%	**3.11**	**96.89**	**100.00**
2020			
YES	110	363	473
%	23.26	76.74	100.00
NO	140	5,528	5,668
%	2.47	97.53	100.00
Total	**250**	**5,891**	**6,141**
%	**4.07**	**95.93**	**100.00**
2022			
YES	168	370	538
%	31.22	68.77	100.00
NO	138	6,316	6,454
%	2.14	97.86	100.00
Total	**306**	**6,686**	**6,992**
%	**4.38**	**95.62**	**100.00**
Total			
YES	372	1,070	1,442
%	25.80	74.20	100.00
NO	382	17,684	18,066
%	2.11	97.89	100.00
Total	**754**	**18,754**	**19,508**
%	**3.87**	**96.13**	**100.00**

Source: *IUTICE* and Own Calculations

Additionally, in 2018 and 2020, the *IUTICE* inquiry contained questions regarding the tasks in which firms employed service robots, and among the most common answers were "Warehouse Management Systems", "Security, Surveillance or Inspection", and "Assembly Work" (see Table 5). In 2022, these questions were replaced by questions regarding the reasons why firms used robots, and the most popular reason was "To Ensure High Precision or Standardized Quality", followed by "To Increase Safety at Work", and "To Expand the Variety of Goods Produced or Services Provided" (see Table 6).

Table 5 – Type of Tasks Performed by Service Robots (Portugal - 2018, 2020 & 2022)

Tasks Performed by Service Robots	N
Surveillance, Security, or Inspection	158
Transport of People and Goods	81
Cleaning	106
Warehouse Management Systems	259
Assembly Work	114
Automatic Replenishment Tasks in Store	30
Construction or Damage Repair	38
Total	**786**

Note: Firms can indicate more than one type of task, hence explaining why the total is higher than the number of firms with service robots.
Source: *IUTICE* and Own Calculations

Table 6 – Reasons Why Firms Use Robots (Portugal - 2018, 2020 & 2022)

Reasons Why Firms Use Robots	N
High Salary Costs	126
Difficulties in Recruiting Human Resources	172
To Increase Safety at Work	475
To Ensure High Precision or Standardized Quality	579
To Expand the Variety of Goods Produced or Services Provided	341
Subsidies or Other Government Incentives	93
Total	**1,786**

Note: Firms can indicate more than one reason to use robots, hence explaining why the total is higher than the number of firms with robots.
Source: *IUTICE* and Own Calculations

Having seen how firms are distributed according to their Robot Usage, and the main tasks and reasons these firms employ robots, it is also important to determine in which activity sectors these firms are present. We do this by merging *IUTICE* with *QP* since the *Códigos de Atividade Económica*[9] available in *IUTICE* are incorrect/outdated and do not allow

[9] Codes used in Portugal to classify each firm in terms of their business activity

for the proper classification of firms. We can observe, in Table A1[10], that firms with robots are mainly present in "Manufacturing Industries" (out of the 1,091 observations of firms that report using robots, 823 belong to this sector – around 75.44%), followed by "Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles" (out of the 1,091 observations, 113 belong to this sector – almost 10.36%), and "Transports and Storage" (out of the 1,091 observations, 32 belong to this sector – nearly 2.93%). However, these are also some of the most widely represented sectors in the sample. It is thus necessary to assess the concentration levels of firms with robots in each sector, instead of analyzing the absolute values. Following this logic, we can state that, in this sample, firms that only use industrial robots are most concentrated in "Manufacturing Industries", with roughly 18.92% of the observations in that sector. On the other hand, observations of firms with only service robots are more concentrated in "Water collection, Treatment and Distribution, Sanitation, Waste Management, and Depollution", with nearly 7.06% of the observations in that sector. Finally, observations of firms that report using both types of robots, similarly to those that only use industrial robots, are mostly concentrated in "Manufacturing Industries", representing 4.94% of the observations in that sector. Overall, "Manufacturing Industries" is clearly the sector of activity where robots are mostly used, with just over 26.04% of the firms in that sector reporting using robots regardless of type, in this sample.

4.2. Robotization and Firms' Productivity

As stated before, for this analysis we calculated three performance indicators from the data available at *SCIE*, namely Real Productivity (production value, per worker, at constant prices of 2012, using the CPI), Real Value Added per Worker, at Factor Costs (the measure of value-added, per worker (at factor costs), available in *SCIE*, at constant prices of 2012, using the CPI), and Real Firm Turnover per Worker (the measure of business volume available in SCIE, per worker, at constant prices of 2012, using the CPI). We also eliminated what we considered outliers in the sample.

Before analyzing the impact of robotization on productivity, we first begin this subchapter by examining a wider period than that for which we have robot usage data to assess if the evolution of productivity and the other performance indicators was abnormal in the small period for which we have that data. For this purpose, we use the spells of *SCIE*

[10] Table A1, in the annex, presents the Distribution of Firms by Robot Usage and Sector of Activity

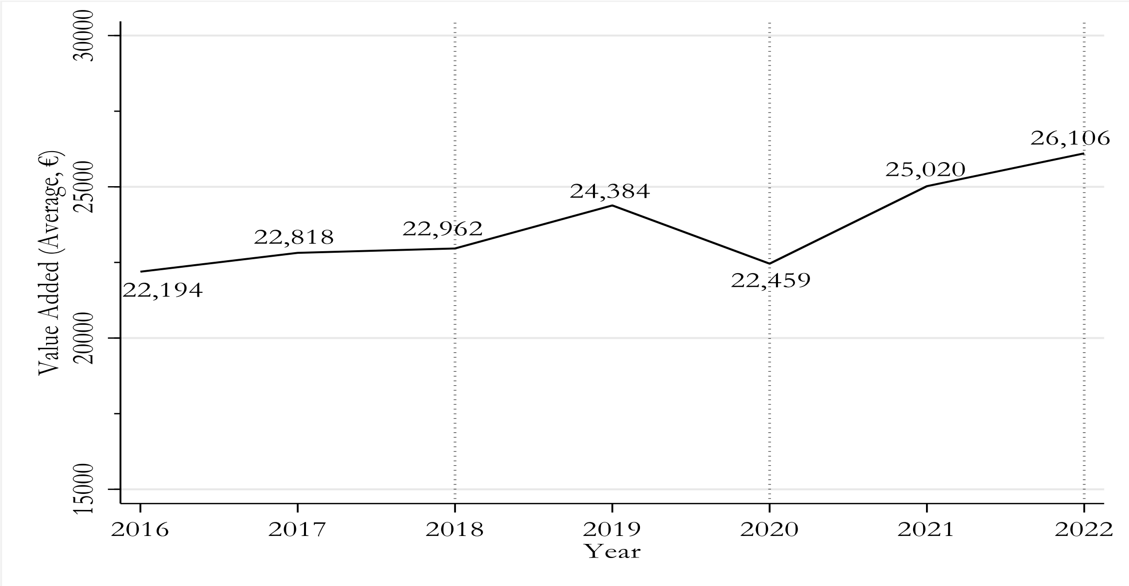
from 2016 to 2022 and obtain figures 1, 2, and 3 (each showing the evolution of one of the indicators we chose). Figure 1 shows the evolution of Real Average Productivity, in Portuguese firms, from 2016 to 2022. It is clear, that besides an overall steady growth of productivity, there was an abrupt decline in 2020 (almost certainly due to the COVID-19 pandemic and its respective lockdowns), that quickly bounced back in 2021 (when there were no longer lockdowns due to the pandemic) and grew by almost 7.3% in 2022. Overall, between 2016 and 2022, Real Average Productivity in Portuguese Firms grew by 15%.

Figure 1 – Real Average Productivity (€) (Portugal - 2016/2022)

Source: *SCIE* and Own Calculations

Concerning Real Value Added per Worker (at Factor Costs), Figure 2 shows the evolution of this indicator for the same period analyzed above, and by comparing the two figures, we see a similar evolution of the two indicators. Overall, between 2016 and 2022, the Average Real Value Added per Worker (at Factor Costs), grew in Portuguese Firms by nearly 17.63%.

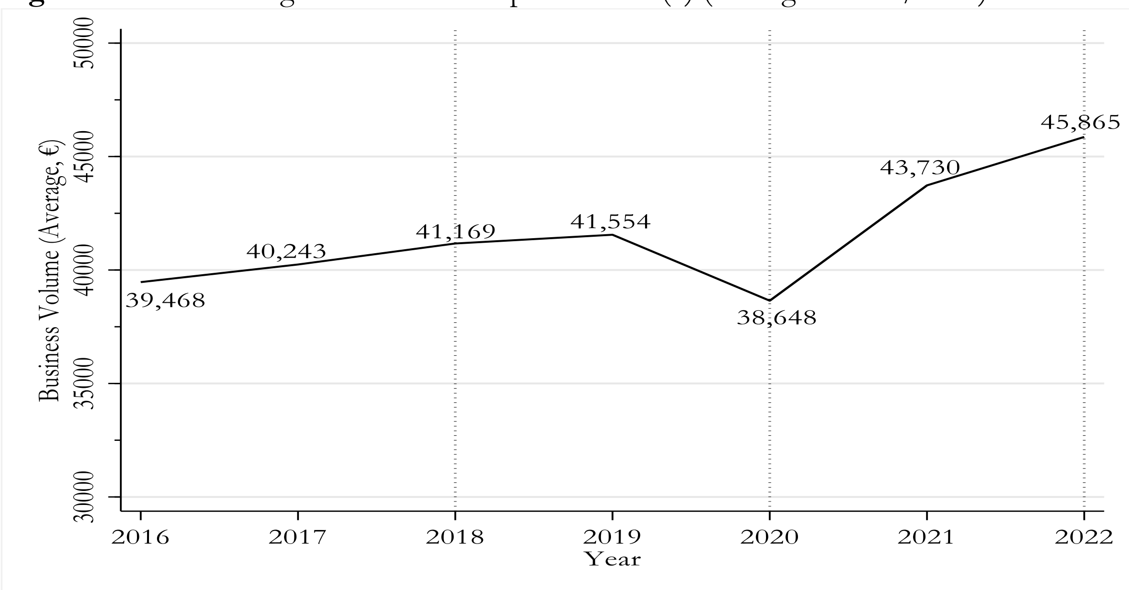
Figure 2 – Real Average Value Added per Worker (at Factor Costs, €) (Portugal - 2016/2022)



Source: *SCIE* and Own Calculations

Finally, Figure 3 shows the evolution, for the same period, of Real Average Firm Turnover per Worker. Once again, the similarity of the evolution of this indicator with those analyzed before is evident. Out of the three indicators, this one was the least affected by the pandemic, falling by only 7% in 2020. Overall, between 2016 and 2022, Real Average Firm Turnover per Worker grew in Portuguese Firms by roughly 16.21%.

Figure 3 – Real Average Firm Turnover per Worker (€) (Portugal - 2016/2022)



Source: *SCIE* and Own Calculations

Having examined the evolution of these indicators, our analysis regarding the impact of robotization on productivity and other performance indicators must bear in mind that the pandemic heavily affected firms, especially in 2020, when analyzing the results obtained.

Starting with a simple analysis of means (Table 7), we find that, in the sample of firms present both in *IUTICE* and *SCIE*, the ones that employ both types of robots are the most productive (€244,096.03), followed by firms with only industrial robots and firms with only service robots. Firms without robots exhibit, on average, the lowest value of productivity (€162,008.42). This analysis is corroborated by an analysis of the median values, with firms using both types of robots widening their lead and appearing as more than twice as productive than firms without robots (€117,810.20 vs €50,489.81).

Table 7 – Real Productivity (€), by Robot Usage (Portugal - Average 2018, 2020 & 2022)

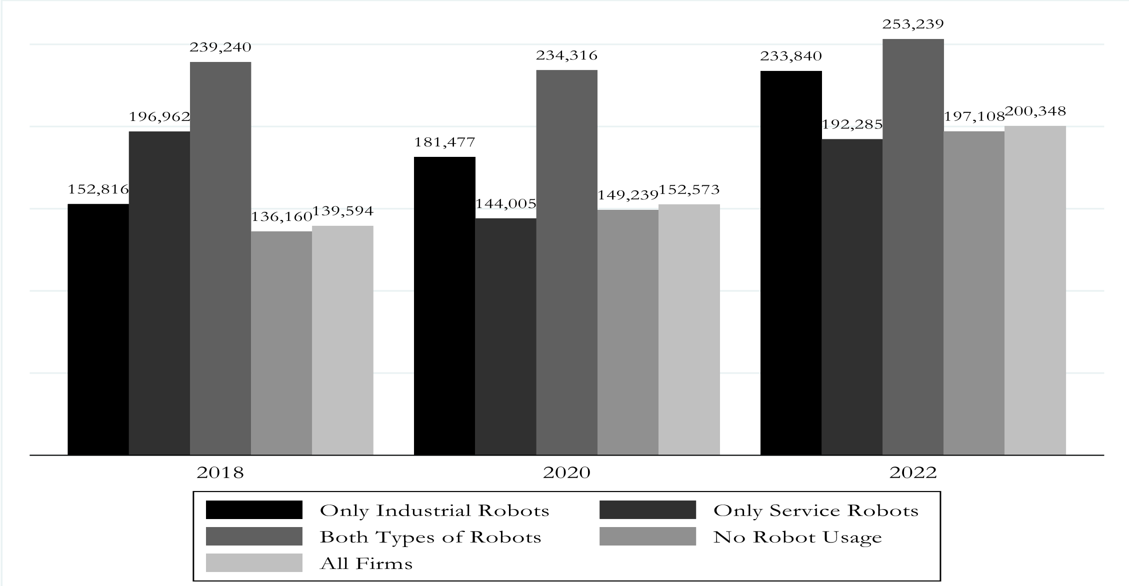
Robot Usage	N	Median	Mean	Min	Max
Only Industrial Robots	1,061	99,868.99	190,746.46	3.245	7,999,344
Only Service Robots	379	72,025.86	175,861.38	4,354.48	4,529,463
Both Types of Robots	368	117,810.20	244,096.03	4,903.69	3,117,212
No Robot Usage	17,338	50,489.81	162,008.42	0.00	10,203,524

Note: The top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command

Source: *IUTICE*, *SCIE*, and Own Calculations

Figure 4 shows the evolution of this indicator between 2018 and 2022, and, contrary to what was observed in the full sample (Figure 1), Real Average Productivity in this sample did not drop in 2020 and even increased (slightly), with only the mean productivity of firms with service robots and firms with both types decreasing in that year. We also observe an increase in the productivity of firms with industrial robots, which almost reached that of firms with both types of robots, in 2022. Additionally, the Real Average Productivity of the whole sample was much higher than that shown in Figure 1, meaning that firms present in *IUTICE* & *SCIE* are overall more productive than those present only in *SCIE*. Indeed, in 2018, the value of the *IUTICE* & *SCIE* sample was nearly 2.3x greater than the value of the *SCIE* sample, and that discrepancy grew to almost 3x, in 2022.

Figure 4 – Real Average Productivity (€), by Robot Usage (Portugal - 2018, 2020 & 2022)



Source: *IUTICE*, *SCIE* and Own Calculations

Moving on to the second indicator we chose, Table 8 presents some descriptive statistics of the Real Value Added per Worker (at Factor Costs), by Robot Usage.

Table 8 – Real Value Added per Worker (at Factor Costs, €), by Robot Usage (Portugal - Average 2018, 2020 & 2022)

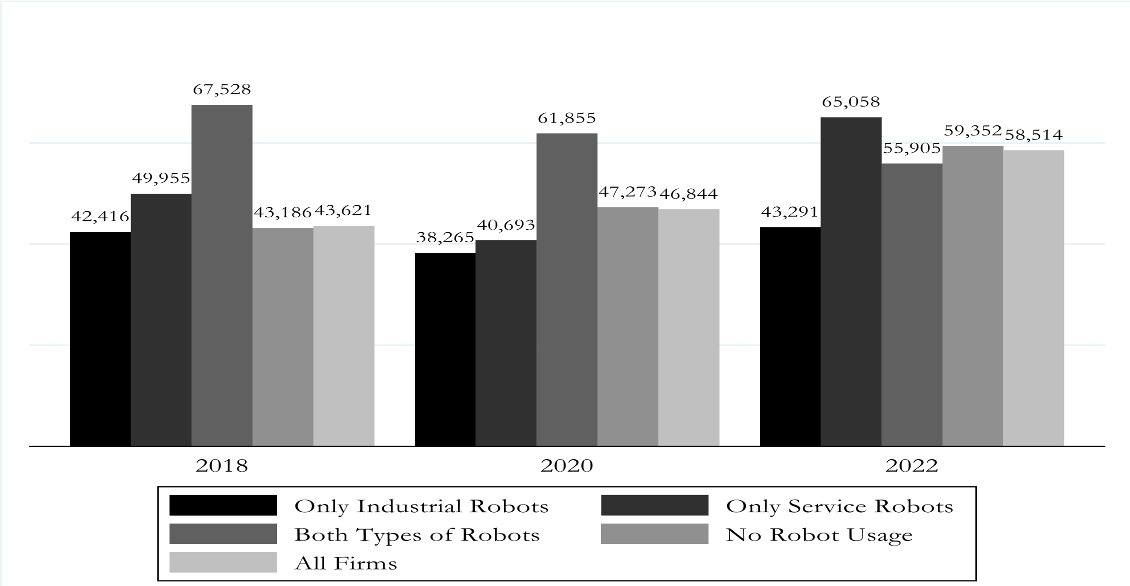
Robot Usage	N	Median	Mean	Min	Max
Only Industrial Robots	1,062	31,614.70	41,309.06	-45,512.23	1,374,457.0
Only Service Robots	379	27,497.22	52,042.03	-53,678.82	1,883,509.9
Both Types of Robots	367	36,811.27	60,601.31	-57,619.97	1,049,154.9
No Robot Usage	17,291	22,906.95	50,216.59	-84,185.75	3,208,399.8

Note: The top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command

Source: *IUTICE*, *SCIE*, and Own Calculations

Looking at Table 8, we find that companies that implement both kinds of robots are the ones that aggregate the most value, having the highest mean and median among the four categories (€60,601.31 and €36,811.27, respectively). On the other hand, companies without robots present the lowest median (€22,906.95) and the second lowest mean (€50,216.59), only higher than that of firms with only industrial robots (€41,309.06). From this analysis, it might seem obvious that companies employing both types of robots are the highest value-adders, while companies that do not utilize them are the lowest aggregators of value. However, we should also look at the evolution of this variable over time, so as not to overlook any relevant data. As such, Figure 5 depicts the time trends of the four categories of firms and of the whole sample.

Figure 5 – Real Average Value Added per Worker (at Factor Costs, €), by Robot Usage (Portugal - 2018, 2020 & 2022)



Source: *IUTICE*, *SCIE*, and Own Calculations

That which seemed obvious in the previous analysis is now put into question, as Figure 5 shows that, not only does the indicator decrease between 2018 and 2022 in firms that use both types of robots, but also increases in firms that do not use robots, making it so that in 2022 the real value added per worker at factor costs was higher, on average, in firms that did not make use of robots in their production activities than in firms that employed both industrial and service robots. Once again, these values are much higher than those present in Figure 2 (when analyzing the whole *SCIE* sample), meaning that the firms present in *IUTICE* are overall engaged in higher value-added activities than those in *SCIE*.

Finally, regarding Real Average Firm Turnover per Worker, Table 9 shows that companies with both types of robots display the highest mean and median among the 4 categories of companies. Even though the mean value is not much higher than that of firms without robots (€385,579 vs €354,086), the median turnover is more than twice as large as that of firms without robots (€142,120 vs €69,176). Firms with only one type of robot also present higher values than their robot-free counterparts, although they are not quite as high as firms with both types.

Table 9 – Real Firm Turnover per Worker (€), by Robot Usage (Portugal - Average 2018, 2020 & 2022)

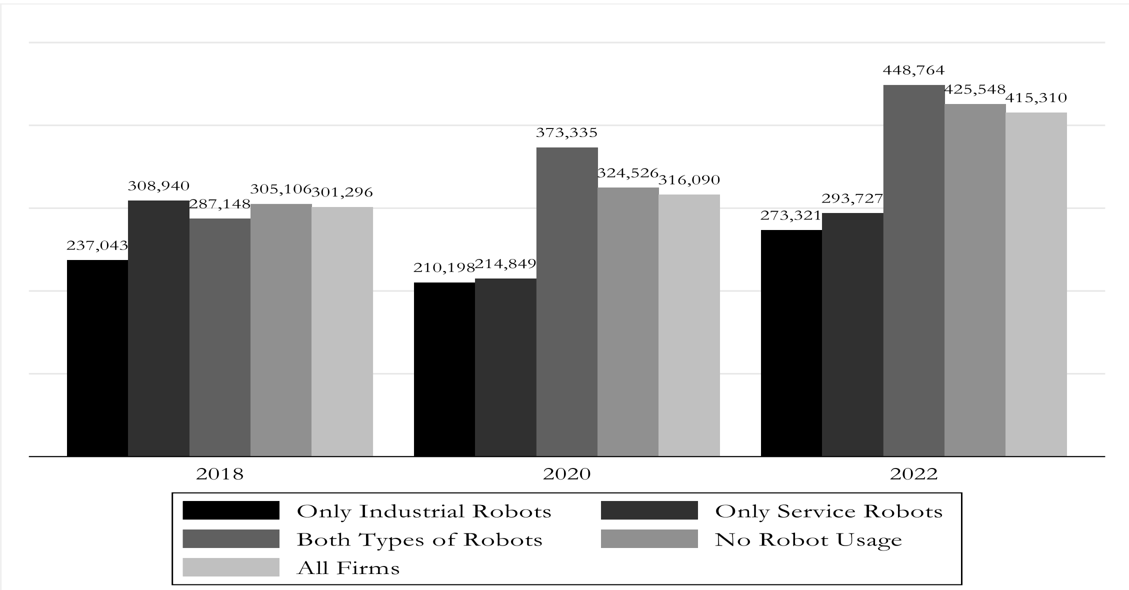
Robot Usage	N	Median	Mean	Min	Max
Only Industrial Robots	1,062	107,045.05	240,522.87	0.00	18,002,110
Only Service Robots	379	100,997.40	268,972.47	0.00	4,449,210
Both Types of Robots	368	142,120.30	385,578.96	4,903.69	15,737,382
No Robot Usage	17,386	69,176.30	354,086.00	0.00	21,342,846

Note: The top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command

Source: *IUTICE*, *SCIE*, and Own Calculations

Figure 6 depicts the temporal evolution of this indicator, between 2018 and 2022. Contrary to the trend observed in value-added, there appears to be an upward trend in firm turnover among firms employing both types of robots. In fact, between 2018 and 2022, Real Average Firm Turnover per Worker grew across all categories of firms (with the exception of firms that Only Use Service Robots), and the biggest growth belonged to firms employing Both Types of Robots. This growth allowed these firms to surpass the Real Average Firm Turnover of firms that did not make use of robots. Once again, when comparing these values with those in Figure 3, we conclude that firms in *IUTICE* & *SCIE* have, on average, greater turnover than those present in *SCIE*.

Figure 6 – Real Average Firm Turnover per Worker (€), by Robot Usage (Portugal - 2018, 2020 & 2022)



Source: *IUTICE*, *SCIE*, and Own Calculations

4.3. Robotization and Firms' Workforce Composition

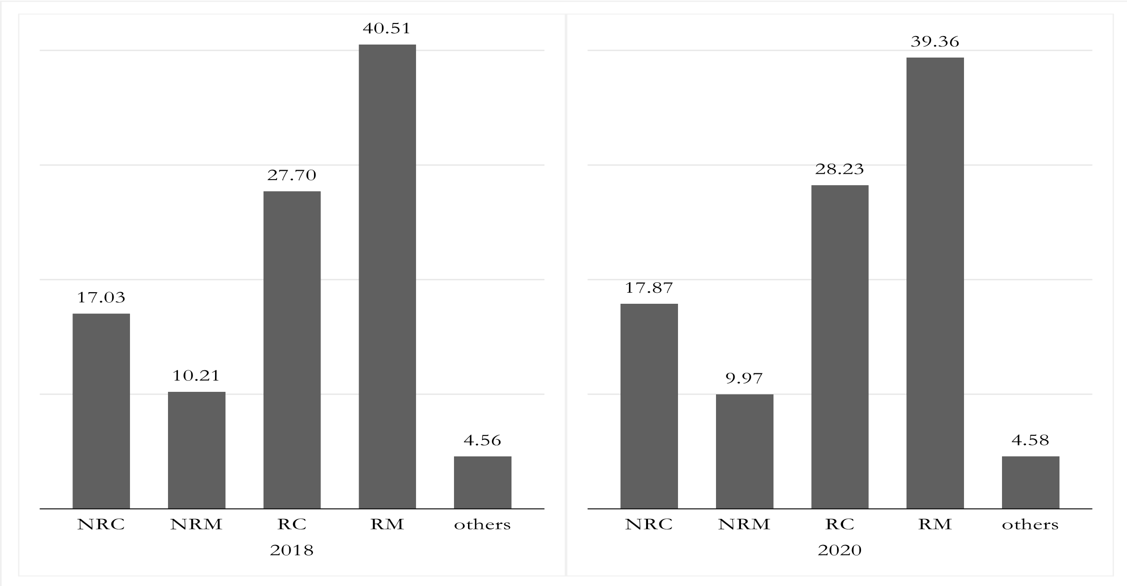
4.3.1. Tasks Composition

Making use of the work of Mihaylov and Tijdens (2019), we examine the task content of occupations in Portuguese firms, by merging the *IUTICE* and *QP* databases and the routine task content of the ISCO-08 occupations dataset proposed by Mihaylov and Tijdens (2019), which translates each job title into the type of task most prominent in that occupation[11], meaning that the matched profession IDs (present in *QP*) are assigned into one of five categories: NRM – Non-Routine Manual, NRC – Non-Routine Cognitive, RC – Routine Cognitive, RM – Routine Manual, and Others. With that, we are able to determine how these types of tasks are distributed within, as well as between, each of the four categories of companies (based on the use of robots), and how they are distributed across some worker-level variables of interest, such as gender, and education. The sample used in this analysis contains 1,693,317 observations over 2 years (2018 and 2020) because the dataset of Mihaylov and Tijdens (2019) did not contain a match for all job IDs present in *QP*, forcing us to drop a few additional observations.

Starting with the distribution of workers by types of tasks performed in firms that only use industrial robots, Figure 7 shows that in 2018, roughly 40.51% of all workers employed in these firms were performing Routine Manual (RM) tasks (making it the dominant category), 27.70% were employed in Routine Cognitive occupations, and only 27.23% were performing Non-Routine tasks. In 2020 the hierarchy remained unchanged although with some variations, such as a decrease of nearly 1.15 pp. in RM tasks, a decrease of 0.24 pp. in NRM tasks, and an increase in all other categories (of which NRC tasks had the highest increase – almost 0.85 pp.).

[11] For instance, if an occupation entails 10 different tasks, and most of them are Routine Manual tasks, that occupation is classified as RM

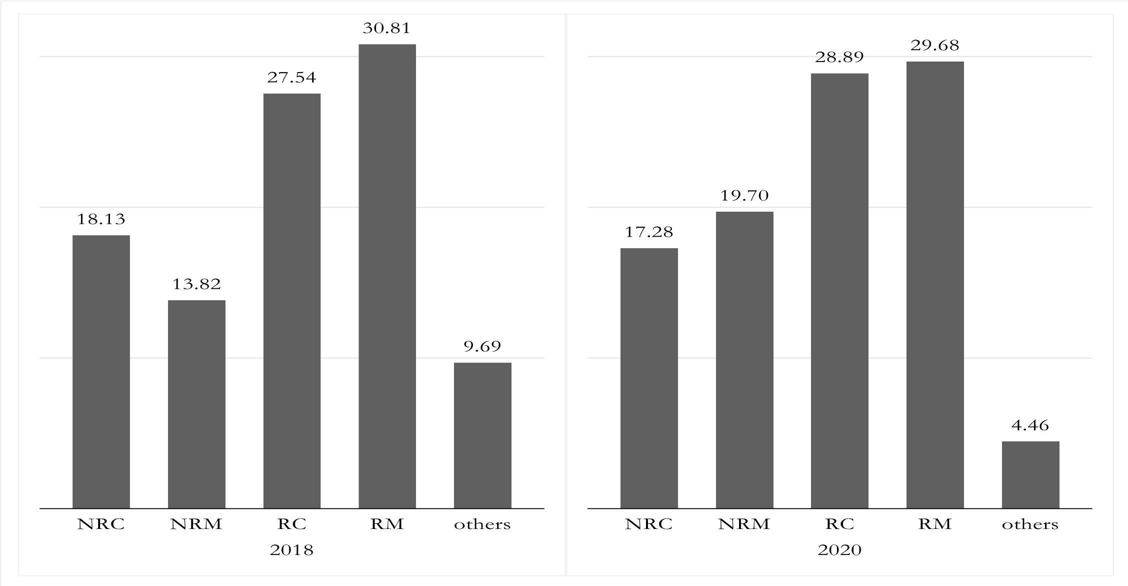
Figure 7 – Distribution of Workers (%) by Types of Tasks Performed in Firms with Only Industrial Robots (Portugal - 2018 & 2020)



Source: *IUTICE*, *QP*, Mihaylov and Tijdens (2019), and Own Calculations

Along the same lines as Figure 7, Figure 8 shows the distribution of workers by types of tasks performed in companies that only use service robots. RM tasks, despite still being the dominant category, do not present such a large lead as they did in firms with only industrial robots. Indeed, RM tasks only made up about 3.27 pp. more than RC tasks in 2018, with that difference being further shortened in 2020 to only roughly 0.79 pp., resulting from an increase in RC tasks and a decrease in RM tasks. Another stark difference between the two figures is the importance of NRM tasks, which are much more prevalent in companies with only service robots and seem to be on an upward trend (between 2018 and 2020 this category of tasks rose by nearly 5.88 pp. – the greatest fluctuation in the period, making it the 3rd most prevalent category in 2020). It thus seems safe to assume that firms with service robots do not have as great a need as firms with industrial robots for RM tasks, while on the other hand have an increased demand for NRM tasks.

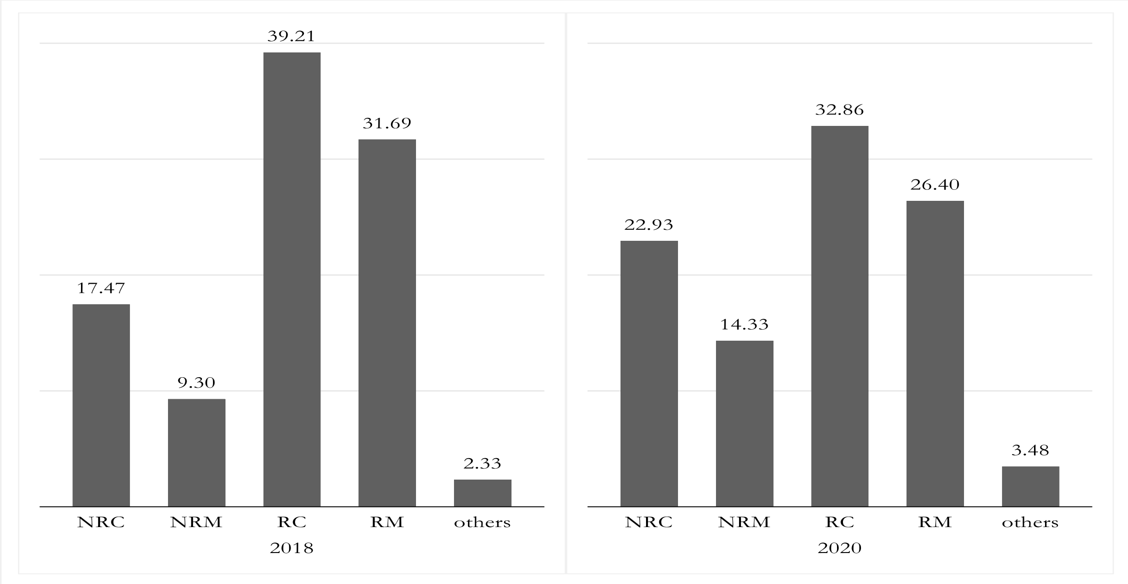
Figure 8 – Distribution of Workers (%) by Types of Tasks Performed in Firms with Only Service Robots (Portugal - 2018 & 2020)



Source: *IUTICE*, *QP*, Mihaylov and Tijdens (2019), and Own Calculations

Moving on to firms that employ both kinds of robots, Figure 9 shows that, contrary to what we have seen so far, workers who perform RC tasks are more in demand than those who perform RM tasks, in these companies. Indeed, in 2018, workers performing RC tasks made up 39.2% of the total workforce in these companies, and even though that value decreased considerably in 2020 (32.86% - a 6.34 pp. variation), it remained the most common task type. Furthermore, the tendency already observed towards a decline in RM tasks is even more pronounced in this category of firms, in which there was a reduction of 5.3 pp. over the analyzed period. Finally, Non-Routine tasks also grew in importance, with NRC tasks climbing by 5.46 pp. and NRM tasks rising by nearly 5.03 pp.

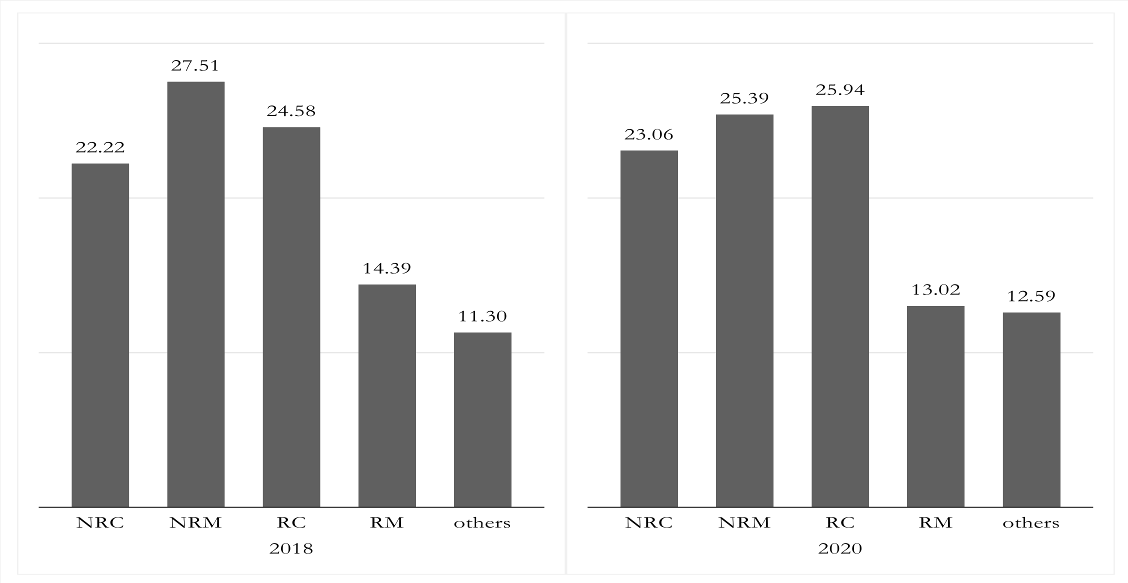
Figure 9 – Distribution of Workers (%) by Types of Tasks Performed in Firms with Both Types of Robots (Portugal - 2018 & 2020)



Source: *IUTICE*, *QP*, Mihaylov and Tijdens (2019), and Own Calculations

Finally, Figure 10 depicts the distribution of workers by types of tasks performed in firms that do not employ robots. These firms present a different distribution of task types, with a less relevant (and declining) role of workers employed in RM occupations. As a matter of fact, even the companies that employ both kinds of robots, which are the ones with relatively fewer workers performing RM tasks, out of the three types of companies using robots, still had, in 2020, more than double the relative weight of workers performing RM tasks (26.40% vs 13.02%). The other three types of tasks have almost equal percentages, especially in 2020, which in itself is another difference from what we have observed so far in firms with robots, as Non-Routine tasks did not have such a presence, especially NRM tasks, which made up about 25.4% of total tasks in firms without robots in 2020, being only comparable to the 19.7% of NRM tasks in firms with only service robots, in the same year.

Figure 10 – Distribution of Workers (%) by Types of Tasks Performed in Firms Without Robots (Portugal - 2018 & 2020)



Source: *IUTICE*, *QP*, Mihaylov and Tijdens (2019), and Own Calculations

Overall, RM tasks seem to be on a downward trajectory, especially in companies that use both types of robots, despite the fact that these tasks still have a very high relative importance in firms that use robots. We can offer some possible justifications for this tendency and for the difference in demand of task types across the categories of firms. The decline in Routine Manual tasks and the increase in Non-Routine tasks, especially in firms with both types of robots, can be linked to the displacement effect that Acemoglu and Restrepo (2019) mention, with workers moving from jobs that are automated to jobs created by automation. Similarly, the dominance of Routine Manual tasks in firms with robots, as compared to firms without robots, can be seen as a case of reverse causality: it is not because firms use robots that there is an increased need for RM tasks, but on the contrary, it is because firms have an above-average need for RM tasks that leads them to implement the usage of robots in their firms. However, it must be noted that these tendencies can be challenged in the long term (with more years of data) or with a larger sample.

4.3.2. Gender and Education Composition

Having studied the composition of the workforce of the different categories of companies by the types of tasks performed, we can now investigate the relationship between the types of tasks and some variables of interest, such as workers' gender and education level.

To this end, Table 10 shows the distribution of each type of task by gender across the four types of firms (i.e. based on their Robot Usage).

Table 10 – Distribution of Workers by Types of Tasks Performed, Gender, and Robot Usage (Portugal – Average 2018 & 2020)

Types of Tasks	Gender		Total
	Females	Males	
Only Industrial Robots			
NRC	10,298	23,115	33,413
%	30.82	69.18	100.00
NRM	3,500	15,796	19,296
%	18.14	81.86	100.00
RC	27,236	26,288	53,524
%	50.89	49.11	100.00
RM	33,694	42,704	76,398
%	44.10	55.90	100.00
Others	3,759	4,989	8,748
%	42.97	57.03	100.00
Total	**78,487**	**112,892**	**191,379**
%	**41.01**	**58.99**	**100.00**
Only Service Robots			
NRC	5,595	9,912	15,507
%	36.08	63.92	100.00
NRM	9,544	5,337	14,881
%	64.14	35.86	100.00
RC	10,690	14,100	24,790
%	43.12	56.88	100.00
RM	5,917	20,578	26,495
%	22.33	77.67	100.00
Others	3,176	2,866	6,042
%	52.57	47.43	100.00
Total	**34,922**	**52,793**	**87,715**
%	**39.81**	**60.19**	**100.00**
Both Types of Robots			
NRC	4,994	11,934	16,928
%	29.50	70.50	100.00
NRM	1,710	8,301	10,011
%	17.08	82.92	100.00
RC	10,571	18,683	29,254
%	36.14	63.86	100.00
RM	7,602	15,964	23,566
%	32.26	67.74	100.00
Others	1,189	1,264	2,453
%	48.47	51.53	100.00
Total	**26,066**	**56,146**	**82,212**
%	**31.71**	**68.29**	**100.00**
No Robot Usage			
NRC	131,489	169,837	301,326
%	43.64	56.36	100.00
NRM	165,443	187,530	352,973
%	46.87	53.13	100.00

RC %	153,940 45.81	182,103 54.19	336,043 100.00
RM %	74,378 40.65	108,593 59.35	182,971 100.00
Others %	100,358 63.24	58,340 36.76	158,698 100.00
Total **%**	**625,608** **46.97**	**706,403** **53.03**	**1,332,011** **100.00**
Total			
NRC %	152,376 41.50	214,798 58.50	367,174 100.00
NRM %	180,197 45.37	216,964 54.63	397,161 100.00
RC %	202,437 45.63	241,174 54.37	443,611 100.00
RM %	121,591 39.30	187,839 60.70	309,430 100.00
Others %	108,482 61.66	67,459 38.34	175,941 100.00
Total **%**	**765,083** **45.18**	**928,234** **54.82**	**1,693,317** **100.00**

Source: *IUTICE*, *QP*, Mihaylov and Tijdens (2019), and Own Calculations

As we can see from the table above, there is a larger male representation in the companies in the sample, which is accentuated in companies that use robots, especially in those that employ both types. Indeed, almost 55% of the workforce in the sample is male, but this proportion increases to approximately 68% when we look solely at the companies that employ both types of robots. If we look at each type of task, we can also see that RM and NRC tasks are the ones most often carried out by men (60.70% and 58.50%, respectively), when considering the sample as a whole. In firms with only industrial robots or with both types of robots, NRM (81.86% and 82.92%, respectively) and NRC (69.18% and 70.50%, respectively) tasks are the ones most performed by men. In firms with only service robots, there is a higher proportion of men in RM (77.67%) and NRC (63.92%) tasks, and a high proportion of women in NRM tasks (64%).

Moving on to the second variable of interest, Table 11 shows the distribution of workers by types of tasks, and educational level, across the four categories of companies.

Table 11 – Distribution of Workers by Types of Tasks Performed, Education Level, and Robot Usage (Portugal - Average 2018 & 2020)

Types of Tasks	Educational Level						Total
	Elementary School	Secondary School	Bachelor	Master	PhD	ND	
Only Industrial Robots							
NRC	5,656	8,227	15,176	4,112	104	138	33,413
%	16.93	24.62	45.42	12.31	0.31	0.41	100
NRM	10,034	8,130	963	161	0	8	19,296
%	52.00	42.13	4.99	0.83	0.00	0.04	100.00
RC	18,419	23,702	10,353	1,009	9	32	53,524
%	34.41	44.28	19.34	1.89	0.02	0.06	100.00
RM	48,885	25,831	1,521	104	1	56	76,398
%	63.99	33.81	1.99	0.14	0.00	0.07	100.00
Others	3,284	3,540	1,647	271	5	1	8,748
%	37.54	40.47	18.83	3.10	0.06	0.01	100.00
Total	**86,278**	**69,430**	**29,660**	**5,657**	**119**	**235**	**191,379**
%	**45.08**	**36.28**	**15.50**	**2.96**	**0.06**	**0.12**	**100.00**
Only Service Robots							
NRC	2,174	3,943	7,774	1,449	128	39	15,507
%	14.02	25.43	50.13	9.34	0.83	0.25	100.00
NRM	11,827	2,674	357	9	0	14	14,881
%	79.48	17.97	2.40	0.06	0.00	0.09	100.00
RC	8,429	10,571	5,105	654	13	18	24,790
%	34.00	42.64	20.59	2.64	0.05	0.07	100.00
RM	15,251	10,410	732	102	0	0	26,495
%	57.56	39.29	2.76	0.38	0.00	0.00	100.00
Others	1,607	3,385	1,005	43	2	0	6,042
%	26.60	56.02	16.63	0.71	0.03	0.00	100.00
Total	**39,288**	**30,983**	**14,973**	**2,257**	**143**	**71**	**87,715**
%	**44.79**	**35.32**	**17.07**	**2.57**	**0.16**	**0.08**	**100.00**
Both Types of Robots							
NRC	2,526	3,921	7,565	2,359	407	150	16,928
%	14.92	23.16	44.69	13.94	2.40	0.89	100.00
NRM	5,135	4,025	823	23	0	5	10,011
%	51.29	40.21	8.22	0.23	0.00	0.05	100.00
RC	11,880	12,121	4,082	925	238	8	29,254
%	40.61	41.43	13.95	3.16	0.81	0.03	100.00
RM	13,679	9,264	568	53	0	2	23,566
%	58.05	39.31	2.41	0.22	0.00	0.01	100.00
Others	1,093	860	419	80	1	0	2,453
%	44.56	35.06	17.08	3.26	0.04	0.00	100.00
Total	**34,313**	**30,191**	**13,457**	**3,440**	**646**	**165**	**82,212**
%	**41.74**	**36.72**	**16.37**	**4.18**	**0.79**	**0.20**	**100.00**
Without Robots							
NRC	48,606	96,609	126,855	27,050	1,310	896	301,326
%	16.13	32.06	42.10	8.98	0.43	0.30	100.00
NRM	250,957	90,841	10,412	366	12	385	352,973
%	71.10	25.74	2.95	0.10	0.00	0.11	100.00
RC	98,117	157,811	69,413	8,776	357	1,569	336,043
%	29.20	46.96	20.66	2.61	0.11	0.47	100.00
RM	126,501	51,722	4,356	219	9	164	182,971
%	69.14	28.27	2.38	0.12	0.00	0.09	100.00

Others	64,065	78,714	14,675	1,192	24	28	158,698
%	40.37	49.60	9.25	0.75	0.02	0.02	100.00
Total	**588,246**	**475,697**	**225,711**	**37,603**	**1,712**	**3,042**	**1,332,011**
%	**44.16**	**35.71**	**16.95**	**2.82**	**0.13**	**0.23**	**100.00**
Total							
NRC	58,962	112,700	157,370	34,970	1,949	1,223	367,174
%	16.06	30.69	42.86	9.52	0.53	0.33	100.00
NRM	277,953	105,670	12,555	559	12	412	397,161
%	69.98	26.61	3.16	0.14	0.00	0.10	100.00
RC	136,845	204,205	88,953	11,364	617	1,627	443,611
%	30.85	46.03	20.05	2.56	0.14	0.37	100.00
RM	204,316	97,227	7,177	478	10	222	309,430
%	66.03	31.42	2.32	0.15	0.00	0.07	100.00
Others	70,049	86,499	17,746	1,586	32	29	175,941
%	39.81	49.16	10.09	0.90	0.02	0.02	100.00
Total	**748,125**	**606,301**	**283,801**	**48,957**	**2,620**	**3,513**	**1,693,317**
%	**44.18**	**35.81**	**16.76**	**2.89**	**0.15**	**0.21**	**100.00**

Note: ND – Not Defined
Source: *IUTICE*, *QP*, Mihaylov and Tijdens (2019), and Own Calculations

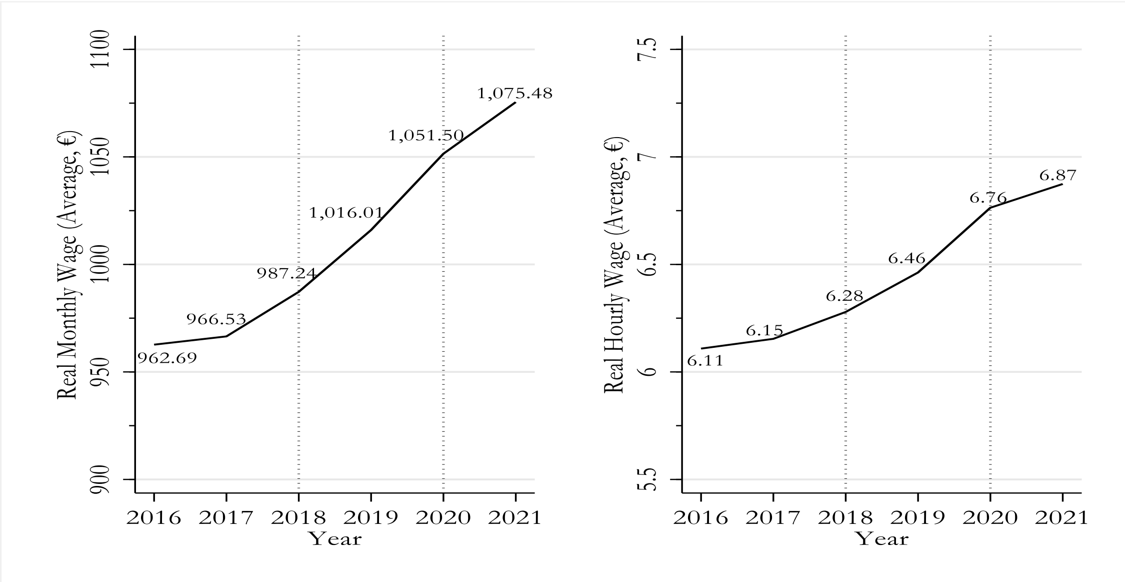
Table 11 shows that most workers in the sample have an educational level of either "Elementary School" (44.18%) or "Secondary School" (35.81%), and out of the 1,693,317 workers, only 2,620 (0.15%) have a PhD. Additionally, by looking into each task type, the data shows that workers executing Manual tasks, such as RM and NRM, tend to have lower educational qualifications (i.e. Elementary education or Secondary education), while workers performing Cognitive tasks, such as RC and NRC, tend to have higher educational qualifications (i.e. bachelor's or master's degree). By comparing the four categories of firms, and regarding NRC, NRM, and RM tasks, companies with robots tend to have more qualified workers than firms without robots. On the other hand, regarding RC tasks, if we compare the firms with Both Types of Robots and firms Without Robots, we can see that there is a polarization (i.e. higher percentage of workers in the extremes of the education level performing these tasks in firms with Both Types of Robots). Indeed, when comparing the percentages of workers with "Elementary School" and workers with "Master" or "PhD", between these two categories of firms, we see that firms with Both Types of Robots present higher values.

Overall, workers in firms with robots tend to have higher educational levels. This is especially true when comparing firms with Both Types of Robots and firms Without Robots. In fact, workers with a bachelor's degree make up for about 4.2% of the total workforce in companies with both types of robots, while only representing roughly 2.8% of the workforce in companies without robots. On a smaller scale, workers with a master's degree account for almost 0.8% of the workforce in companies with both types, while only amounting to 0.13% of the workforce in robot-free companies.

4.4. Robotization and Wages

In this subchapter, we present the results of the wage descriptive analysis. We begin by showing how wages evolved over a longer period than that for which we have robot usage data, in order to see if there was an abnormal evolution (like COVID-19 did to firms' productivity). Figure 11 presents the spells from 2016 to 2021 of the *QP* dataset, depicting the temporal evolution of both the Real Average Monthly Wages[12] and the Real Average Hourly Wages[13] (both at constant prices of 2012, discounted at the CPI).

Figure 11 – Real Average Monthly Wage and Real Average Hourly Wage (€) (Portugal - 2016/2021)



Source: *QP* and Own Calculations

Figure 11 shows that wages have been steadily growing over the years, with the period from 2018 to 2020 being the one where wages grew the most in the analyzed period. Indeed, Real Average Monthly Wages grew by 6.51%, and Real Average Hourly Wages grew by roughly 7.64% in those two years. Our analysis of the impact of robotization on wages keeps that in mind, and besides assessing whether or not firms with robots increase wages at a faster rate than firms without robots, we assess whether firms with robots increase wages

[12] The Monthly Wage corresponds to the sum of the Base Wage and the Regular Benefits earned by the worker
[13] The Hourly Wage corresponds to the Monthly Wage divided by the number of Hours Worked in the month

quicker than the real average wage of the economy. Once again, we drop outlier values from the sample.

Table 12 presents some of the descriptive statistics for the Real Monthly Wage across the four categories of companies. As can be seen in the table, the companies with both kinds of robots are the ones with the highest mean and median values, out of all the categories, presenting a Real Median Monthly Wage of €1,104.20 and a Real Average Monthly Wage of €1,382.54. By contrast, companies that do not employ robots present the lowest median (€804.79) and average (€1,042.35) real wages, out of the four categories. Finally, firms with only service robots present higher median (€1,051.43 vs €947.44) and mean (€1,265.88 vs €1,215.28) values than the firms with only industrial robots.

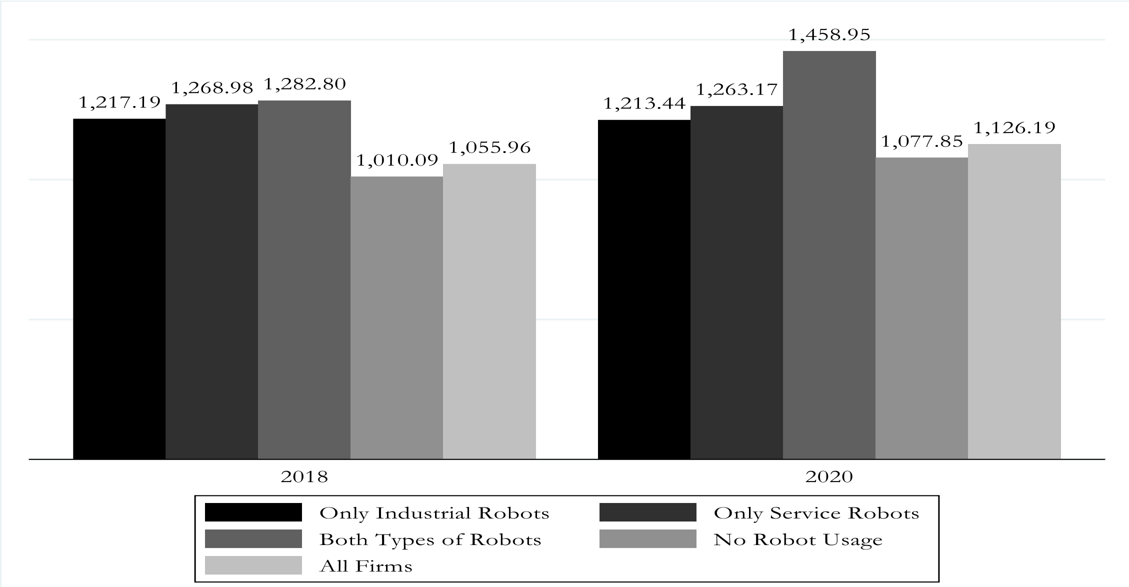
Table 12 – Real Monthly Wage (€), by Robot Usage (Portugal - Average 2018 & 2020)

Robot Usage	N	Median	Mean	Min	Max
Only Industrial Robots	180,922	947.44	1,215.28	26.09	6,801.70
Only Service Robots	83,698	1,051.43	1,265.88	26.19	6,798.05
Both Types of Robots	78,640	1,104.20	1,382.54	26.35	6,798.62
No Robot Usage	1,260,790	804.79	1,042.35	26.07	6,801.31

Note: The top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command
Source: *IUTICE*, *QP,* and Own Calculations

Concerning the temporal evolution of the Real Average Monthly Wages, it can be seen in Figure 12 that, between 2018 and 2020, firms with both kinds of robots and firms that do not use robots saw an increase in Real Average Monthly Wages, while firms with only one kind of robot experienced a slight decrease. Overall, on average, firms that employed robots presented higher wages in both years. In particular, in 2020, we observe a considerable increase in wages for firms that employ Both Types of Robots (reaching almost €1,459 and furthering the lead over the other categories of firms).

Figure 12 – Real Average Monthly Wage (€), by Robot Usage (Portugal - 2018 & 2020)



Source: *IUTICE*, *QP,* and Own Calculations

Since firms with robots tend to have higher Real Average Monthly Wages (Table 12) it is worth checking whether this translates into higher Real Average Hourly Wages. Making a similar analysis as we did before, we can confirm that firms with robots tend to have higher Real Hourly Wages, on average, than firms without robots. As seen in Table 13, the hierarchy established in Table 12 remains unchanged. Firms that possess both types of robots present the highest values, with a Real Median Hourly Wage of €6.62 and a Real Average Hourly Wage of €8.31, which starkly contrasts with the values of the category of firms without robots (€4.97 and €6.73, respectively). Much like with Real Monthly Wages, firms with only service robots present higher Real Median/Average Hourly Wages than firms with only industrial robots.

Table 13 – Real Hourly Wage (€), by Robot Usage (Portugal - Average 2018 & 2020)

Robot Usage	Count	Median	Mean	Min	Max
Only Industrial Robots	180,714	5.697	7.572	3.173	42.304
Only Service Robots	83,427	6.396	7.972	3.169	42.299
Both Types of Robots	78,656	6.615	8.312	3.199	42.306
No Robot Usage	1,261,115	4.972	6.733	3.166	42.301

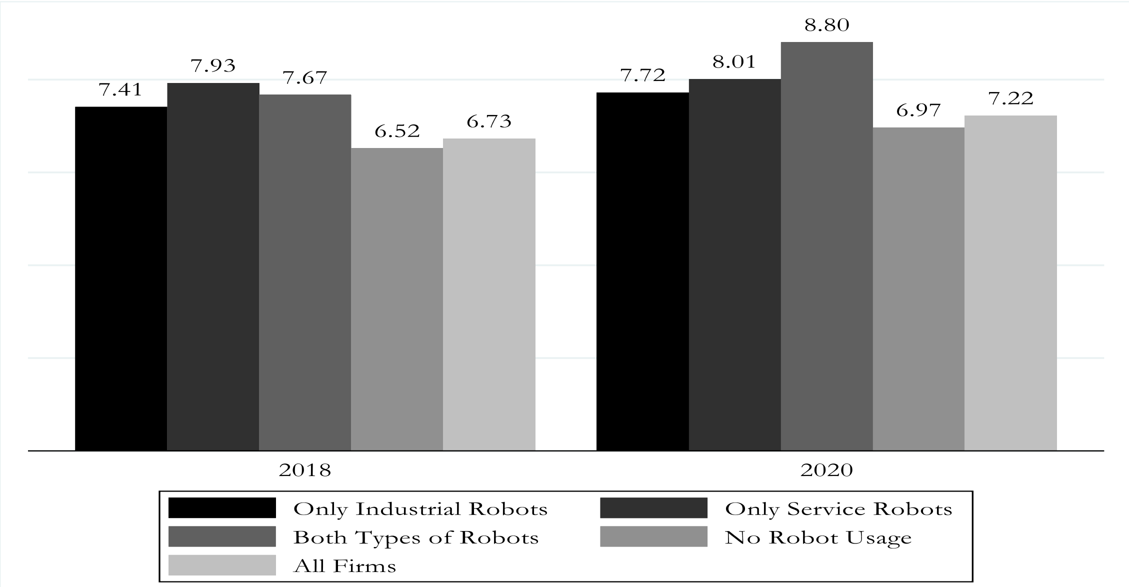
Note: The top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command

Source: *IUTICE*, *QP*, and Own Calculations

Figure 13 shows how these wages developed between 2018 and 2020, and we can conclude that, in contrast to what we saw in Figure 12, all categories experienced an increase in value, with the greatest increase being in the category of firms with both kinds of robots

(14.77%), and the lowest increase being that of firms with only service robots (1.05%). Also in contrast to Figure 12, where the real average wage of firms without robots grew more than the average of the sample (6.71% vs 6.65%), the real average hourly wage in those firms grew less than the average of the sample (6.91% vs 7.34%).

Figure 13 – Real Average Hourly Wages (€), by Robot Usage (Portugal - 2018 & 2020)



Source: *IUTICE*, *QP,* and Own Calculations

Finally, we examine the distribution of workers by types of tasks performed, wage levels, and robot usage, displayed below in Table 14. The first conclusion that we reach when looking at each type of task is that, regardless of the type of company, Cognitive tasks are better paid than Manual tasks, with an emphasis on NRC tasks. So much so that more than half of the workers doing NRC tasks are paid at least €1,500 a month (well above the national minimum wage[14]), and out of the 46,912 workers earning at least €3,750 a month, 36,774 of them undertake NRC tasks (approx. 78.39%). Workers performing RC tasks, despite being better paid than workers performing Manual tasks, are mostly paid between €750 to €1,499.99 monthly (roughly 53% of the workers doing RC tasks), falling short when compared to NRC tasks. Looking into Manual tasks, we can see that workers carrying out RM tasks are, on average, better paid than those undertaking NRM tasks, and one thing stands out: the magnitude of workers, doing NRM tasks, getting paid less than €600 a month (40.66% of the workers in those types of tasks), which can only be explained, *ceteris paribus*, by the nature of the jobs related to those tasks (e.g., part-time or odd jobs). Additionally, by

[14] In 2022, the National Minimum Wage in Portugal was set at €705 a month

comparing the four categories of firms, we can see that, not only do firms with robots pay on average higher wages than firms without robots, but they also pay better across all types of tasks. Indeed, if we compare the wages earned in each type of task in companies with both types of robots with those earned in robot-free companies, we can conclude that there is a wage premium across all task types in favor of the first. That premium is especially noticeable in the wages earned by workers undertaking NRM tasks (while in companies without robots, nearly 53.6% of the workforce in those types of tasks get paid less than €750, in companies with both kinds of robots that figure drops to only 16.5%).

This descriptive analysis seems to suggest that firms equipped with robots (particularly those that have both types) are, on average, more productive and have a more qualified and better-paid workforce than firms without robots. However, these conclusions may be tainted with endogeneity (i.e. there may be one or more underlying factors, not accounted for in the analysis, driving these findings), and it is therefore crucial to try to validate these conclusions with an econometric analysis. Thus, the next chapter presents the results obtained from the econometric approach.

Table 14 – Distribution of Workers by Task Types, Wages, and Robot Usage (Portugal - Average 2018 & 2020)

Types of Tasks	Real Monthly Wage (€)								Total
	< 600	[600; 749.99]	[750; 999.99]	[1,000; 1,499.99]	[1,500; 2,499.99]	[2,500; 3,749.99]	>= 3,750	WW	
Only Industrial Robots									
NRC	1,693	297	2,312	7,744	11,091	5,619	3,697	960	33,413
%	5.07	0.89	6.92	23.18	33.19	16.82	11.06	2.87	100.00
NRM	1,569	893	4,310	6,775	3,760	1,214	266	509	19,296
%	8.13	4.63	22.34	35.11	19.49	6.29	1.38	2.64	100.00
RC	5,402	3,185	14,342	16,178	7,695	2,295	2,244	2,183	53,524
%	10.09	5.95	26.80	30.23	14.38	4.29	4.19	4.08	100.00
RM	13,375	9,446	26,831	17,763	5,050	439	56	3,438	76,398
%	17.51	12.36	35.12	23.25	0.66	0.57	0.07	4.50	100.00
Others	527	551	2,577	2,280	1,688	609	226	290	8,748
%	6.02	6.30	29.46	2.61	19.30	6.96	2.58	3.32	100.00
Total	**22,566**	**14,372**	**50,372**	**50,740**	**29,284**	**10,176**	**6,489**	**7,380**	**191,379**
%	**11,79**	**7.51**	**26.32**	**26.51**	**15.30**	**5.32**	**3.39**	**3.86**	**100.00**
Only Service Robots									
NRC	360	93	899	2,514	5,716	3,206	2,389	330	15,507
%	2.32	0.60	5.80	16.21	36.86	20.67	15.41	2.13	100.00
NRM	8,294	1,207	2,584	1,343	516	61	3	873	14,881
%	55.74	8.11	17.36	9.02	3.47	0.41	0.02	5.87	100.00
RC	1,469	1,225	5,755	8,277	5,789	1,295	491	489	24,790
%	5.93	4.94	23.22	33.39	23.35	5.22	1.98	1.97	100.00
RM	3,142	1,739	5,939	10,052	3,543	864	260	956	26,495
%	11.86	6.56	22.42	37.94	13.37	3.26	0.98	3.61	100.00
Others	1,930	438	2,326	647	267	140	55	239	6,042
%	31.94	7.25	38.50	10.71	4.42	2.32	0.91	3.96	100.00
Total	**15,195**	**4,702**	**17,503**	**22,833**	**15,831**	**5,566**	**3,198**	**2,887**	**87,715**
%	**17.32**	**5.36**	**19.95**	**26.03**	**18.05**	**6.35**	**3.65**	**3.29**	**100.00**
Both Types of Robots									
NRC	323	92	1,432	3,014	5,848	3,446	2,390	383	16,928
%	1.91	0.54	8.46	17.80	34.55	20.36	14.12	2.26	100.00
NRM	1,176	479	3,864	2,429	1,389	254	37	383	10,011
%	11.75	4.78	38.60	24.26	13.87	2.54	0.37	3.83	100.00

RC	1,626	1,766	7,911	7,312	7,928	1,657	408	646	29,254
%	5.56	6.04	27.04	24.99	27.10	5.66	1.39	2.21	100.00
RM	2,552	2,524	6,532	5,412	4,468	796	19	1,263	23,566
%	10.83	10.71	27.72	22.97	18.96	3.38	0.08	5.36	100.00
Others	147	64	529	914	524	104	47	124	2,453
%	5.99	2.61	21.57	37.26	21.36	4.24	1.92	5.06	100.00
Total	**5,824**	**4,925**	**20,268**	**19,081**	**20,157**	**6,257**	**2,901**	**2,799**	**82,212**
%	**7.08**	**5.99**	**24.65**	**23.21**	**24.52**	**7.61**	**3.53**	**3.40**	**100.00**
No Robot Usage									
NRC	36,345	11,635	39,862	54,302	77,067	42,565	28,298	11,252	301,326
%	12.06	3.86	13.23	18.02	25.58	14.13	9.39	3.73	100.00
NRM	150,435	38,670	89,114	41,377	13,416	3,108	463	16,390	352,973
%	42.62	10.96	25.25	11.72	3.80	0.88	0.13	4.64	100.00
RC	65,512	27,898	93,909	81,337	43,275	10,843	4,179	9,090	336,043
%	19.50	8.30	27.95	24.20	12.88	3.23	1.24	2.71	100.00
RM	48,683	28,169	56,529	31,158	8,557	1,060	161	8,654	182,971
%	26.61	15.40	30.90	17.03	4.68	0.58	0.09	4.73	100.00
Others	52,159	14,606	56,620	19,747	5,436	1,672	1,223	7,235	158,698
%	32.87	9.20	35.68	12.44	3.43	1.05	0.77	4.56	100.00
Total	**353,134**	**120,978**	**336,034**	**227,921**	**147,751**	**59,248**	**34,324**	**52,621**	**1,332,011**
%	**26.51**	**9.08**	**25.23**	**17.11**	**11.09**	**4.45**	**2.58**	**3.95**	**100.00**
Total									
NRC	38,721	12,117	44,505	67,574	99,722	54,836	36,774	12,925	367,174
%	10.55	3.30	12.12	18.40	27.16	14.93	10.02	3.52	100.00
NRM	161,474	41,249	99,872	51,924	19,081	4,637	769	18,155	397,161
%	40.66	10.39	25.15	13.07	4.80	1.17	0.19	4.57	100.00
RC	74,009	34,074	121,917	113,104	64,687	16,090	7,322	12,408	443,611
%	16.68	7.68	27.48	25.50	14.58	3.63	1.65	2.80	100.00
RM	67,752	41,878	95,831	64,385	21,618	3,159	496	14,311	309,430
%	21.90	13.53	30.97	20.81	6.99	1.02	0.16	4.62	100.00
Others	54,763	15,659	62,052	23,588	7,915	2,525	1,551	7,888	175,941
%	31.13	8.90	35.27	13.41	4.50	1.44	0.88	4.48	100.00
Total	**396,719**	**144,977**	**424,177**	**320,575**	**213,023**	**81,247**	**46,912**	**65,687**	**1,693,317**
%	**23.43**	**8.56**	**25.05**	**18.93**	**12.58**	**4.80**	**2.77**	**3.88**	**100.00**

Note: WW – Without Wage
Source: *IUTICE*, *QP*, Mihaylov and Tijdens (2019), and Own Calculations

5. Econometric Approach

In this chapter we present our econometric approach to the impacts of robotization on firm productivity and workers' wages. For our deterministic functions, we draw inspiration from the studies by Amador and Silva (2023) and Amador (2024), both of which, as we have already mentioned, use the same databases as us, but adopt a different approach.

5.1. Robot Usage and Productivity

5.1.1. Econometric Model

We begin our econometric approach by studying the impact of robotization on firm productivity, and we do so by merging *IUTICE* with *SCIE* and some variables of *QP*, which corresponds to a sample of 10,535 firms. Analyzing the correlation between the use of robots and our performance measures, we can see in Table A2[15] that the correlations established are very weak, although significant. As such, we estimate three specifications of the same econometric model, using Ordinary Least Squares (OLS), in order to assess if these correlations hold. The estimated model is as follows:

(5.1)

$$Ln\_Prod_{it} = \alpha + \gamma_1 Only\_Ind_{it} + \gamma_2 Only\_Serv_{it} + \gamma_3 Both\_Types_{it} + \boldsymbol{\beta}_i \mathbf{X}_{it} + \boldsymbol{\theta}_i \mathbf{W}_{it} + \delta_t + \epsilon_{it}$$

where the dependent variable Ln_Prod_{it} corresponds to the Log of Real Production per Worker (our selected measure of productivity) of firm i, in the year t, with t = {2018,2020}. α is the constant term. $Only\_Ind_{it}$ is a dummy variable indicating if company i only uses industrial robots, in the year t. $Only\_Serv_{it}$ is a dummy variable indicating if company i only uses service robots, in the year t. $Both\_Types_{it}$ is a dummy variable indicating if company i uses both types of robots, in the year t. $\mathbf{X}_{it}$ are firm-level characteristics such as the log of social capital, the log of number of workers, firm age, ownership, location, and industry. $\mathbf{W}_{it}$ are workforce characteristics, such as percentage of female workers, percentage of old workers (more than 55 years old), and percentage of workers with higher education. Finally, δ_t are time-fixed effects, and ϵ_{it} is the error term.

[15] Table A2, in the annex, present the pair-wise correlations between our robot usage dummy variables and the dependent variables of our productivity analysis

We make similar regressions for the Real Value Added per Worker (at Factor Costs) and for the Real Firm Turnover per Worker. The summary statistics of the variables included in these models are present in Table A3, in the annex.

5.1.2. Results

Table 15 shows the relevant estimates of regression (5.1). Starting with Table 15, and looking into our preferred specification, we can see that firms with only industrial robots present a positive and significant (for a significance level of 0.05) correlation with our measure of productivity. Firms with only service robots, on the other hand, present a positive but non-significant correlation, meaning that these firms are not significantly more productive than those without robots. Finally, firms that employ both types of robots present a positive and significant (at a 0.01 significance level) correlation with productivity, that even surpasses that of firms with only industrial robots. As such, we confirm previous results based on our descriptive analysis: firms with both types of robots are, on average, more productive than those without robots and are even more productive than those who only employ one type of robot. Indeed, a firm that employs both types of robots has, on average, a Real Productivity that is 19.8% higher than that of a similar firm without robots.

Table 15 – OLS Results: Real Productivity (Portugal - 2018 & 2020)

Variables	Log Real Productivity		
Robot Usage			
Only Industrial Robots	0.0872** (0.0407)	0.0861** (0.0381)	0.0907** (0.0381)
Only Service Robots	0.0579 (0.0643)	0.0430 (0.0582)	0.0519 (0.0582)
Both Types of Robots	0.215*** (0.0702)	0.192*** (0.0666)	0.198*** (0.0665)
Constant	9.184*** (0.396)	9.339*** (0.312)	9.367*** (0.308)
Firm Characteristics	YES	YES	YES
Workforce Characteristics	NO	YES	YES
Time Dummies	NO	NO	YES
Nº obs. (Firms)	10,535	10,535	10,535
R^2	0.363	0.414	0.417

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are shown in parentheses, clustered by firm ID. Regarding the dependent variable, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped. "Robot Usage" is a set of dummy variables

that characterize each firm according to its robot usage, and the omitted category is "No Robot Usage". The full specification is presented in Table A4[16]
Source: *IUTICE*, *SCIE*, *QP*, and Own Calculations

Moving on to our second indicator, Table 16 shows the relevant estimates of the Real Value Added per Worker model. As we can see, unlike with productivity, firms with only industrial robots are not significantly different than those who do not use them, in terms of real value added per worker. Firms with only service robots present a negative correlation with value-added, but it is also not significantly different than that of firms without robots. Finally, firms with both types present a positive and significant (at a 0.01 significance level) correlation with Real Value Added per Worker (at Factor Costs). As such, only firms that make use of both kinds of robots are statistically engaged in higher value-added activities than firms without robots. On average, a firm that employs both types of robots engages in an activity with a Real Value Added per Worker (at Factor Costs) 18.3% higher than that of a similar firm that does not use robots.

Table 16 – OLS Results: Real Value Added per Worker, at Factor Costs (Portugal - 2018 & 2020)

Variables	Log Real Value Added per Worker (at Factor Costs)		
Robot Usage			
Only Industrial Robots	0.0128 (0.0331)	0.0116 (0.0302)	0.0141 (0.0302)
Only Service Robots	-0.0122 (0.0545)	-0.0222 (0.0478)	-0.0173 (0.0477)
Both Types of Robots	0.202*** (0.0617)	0.179*** (0.0573)	0.183*** (0.0573)
Constant	8.817*** (0.289)	8.972*** (0.216)	8.987*** (0.214)
Firm Characteristics	YES	YES	YES
Workforce Characteristics	NO	YES	YES
Time Dummies	NO	NO	YES
Nº obs. (Firms)	10,535	10,535	10,535
R^2	0.305	0.353	0.354

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are shown in parentheses, clustered by firm ID. Regarding the dependent variable, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped. "Robot Usage" is a set of dummy variables that characterize each firm according to its robot usage, and the omitted category is "No Robot Usage"
Source: *IUTICE*, *SCIE*, *QP*, and Own Calculations

[16] Table A4, in the annex, presents the OLS estimates for the full specification of regression (5.1)

At last, Table 17 shows the relevant estimates of the Real Firm Turnover per Worker model. Firms with only one type of robot are not significantly different from firms without robots, in terms of Real Firm Turnover per Worker. Firms that employ both kinds of robots, on the other hand, and like with the other performance indicators, present higher turnover per worker, when compared with firms without robots. On average, these firms have a Real Turnover per Worker that is 20.7% higher than that of similar firms that do not employ robots.

Table 17 – OLS Results: Real Firm Turnover per Worker (Portugal - 2018 & 2020)

Variables	Real Firm Turnover per Worker		
Robot Usage			
Only Industrial Robots	0.0113 (0.0433)	0.00674 (0.0410)	0.0106 (0.0410)
Only Service Robots	0.0126 (0.0736)	0.00197 (0.0692)	0.00945 (0.0691)
Both Types of Robots	0.229*** (0.0737)	0.201*** (0.0706)	0.207*** (0.0705)
Constant	9.589*** (0.711)	9.779*** (0.608)	9.803*** (0.608)
Firm Characteristics	YES	YES	YES
Workforce Characteristics	NO	YES	YES
Time Dummies	NO	NO	YES
Nº obs. (Firms)	10,535	10,535	10,535
R^2	0.425	0.460	0.461

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are shown in parentheses, clustered by firm ID. Regarding the dependent variable, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped. "Robot Usage" is a set of dummy variables that characterize each firm according to its robot usage, and the omitted category is "No Robot Usage"
Source: *IUTICE*, *SCIE*, *QP*, and Own Calculations

5.2. Robot Usage and Wages

5.2.1. Econometric Model

For the wage analysis, we merge *IUTICE* with *QP*, and end up with a sample of 1,583,170 workers. Following the same line of thought of the productivity analysis, we begin by looking into Table A5[17], which presents the pair-wise correlations between the use of robots and wages. Once again, these correlations, although significant, are very weak, which

[17] Table A5, in the annex, presents the pair-wise correlations between our Robot Usage dummies and the dependent variables of the wage analysis

compels us to estimate OLS models as to determine if indeed there is a correlation between robots and wages. The estimated model is as follows:

(5.2)

$$\text{Log(Wage}_{it}) = \alpha + \gamma_1 \text{Only\_Ind}_{it} + \gamma_2 \text{Only\_Serv}_{it} + \gamma_3 \text{Both\_Types}_{it} + \boldsymbol{\beta}_i \mathbf{W}_{it} + \boldsymbol{\theta}_i \mathbf{X}_{it} + \delta_t + \varepsilon_{it}$$

where the dependent variable Log(Wage_{it}) corresponds to the logarithm of the Real Monthly Wage of worker i, in the year t, with t = {2018,2020}. Only_Ind_{it} is a dummy variable indicating if company i only uses industrial robots, in the year t. Only_Serv_{it} is a dummy variable indicating if company i only uses service robots, in the year t. Both_Types_{it} is a dummy variable indicating if company i uses both types of robots, in the year t. $\mathbf{W}_{it}$ are worker-level characteristics such as age, gender, nationality, education level, qualifications, job ID, tenure, and the type and nature of the contract. $\mathbf{X}_{it}$ are firm-level characteristics such as the log of the number of workers, location, and industry. Finally, δ_t is a time fixed effect, and ε_{it} is the error term.

We make an additional model, similar in all aspects to (5.2), but with the dependent variable being the logarithm of the Real Hourly Wage, which serves as a robustness check to the results obtained in the wage analysis. Table A6, in the annex, presents the summary statistics of the variables used in both regressions.

5.2.2. Results

Table 18 presents the relevant estimates of regressions (5.2). Looking into it, we observe that workers in firms that use robots (regardless of type) earn higher Real Monthly Wages than similar workers in firms that do not employ robots. Once again, workers in firms that make use of both types of robots present the highest Real Monthly Wages. Indeed, a worker employed in a firm that uses both types of robots earns, on average, a Real Monthly Wage that is 15.8% higher than that of a worker in a similar firm that does not use robots.

Table 18 – OLS Results: Real Monthly Wage (Portugal - 2018 & 2020)

Variables	**Log Real Monthly Wage**		
Robot Usage			
Only Industrial Robots	0.0635*** (0.00129)	0.0527*** (0.00138)	0.0494*** (0.00139)
Only Service Robots	0.0968*** (0.00168)	0.0350*** (0.00174)	0.0315*** (0.00174)
Both Types of Robots	0.167*** (0.00175)	0.164*** (0.00180)	0.158*** (0.00181)
Constant	5.650*** (0.00924)	5.892*** (0.0253)	5.887*** (0.0254)
Worker Characteristics	YES	YES	YES
Firm Characteristics	NO	YES	YES
Time Dummies	NO	NO	YES
Nº obs. (Workers)	1,583,170	1,583,170	1,583,170
R^2	0.581	0.606	0.607

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are shown in parentheses, clustered by worker ID. Regarding the dependent variable, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped. "Robot Usage" is a set of dummy variables that characterize each firm according to its robot usage, and the omitted category is "No Robot Usage". The full specification is presented in Table A7[18]
Source: *IUTICE*, *QP*, and Own Calculations

As a robustness check, Table 19 presents similar conclusions. Robots (regardless of type) have a positive and significant (at a 0.01 significance level) correlation with Real Hourly Wages. This is especially true when comparing a firm that employs both types of robots with a firm that does not use them. Indeed, a worker in the former earns, on average, a 13.9% higher Real Hourly Wage than a worker in the latter.

[18] Table A7, in the annex, presents the OLS estimates for the full specification of regression (5.2)

Table 19 – OLS Results: Real Hourly Wage (Portugal - 2018 & 2020)

Variables	**Log Real Hourly Wage**		
Robot Usage			
Only Industrial Robots	0.0509***	0.0695***	0.0657***
	(0.00108)	(0.00115)	(0.00115)
Only Service Robots	0.0695***	0.0169***	0.0128***
	(0.00126)	(0.00135)	(0.00135)
Both Types of Robots	0.125***	0.146***	0.139***
	(0.00145)	(0.00147)	(0.00147)
Constant	1.533***	1.647***	1.641***
	(0.00530)	(0.0164)	(0.0165)
Worker Characteristics	YES	YES	YES
Firm Characteristics	NO	YES	YES
Time Dummies	NO	NO	YES
Nº obs. (Workers)	1,583,170	1,583,170	1,583,170
R^2	0.616	0.647	0.650

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are shown in parentheses, clustered by worker ID. Regarding the dependent variable, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped. "Robot Usage" is a set of dummy variables that characterize each firm according to its robot usage, and the omitted category is "No Robot Usage"
Source: *IUTICE*, *QP*, and Own Calculations

6. Conclusion

In this study, we analyze the impact of the use of robots on productivity, employment, and wages both from a descriptive perspective and from an econometric perspective. The literature available, regarding the impacts of robotization on Portuguese firms, is scarce and is mainly focused on the productivity side of the topic (e.g., Amador & Silva (2023), and Amador (2024)). This compels us to further develop the topic of robotization by not only analyzing its impact on some performance indicators such as Real Productivity (measured by the real value of production per worker), Real Value Added per Worker (at Factor Costs), and Real Firm Turnover per Worker but also extending the analysis into the impacts on employment and wages.

To this end, we use three databases, namely *IUTICE*, *SCIE*, and *QP*, which contain microdata at the worker and firm level. *IUTICE* is an annual survey containing information regarding the usage of ICT technologies in Portuguese firms (in the 2018, 2020, and 2022 editions, it contains questions regarding Robot Usage). *SCIE* is an annual survey that contains financial information on Portuguese firms, and we use it to obtain information on the performance indicators we analyze. *QP* is a standardized annual administrative survey that contains much information regarding the majority of Portuguese workers and Portuguese firms, but we mainly use it to obtain information on workers' wages.

By merging our main database (*IUTICE*) with *SCIE* we analyze the impact on productivity, and by merging it with *QP* we analyze the impact of robotization on employment and wages. Throughout the analysis, we classify firms into four categories, according to their robot usage (Only Industrial Robots, Only Service Robots, Both Types of Robots, and No Robot Usage). This classification allows us to deepen our analysis, by distinguishing the impacts of robotization on productivity, employment, and wages, based on the type of robot the firm uses.

From our descriptive and econometric analysis, we show that firms with Only Industrial Robots and firms with Both Types of Robots tend to be more productive than those that do not utilize robots, with special relevance to the latter. On the other hand, regarding the value added per worker of the activities in which these firms engage and their turnover (per worker), we find that only firms that employ Both Types of Robots present significantly higher values. Those using only one type of robot do not present statistically different values than their robot-free counterparts. As such, only firms employing Both Types of Robots show consistently higher values than robot-free firms, across the three performance indicators.

Regarding the employment side of our study, we find that firms with robots have a higher predominance of workers performing Routine Manual tasks than firms without robots, even though there appears to be a downward trend in this type of task (that is more pronounced in firms with robots). We argue that this can be a case of reverse causality: it is not because firms use robots that there is an increased need for Routine Manual tasks, but on the contrary, it is because firms have an above-average need for Routine Manual tasks that leads them to implement the usage of robots in their firms. On the other hand, despite an upward trend in Non-Routine tasks, these seem to be more common in robot-free firms than in their robot-using counterparts. These findings can be linked to the Displacement Effect presented by Acemoglu and Restrepo (2019), where workers move from jobs that are automated to jobs created by automation. In terms of the workforce, companies with robots generally feature a greater share of men and more qualified workers.

As for the wage analysis, we conclude that workers in firms equipped with robots tend to be paid higher monthly and hourly wages, especially when the firms employ Both Types of Robots. This remains true across the various types of tasks, even though we note a bigger difference in Non-Routine Cognitive tasks.

Although we believe that the conclusions reached in this study are valid for Portuguese firms, they are limited by the size of the sample, as the *IUTICE* survey only covers a small representative number of firms. Additionally, since in our econometric analysis, our variables of interest are dummy variables, we only study the effect of adopting the first robot in the firm (the impact of going from 0 to 1). Indeed, since we do not have data for the number of robots each firm owns, it is not possible to study the effect of adding an additional robot.

Finally, we present some lines of future research. It would be interesting to investigate which job titles are most common in each type of task (in robot-using firms), to be able to better characterize their workforces, as well as to understand their needs in terms of jobs. In addition, it could be relevant to use statistical inference or machine learning models to obtain more data and, consequently, more robust results. Replicating our study with more recent data (e.g., when the data for the 2022' edition of *QP* is available) also seems worthwhile.

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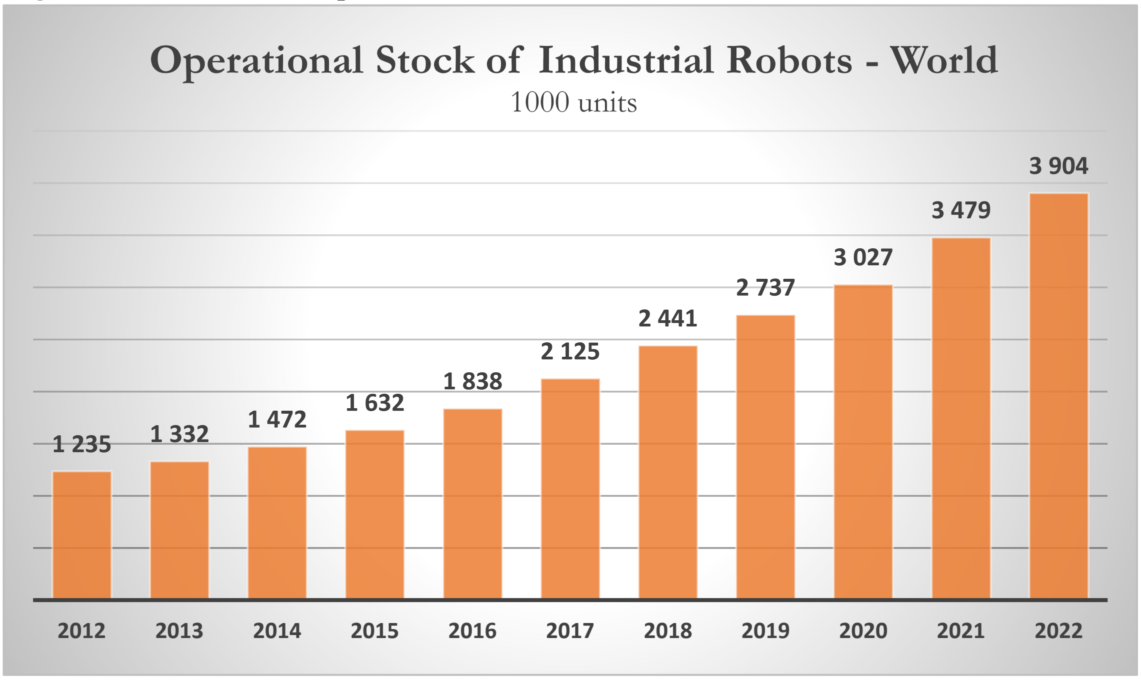
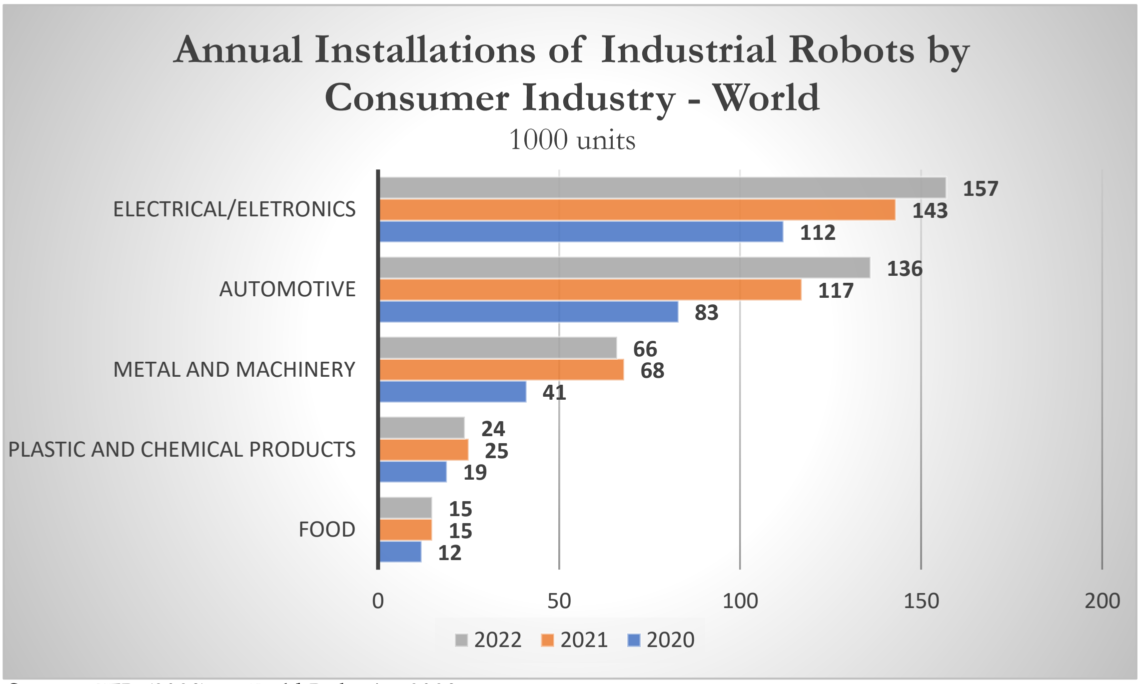
Annex

Figure A1 – Worldwide Operational Stock of Industrial Robots



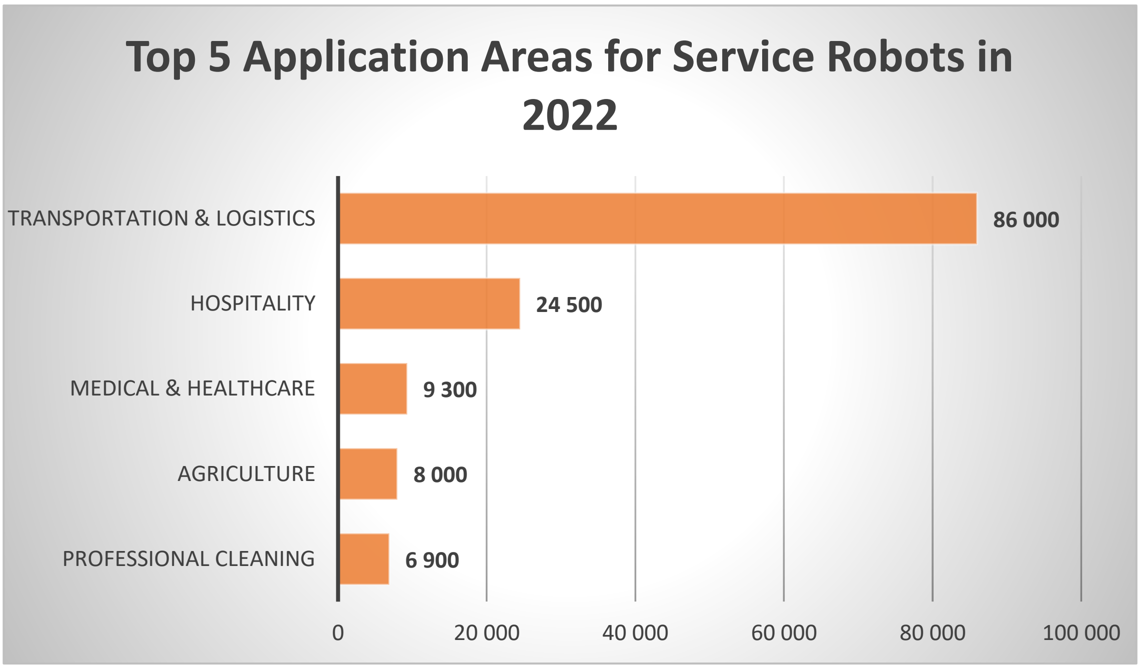
Source: IFR (2023) – World Robotics 2023

Figure A2 – Worldwide Annual Installations of Industrial Robots by Consumer Industry



Source: IFR (2023) – World Robotics 2023

Figure A3 – Top 5 Application Areas for Service Robots in 2022



Source: IFR (2023) – World Robotics 2023

Table A1 – Distribution of Firms by Robot Usage and Sector of Activity (Portugal - Average 2018 & 2020)

Sector of Activity	Robot Usage				Total
	Both Types of Robots	Only Industrial Robots	Only Service Robots	No Robot Usage	
A - Agriculture, Animal Production, Hunting, Forestry, and Fishing	0	0	0	10	10
B - Extractive industries	0	0	0	2	2
C - Manufacturing Industries	156	598	69	2,337	3,160
D - Electricity, Gas, Steam, Hot and Cold Water, and Cold Air	0	0	4	67	71
E - Water collection, Treatment, and Distribution; Sanitation, Waste Management, and Depollution	1	2	12	155	170
F - Construction	5	10	13	492	520
G - Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles	19	40	54	2,303	2,416
H - Transports and Storage	4	3	25	492	524
I - Accommodation, Catering, and Similar Activities	2	2	18	1,497	1,519
J - Information and Communication Activities	1	2	6	786	795
K - Financial and insurance activities	0	0	0	18	18
L - Real Estate Activities	0	2	6	512	520
M - Consultancy, Scientific, Technical and Similar Activities	2	2	6	499	509
N - Administrative Activities and Support Services	6	4	13	712	735
Q - Human health and social support activities	0	0	0	4	4
R - Artistic, entertainment, sporting, and recreational activities	0	0	0	9	9
S - Other Service Activities	0	1	3	97	101
Total	**196**	**666**	**229**	**9,992**	**11,083**

Source: *IUTICE*, *QP*, and Own Calculations

Table A2 – Pair-Wise Correlations of Relevant Variables – Productivity Analysis

Pair-Wise Correlations	Only Industrial Robots	Only Service Robots	Both Types of Robots	No Robot Usage	Log Real Turnover per Worker	Log Real Value Added per Worker (at Factor Costs)	Log Real Productivity
Only Industrial Robots	1.000						
Only Service Robots	-0.038***	1.000					
Both Types of Robots	-0.035***	-0.020**	1.000				
No Robot Usage	-0.767***	-0.435***	-0.405***	1.000			
Log Real Turnover per Worker	0.048***	0.028***	0.070***	-0.083***	1.000		
Log Real Value Added per Worker (at Factor Costs)	0.062***	0.026***	0.078***	-0.097***	0.720***	1.000	
Log Real Productivity	0.124***	0.035***	0.099***	-0.160***	0.827***	0.780***	1.000

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; Regarding the Real Turnover per Worker, Real Value Added per Worker (at Factor Costs), and Real Productivity, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped
Source: *IUTICE*, *SCIE*, and Own Calculations

Table A3 – Summary Statistics of Variables Used in Econometric Productivity Analysis (Portugal - Average 2018 & 2020)

Variables	N	Mean	SD	Min	Max
Log Real Productivity	10,535	11.01	1.06	6.95	15.33
Log Real Firm Turnover per Worker	10,535	11.38	1.25	5.25	16.27
Log Real Value Added per Worker (at Factor Costs)	10,535	10.11	0.94	1.91	13.86
Only Industrial Robots (Dummy = 1 if the firm only uses industrial robots in that year)	10,535	0.06	0.24	0	1
Only Service Robots (Dummy = 1 if the firm only uses service robots in that year)	10,535	0.02	0.14	0	1
Both Types of Robots (Dummy = 1 if the firm uses both types of robots in that year)	10,535	0.02	0.13	0	1
No Robot Usage (Dummy = 1 if the firm does not use robots in that year)	10,535	0.90	0.30	0	1
Log Capital (Logarithm of the firms' social capital)	10,535	11.47	2.72	0	22.10
Log Number of Workers	10,535	3.02	1.90	0	10.13
Firm Age (in years)	10,535	24.98	16.93	0	231
Foreign (Dummy = 1 if at least 50% of the firm capital is foreign)	10,535	0.13	0.34	0	1
Percentage Female (Percentage of female workers in the firm)	10,535	0.40	0.28	0	1
Percentage Higher Education (Percentage of workers with higher education, in the firm)	10,535	0.21	0.27	0	1
Percentage Old (Percentage of workers with at least 55 years, in the firm)	10,535	0.16	0.19	0	1
NUT2 (Set of dummy variables indicating the location of the firm, at a *NUT2* level)	-	-	-	-	-
CAE (Set of dummy variables indicating the sector of activity of the firm)	-	-	-	-	-
Year	-	-	-	-	-

Source: *IUTICE*, *SCIE*, *QP*, and Own Calculations

Table A4 – OLS Results: Real Productivity Regression - Full Specification (Portugal - Average 2018 & 2020)

Variables	Log Real Productivity		
Robot Usage			
Only Industrial Robots	0.0872**	0.0861**	0.0907**
	(0.0407)	(0.0381)	(0.0381)
Only Service Robots	0.0579	0.0430	0.0519
	(0.0643)	(0.0582)	(0.0582)
Both Types of Robots	0.215***	0.192***	0.198***
	(0.0702)	(0.0666)	(0.0665)
Log Capital	0.220***	0.194***	0.193***
	(0.00661)	(0.00631)	(0.00631)
Log Number of Workers	-0.155***	-0.140***	-0.140***
	(0.00895)	(0.00866)	(0.00866)
Firm Age	-0.00293***	-0.00162**	-0.00146**
	(0.000684)	(0.000649)	(0.000648)
Foreign	0.592***	0.463***	0.463***
	(0.0385)	(0.0361)	(0.0361)
NUT2			
Algarve	0.0210	0.0716*	0.0672
	(0.0431)	(0.0423)	(0.0420)
Centro	0.0287	0.0485**	0.0480**
	(0.0246)	(0.0235)	(0.0235)
Lisboa	0.205***	0.179***	0.179***
	(0.0256)	(0.0244)	(0.0244)
Alentejo	0.120**	0.141***	0.142***
	(0.0480)	(0.0447)	(0.0449)
Açores	0.0115	0.0580	0.0539
	(0.0772)	(0.0711)	(0.0711)
Madeira	-0.0608	-0.0171	-0.0202
	(0.0699)	(0.0693)	(0.0689)
CAE			
B	0.360	0.520	0.590
	(0.538)	(0.471)	(0.470)
C	-0.126	-0.000271	0.0138
	(0.393)	(0.309)	(0.305)
D	0.837*	0.800**	0.814**
	(0.430)	(0.349)	(0.346)
E	-0.294	-0.215	-0.206
	(0.403)	(0.321)	(0.317)
F	-0.160	-0.124	-0.111
	(0.395)	(0.311)	(0.306)
G	-0.425	-0.381	-0.367
	(0.393)	(0.309)	(0.304)
H	-0.128	-0.0132	0.00576

	(0.396)	(0.313)	(0.308)
I	-0.842**	-0.609**	-0.589*
	(0.393)	(0.309)	(0.305)
J	-0.158	-0.499	-0.489
	(0.394)	(0.310)	(0.306)
K	-0.403	-0.745*	-0.741*
	(0.487)	(0.428)	(0.424)
L	0.0553	0.0868	0.101
	(0.395)	(0.312)	(0.307)
M	-0.223	-0.488	-0.474
	(0.395)	(0.312)	(0.307)
N	-0.561	-0.513	-0.498
	(0.396)	(0.312)	(0.308)
Q	-0.210	-0.431	-0.469
	(0.443)	(0.392)	(0.388)
R	-0.0624	-0.0434	-0.0198
	(0.527)	(0.449)	(0.446)
S	-0.654	-0.648**	-0.633**
	(0.400)	(0.318)	(0.314)
Percentage Female		-0.303***	-0.300***
		(0.0379)	(0.0379)
Percentage Higher Education		0.997***	1.007***
		(0.0522)	(0.0522)
Percentage Old		-0.393***	-0.378***
		(0.0501)	(0.0502)
Year			
2020			-0.104***
			(0.0132)
Constant	9.184***	9.339***	9.367***
	(0.396)	(0.312)	(0.308)
Nº obs. (Firms)	10,535	10,535	10,535
R^2	0.363	0.414	0.417

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are shown in parentheses, clustered by firm ID. Regarding the dependent variable, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped. "Robot Usage" is a set of dummy variables that characterize each firm according to its robot usage, and the omitted category is "No Robot Usage"
Source: *IUTICE*, *SCIE*, *QP*, and Own Calculations

Table A5 – Pair-Wise Correlations of Relevant Variables – Wage Analysis

Pair-Wise Correlations	Only Industrial Robots	Only Service Robots	Both Types of Robots	No Robot Usage	Log Real Hourly Wage	Log Real Monthly Wage
Only Industrial Robots	1.000					
Only Service Robots	-0.084***	1.000				
Both Types of Robots	-0.081***	-0.053***	1.000			
No Robot Usage	-0.684***	-0.449***	-0.435***	1.000		
Log Real Hourly Wage	0.061***	0.066***	0.085***	-0.128***	1.000	
Log Real Monthly Wage	0.091***	0.054***	0.099***	-0.151***	0.773***	1.000

Note: *** p<0.01, ** p<0.05, * p<0.1; Regarding Real Monthly Wage and Real Hourly Wage, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped
Source: *IUTICE*, *QP*, and Own Calculations

Table A6 – Summary Statistics of Variables Used in Econometric Wage Analysis (Portugal - Average 2018 & 2020)

Variables	N	Mean	SD	Min	Max
Log Real Monthly Wage	1,586,967	6.75	0.75	3.26	8.82
Log Real Hourly Wage	1,586,967	1.79	0.49	1.15	3.74
Only Industrial Robots (Dummy = 1 if the firm only uses industrial robots in that year)	1,586,967	0.11	0.32	0	1
Only Service Robots (Dummy = 1 if the firm only uses service robots in that year)	1,586,967	0.05	0.22	0	1
Both Types of Robots (Dummy = 1 if the firm uses both types of robots in that year)	1,586,967	0.05	0.22	0	1
No Robot Usage (Dummy = 1 if the firm does not use robots in that year)	1,586,967	0.79	0.41	0	1
Male (Dummy = 1 if the worker is male)	1,586,967	0.55	0.50	0	1
Full Time (Dummy = 1 if the worker has a full-time contract)	1,586,967	0.89	0.31	0	1
Without Term (Dummy = 1 if the worker has a no-term contract)	1,586,967	0.67	0.47	0	1
Fixed Term (Dummy = 1 if the worker has a fixed-term contract)	1,586,967	0.33	0.47	0	1
Portuguese (Dummy = 1 if the worker has Portuguese nationality)	1,586,967	0.94	0.24	0	1
Age (in years)	1,586,967	39.46	11.59	18	68
Age Squared (in years)	1,586,967	1,691.28	948.19	324	4,624
Tenure (in years)	1,586,967	8.13	9.68	0	76
Tenure Squared (in years)	1,586,967	159.85	299.20	0	5,776
Senior Management (Dummy = 1 if worker is part of Senior Management)	1,586,967	0.07	0.26	0	1
Middle Management (Dummy = 1 if the worker is part of Middle Management)	1,586,967	0.05	0.21	0	1

Foremen, Masters, and Team Leaders (Dummy = 1 if the worker is a Foreman, Master, or Team Leader)	1,586,967	0.06	0.24	0	1
Highly Qualified Professionals (Dummy = 1 if worker is a Highly Qualified Professional)	1,586,967	0.09	0.29	0	1
Qualified Professionals (Dummy = 1 if the worker is a Qualified Professional)	1,586,967	0.35	0.48	0	1
Semi-qualified Professionals (Dummy = 1 if the worker is a Semi-qualified Professional)	1,586,967	0.22	0.41	0	1
Not Qualified Professionals (Dummy = 1 if the worker is not a qualified professional)	1,586,967	0.14	0.34	0	1
Trainees, practitioners, and apprentices (Dummy = 1 if the worker is a Trainee, Practitioner, or Apprentice)	1,586,967	0.03	0.16	0	1
Elementary School (Dummy = 1 if the worker has an Elementary School education level)	1,586,967	0.44	0.50	0	1
Secondary School (Dummy = 1 if the worker has a Secondary School education level)	1,586967	0.36	0.48	0	1
Bachelor (Dummy = 1 if the worker has a Bachelor's education level)	1,586,967	0.17	0.37	0	1
Master (Dummy = 1 if the worker has a Master education level)	1,586,967	0.03	0.17	0	1
PhD (Dummy = 1 if the worker has PhD education level)	1,586,967	0.001	0.04	0	1
Log number of workers	1,586,967	6.88	1.76	0	10.13
Job ID (Set of dummy variables indicating the type of occupation according to the Portuguese Classification of Occupations - 1 digit)	-	-	-	-	-
NUT2 (Set of dummy variables indicating the location of the firm, at a *NUT2* level)	-	-	-	-	-
CAE (Set of dummy variables indicating the sector of activity of the firm)	-	-	-	-	-
Year	-	-	-	-	-

Source: *IUTICE*, *QP*, and Own Calculations

Table A7 – OLS Results: Real Monthly Wage Regression - Full Specification (Portugal - Average 2018 & 2020)

Variables	Real Monthly Wage		
Robot Usage			
Only Industrial Robots	0.0635***	0.0527***	0.0494***
	(0.00129)	(0.00138)	(0.00139)
Only Service Robots	0.0968***	0.0350***	0.0315***
	(0.00168)	(0.00174)	(0.00174)
Both Types of Robots	0.167***	0.164***	0.158***
	(0.00175)	(0.00180)	(0.00181)
Male	0.152***	0.139***	0.139***
	(0.00111)	(0.00109)	(0.00109)
Nature of Contract			
Full Time	0.752***	0.738***	0.738***
	(0.00233)	(0.00229)	(0.00229)
Type of Contract			
Without Term	0.152***	0.0403***	0.0390***
	(0.00174)	(0.00199)	(0.00199)
Fixed Term	-0.0226***	-0.122***	-0.115***
	(0.00229)	(0.00272)	(0.00275)
Portuguese	0.0249***	-0.0100***	-0.00478*
	(0.00271)	(0.00263)	(0.00263)
Age	0.0174***	0.0177***	0.0177***
	(0.000406)	(0.000385)	(0.000385)
Age Squared	-0.000173***	-0.000165***	-0.000167***
	(4.76e-06)	(4.51e-06)	(4.51e-06)
Tenure	0.0163***	0.0137***	0.0139***
	(0.000169)	(0.000160)	(0.000161)
Tenure Squared	-0.000165***	-0.000167***	-0.000170***
	(4.89e-06)	(4.55e-06)	(4.55e-06)
Qualification			
Senior Management	0.451***	0.431***	0.431***
	(0.00375)	(0.00356)	(0.00356)
Middle Management	0.341***	0.337***	0.337***
	(0.00356)	(0.00338)	(0.00338)
Foremen, Masters, and Team Leaders	0.268***	0.279***	0.280***
	(0.00339)	(0.00318)	(0.00318)
Highly Qualified Professionals	0.158***	0.145***	0.144***
	(0.00300)	(0.00284)	(0.00283)
Qualified Professionals	-0.0329***	-0.0224***	-0.0219***
	(0.00273)	(0.00254)	(0.00253)
Semi-qualified Professionals	-0.0736***	-0.0424***	-0.0448***
	(0.00277)	(0.00257)	(0.00256)
Non-Qualified Professionals	-0.0663***	0.00672**	0.00113

	(0.00271)	(0.00275)	(0.00275)
Education			
Secondary School	0.142***	0.117***	0.114***
	(0.00137)	(0.00131)	(0.00131)
Bachelor	0.324***	0.293***	0.290***
	(0.00195)	(0.00187)	(0.00187)
Master	0.333***	0.288***	0.283***
	(0.00301)	(0.00292)	(0.00292)
PhD	0.475***	0.426***	0.420***
	(0.0103)	(0.0105)	(0.0105)
Job ID			
2	-0.254***	-0.278***	-0.279***
	(0.00365)	(0.00361)	(0.00362)
3	-0.315***	-0.337***	-0.339***
	(0.00390)	(0.00384)	(0.00384)
4	-0.451***	-0.443***	-0.445***
	(0.00403)	(0.00400)	(0.00400)
5	-0.472***	-0.509***	-0.510***
	(0.00411)	(0.00411)	(0.00411)
6	-0.810***	-0.760***	-0.767***
	(0.0106)	(0.0104)	(0.0104)
7	-0.477***	-0.520***	-0.522***
	(0.00417)	(0.00412)	(0.00412)
8	-0.463***	-0.511***	-0.512***
	(0.00416)	(0.00417)	(0.00417)
9	-0.660***	-0.627***	-0.627***
	(0.00456)	(0.00442)	(0.00442)
Log Number of Workers		-0.0128***	-0.0125***
		(0.000321)	(0.000321)
NUT2			
Algarve		0.134***	0.137***
		(0.00388)	(0.00388)
Centro		-0.0134***	-0.0140***
		(0.00137)	(0.00136)
Lisboa		0.0861***	0.0869***
		(0.00108)	(0.00108)
Alentejo		0.00429	0.00360
		(0.00269)	(0.00268)
Açores		0.0496***	0.0500***
		(0.00357)	(0.00356)
Madeira		0.0966***	0.0949***
		(0.00335)	(0.00335)
CAE			
B		0.0687	0.0188
		(0.0613)	(0.0613)
C		0.0200	-0.00166
		(0.0236)	(0.0237)

D		0.473***	0.449***
		(0.0238)	(0.0239)
E		-0.0543**	-0.0786***
		(0.0237)	(0.0238)
F		-0.0392*	-0.0635***
		(0.0237)	(0.0238)
G		0.0527**	0.0274
		(0.0236)	(0.0237)
H		0.117***	0.0940***
		(0.0236)	(0.0237)
I		-0.128***	-0.153***
		(0.0237)	(0.0237)
J		0.00127	-0.0231
		(0.0237)	(0.0237)
K		0.137***	0.116***
		(0.0268)	(0.0270)
L		-0.0627**	-0.0849***
		(0.0247)	(0.0247)
M		-0.0206	-0.0454*
		(0.0237)	(0.0238)
N		-0.273***	-0.296***
		(0.0237)	(0.0237)
Q		-0.317**	-0.313**
		(0.137)	(0.137)
R		-0.154**	-0.178***
		(0.0678)	(0.0665)
S		-0.205***	-0.229***
		(0.0256)	(0.0256)
Year			
2020			0.0513***
			(0.000824)
Constant	5.650***	5.892***	5.887***
	(0.00924)	(0.0253)	(0.0254)
Nº obs. (Workers)	1,583,170	1,583,170	1,583,170
R^2	0.581	0.606	0.607

Note: *** p<0.01, ** p<0.05, * p<0.1; Robust standard errors are shown in parentheses, clustered by worker ID. Regarding the dependent variable, the top and bottom 0.5% of the distribution values were replaced by missing values, using the Winsor2 command, and subsequently dropped. "Robot Usage" is a set of dummy variables that characterize each firm according to its robot usage, and the omitted category is "No Robot Usage
Source: *IUTICE*, *QP*, and Own Calculations