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Effect of Usage of Industrial Robots on Quality, Labor Productivity, Exports and Environment

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Abstract: Industrial robots are slowly but surely entering manufacturing companies. This paper explores the effects that robots have on productivity, exports, quality, sustainability and labor in European manufacturing companies. There is lack of research on industrial robot usage and its effects in developed countries. Most research is done on Chinese companies and often the data is outdated. The data in this paper is from the European Manufacturing Survey project conducted in 2022 and includes 476 manufacturing companies. Results of the effects of Industrial robots on Quality, Labor Productivity, Exports and Environmental saving technologies are done by use of T-test between industrial robots' adopters and non-adopters. However, the effect of higher investment into environmental technology by industrial robots' adopters was researched by 2-step OLS regression analysis with control variables representing the contextual characteristics of companies. The results show positive effects on all variables. Results show that larger usage of robots are in low to medium-technology-intensity industries, that robots contribute to labor productivity, exports and that companies employing robots usually also employ environmentally saving technologies.

Keywords: Industrial robots; productivity; quality; exports; environmental; sustainability; European manufacturing survey

1. Introduction

Industrial robots are becoming safer and more affordable so many companies are implementing them in their production as costs of robots also decrease. According to the International Federation of Robotics (IFR) in 2024 current global robot installations base is at an all-time high of around 4 million units, as a solution for labor shortages. Main reason for robot adoption is quality (less scrap), increase of manufacturing productivity (faster cycle time), improved worker safety, reduction of work-in-progress, greater flexibility in the manufacturing process and reduction of costs. 79% of global robot installations are in five countries China, Japan, the United States, the Republic of Korea, and Germany [1]. In 2020, 3 million robots (32%) were installed in China [2]. There is vast literature on how robotics increase growth and possibly replace humans, but nothing has been written about the current state. Even the IFR report analyses just few main countries. Duan et al. [2] have performed a comprehensive literature research on the topic. Most research conducted in developed countries are looking at the country level and not from the company level. Therefore, this is one gap that we aim to fill with this research. A research from [3] theoretically predicts that robots will negatively influence jobs and wages in US. We investigate influence of robots with a survey and check the statements provided by [3] that robots have negative effect on employment with up to date large scale survey on manufacturing companies in Europe. But, Aggogeri et al. [4] in a recent survey of 660 Italian companies show that not only productivity rose by implementing industrial robots but, also that there were no layoffs. The same shows [5] for Europe on IFR data. Therefore, one goal is to check these conflicting findings in the literature, do robots really decrease number of employees. Acemoglu et al. [6] used French manufacturing company data and found that industrial robot use can increase manufacturing output and productivity growth. Kromann et al. [7] found that industrial robots have a positive impact on productivity. Graetz & Michaels [8] found that the use of industrial robots

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increases labor productivity and total factor productivity, using industrial robot data from 17 countries as a sample. Cheng & Yuan [9] found that the use of robots has a positive effect on productivity and quality through innovation of products and processes. They have proved that robots improve productivity but on the data from 2019 and earlier [9]. Therefore, our goal is to check do robots increase productivity and decrease scrap rate in our sample of newer data. In this work we will analyze robots' effects on productivity, quality, exports and sustainability. Exports are especially important for GDP growth and jobs creation especially for countries with small local market [10]. Companies are pursuing sustainability to increase operational efficiency by reducing costs and waste, respond to or reach new customers and increase competitive advantage, protect and strengthen brand and reputation and build public trust [11], [12], and robots can help with that.

We will analyze four slightly less developed countries (Spain, Slovakia, Slovenia, Croatia) than the five countries stated in the IFR report [1] (China, Japan, the United States, the Republic of Korea, and Germany). According to that report Spain and France have the lowest density of robots, while Slovakia, Slovenia and Croatia are not mentioned. According to [13] there is the question if the worldwide diffusion of industrial robots contributes to a widening or closing of the productivity gap between rich and poorer economies. Additionally, we will raise questions about contingence factors such as company size, product complexity, and technological intensity.

2. Literature review

2.1. Industrial robots

Industrial robots in our paper are divided into four groups: robots for manufacturing processes and robots for handling, as well as autonomous mobile robots and collaborative robots (cobots). Typically, robots for manufacturing processes are multi-purpose machines consist of at least one reprogrammable robotic arm, or a manipulator, that operates on three axes or more. Robots for manufacturing processes are robots that do repetitive tasks with higher accuracy than humans and due to their stable functioning produce, fewer errors and scrap [14]. They are used for various tasks including; grinning, drilling, cutting, polishing and the like. Technology is not randomly adopted but done so with an expected return on that investment. For instance, in terms of cutting machines, mechanical cutting robots matter more for quality upgrading. The engineering literature and recent descriptive studies highlight several possible mechanisms through which robots may lead to product quality improvements. Robots enable greater accuracy and precision for repetitive tasks, reducing production error, and thereby increasing product quality [15]. Soori et al. [16] show that today's robots also make significant contributions to energy savings. Some of the main factors that can affect the energy consumption of industrial robots include:

(1) Type of robot: Different types of robots have different energy requirements. For example, a large, heavy-duty robot may require more energy to operate than a small, lightweight robot;

(2) Task performance: The energy consumption of a robot will also depend on the type of task it is performing. Tasks that require a lot of movement or heavy lifting may require more energy than tasks that are more static, and

(3) Operating conditions: The energy consumption of a robot can also be affected by the operating conditions, such as temperature, humidity, and the presence of dust or other contaminants.

Cheng and Yuan [9] with their simulation prove that energy consumption can be reduced by 22%. Also, the use of industrial robots reduces total carbon emissions [17].

Material handling industrial robots are well equipped to load and unload heavy materials, as well as pack and select products. By automating the processes associated with transferring parts between different pieces of equipment, tedious and hazardous tasks are taken care of without the risk of injury [18].

Autonomous mobile robots are a special class of robotic systems that can move a payload from one location to the other or perform a specific task. They allow efficient, precise, and streamlined workflow that makes human work less arduous. However, their widespread application is still limited due to the lack of efficient power systems for use in diverse and largely

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unknown/uncontrolled environments [19]. According to [20] and [21], that kind of robots are mostly used in warehouses. Those robots have advanced vision systems to precisely grasp objects [22].

A collaborative robot, or cobot, enables users to work closely with it through direct communication without the use of traditional barricades. Cobots can be used for a variety of tasks, from communication robots in public areas and logistic or supply chain robots that move materials inside a building, to articulated or industrial robots that assist in automating tasks which are not ergonomically sound, such as assisting individuals in carrying large parts, or assembly lines. Among the main advantages of using cobots in the workplace is the avoidance of injuries. Cobots cannot perform heavy lifting because they were not designed for that purpose. They are not completely automated to handle complex tasks [23].

2.2. Labor productivity

Labor productivity growth drives economic growth and plays a central role for the wealth and development of nations and the improvement of living standards [13]. The test results of various mechanisms jointly show that the application of industrial robots has a systematic impact on the production and operation activities of companies by expanding their production scale, improving production efficiency, and upgrading production skills, thereby increasing the overall demand for labor [24]. One reason why we still have high labor productivity despite more robots is that robots may be expensive to buy, maintain, and operate, and they may be more inflexible in adjusting to new tasks or unforeseen situations [25]. Automation has not only increased labor productivity, but also created new tasks. For example, a newer model of a welding robot, that can weld faster and more accurately than an earlier model, will increase productivity without displacing workers. Last, new automation technologies can create new tasks that need to be performed by labor [26]. Yuan and Lu [27] go so far as to state that by robot installation, not only the increase of productivity, but the whole country can become more competitive. Acemoglu et al. [28] in a very detailed analysis show that companies adopting robots, perform better than competitors who do not invest into robots. Also, the share of their replaceable employees is far lower than in non-adopters' group, and their workers are more competent.

2.3. Quality

At the company-level, businesses that produce higher quality goods have higher revenue and employment, pay higher wages, are more productive and sell their goods to a greater variety of markets [29]. Yang and Liu [30] researched quality among China manufacturing companies and robot adoption. They state that China is now quality oriented instead of volume oriented and that this subject is not investigated at all. They state that industrial robots have characteristics of permeability, substitutability and synergism, so they can gradually infiltrate into all aspects of manufacturing production, thus changing the operation mode of the manufacturing industry. Secondly, they state that industrial robots improve the production quality of the manufacturing industry through improving production methods and optimizing the management mode. However, Azamfirei et al. [31] warn that simply investing in robot error detection will not solve the quality issues, unless people do not react on, and change the process due to a defective part.

2.4. Exports

Export quality has attracted a great deal of attention because of its importance for the development and growth [15]. Zhang et al. [32] researched industrial robots and exports in China and conclude that adopters of industrial robots far outweigh non-adopters. But they also say that most SMEs are in non-adopters group. Li et al. [33] find that the industrial robot applications have positive effects on exports by reducing export costs and upgrading product technology. This effect is stronger in economically advanced countries. Moreover, technological innovation and educational investment amplify the impact of industrial robots on exports [34]. According to [10], it is not necessary for exports to exceed imports, rather the productivity gains will contribute to raise in GDP.

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Nevertheless, Yang [35] shows that that exporters are also more innovative companies and thus more competitive. However, the analysis was performed on China manufacturing in period 2004-2007.

2.5. Sustainability

It was already mentioned that introducing new robots can save energy [16]. Zhu et al. [36] conclude that they do not know the specific channel by which robot adoption is linked to a reduction in pollution, but their empirical findings prove so. Yang and Liu [30] also prove that companies with higher level of industrial intelligence also have more environmentally friendly technologies, but also do not research why. They only state that industrial robots improve the production quality of the manufacturing industry through improving production methods and optimizing the management mode, prompting the manufacturing company to implement energy-saving and emission reduction behaviors to achieve green development. Companies do not prioritize environmental sustainability as they increasingly use robots. Transforming production by implementing industrial robots, there will be subsequent changes in productivity and the way of using resources and treating wastes. Thus, the effect of robot adoption on pollution emission could be mediated by the productivity change or intervention in the production Cheng et al. [9].

2.6. Research hypothesis formulation

So far, we have seen that there is no research of robot implementation in less developed European countries such as Spain, Slovakia, Slovenia and Croatia. Those countries by IFR report than are in low density adoption of robots. Robot density is the number of operational industrial robots relative to the number of employees [1]. However, IFR report only looks at regional and country density of robots and not individual company. As we have described in theoretical review, most research is done on the country level and not individual company level, usually using old IFR data. Some valuable exceptions are research in France [6], the Netherlands [28] and Italy [4]. If by adopting robots a company becomes more competitive than we should see the same pattern in less developed countries. Therefore, the first hypothesis is concerned with productivity. We pose the first hypothesis that in companies adopting robots we will see a labor productivity growth, despite that those are less developed countries.

H1: In companies that adopted robots we will see higher productivity than in non-adopters.

Also, we will research if the number of employees dropped because of robots' installation. Chung et al. [26] and Acemoglu et al. [3] show that the number of workers did not decrease because of robot installation. Though, they state that in the long run the decrease in jobs may happen, but not in short term. Therefore, we will research if the number of workers has decreased in manufacturing companies that have installed industrial robots. Since we have data on number of workers in a company in 2022 and 2019, that can be easily assessed. Therefore, the second hypothesis is:

H2: There is no statistically significant difference in the number of workers in three-year period in companies that have industrial robots.

The third hypothesis is about quality. The effects of industrial robots on quality was only researched in China [29] and [30]. We will measure quality through scrap rate between adopters and non-adopters. Therefore, the third hypothesis is:

H3: Adopters of industrial robots will have statistically significantly lower scrap rate than non-adopters.

Exports are almost exclusively researched only in China [15], Zhang et al. [32] and Li et al. [33]. There is no research in on exports in European countries. Our countries Spain, Slovakia, Slovenia and Croatia depend heavily on exports. Exports of goods and services in % of GDP in 2023 [37] for researched countries are: Spain (39%), Slovakia (91,4%), Slovenia (84%) and Croatia (54%). Apart from Spain, all other researched countries export more than 50% of their goods and services. Exports are important especially for small countries with a small market and rely heavily on exports. So, our fourth hypothesis is:

H4: Adopters of industrial robots will have statistically significant higher exports than non-adopters.

Yang and Liu [30] reveal that companies adopting robots also have much more energy friendly technologies. They do not know why. This is an interesting conundrum, not explained yet in current literature. We will analyze using technologies for recuperating energy and technologies for reuse of water. As with all current research we hypothesize that industrial robots' adopters have higher usage of these ecological technologies. So, the fifth hypothesis is

H5: Adopters of industrial robots will have statistically significant higher usage of ecological technology than non-adopters.

But there is still this open question why. Cheng et al. [9] states that sustainability is mediated by the productivity change or intervention in the production. We will analyze industrial robots on environmentally friendly technologies and conceptual factors of the manufacturing company such as company size (number of employees), product complexity, industry, technological intensity factors that might play a role in explaining why robots are usually accompanied with technologies for recuperating waste energy and water recycling.

3. Materials and Methods

The full description of European Manufacturing Survey (EMS) coordinated by the Fraunhofer Institute for Systems and Innovation Research (ISI) [38], the largest European survey of manufacturing activities and designed by the guides of Survey Research Centre [39] can be found in [40].

The survey is conducted among manufacturing companies above 20 employees (NACE Revision 2 codes from 10 to 31). The survey was conducted in 2022 and we obtained 476 answers; Spain (86), Slovakia (102), Slovenia (146) and Croatia (142). Since we are using four countries, we tested a potential sample bias using Levene's test for equality of variances and a t-test for the equality of means between early and late respondents for each sample. There were no differences in means or variation between the two groups, consequently, there is no evidence of a significant difference in the populations [41].

For common method variance, techniques suggested by [42] to reduce this risk were used. The order of the questions was mixed that it was hard for the respondent to directly associate the variables. Last, we calculated the Harman's single-factor test with an exploratory factor analysis to address common method bias [42] on joint four-country data. This test including all the independent and dependent variables resulted in a first factor that explained only 19% of the observed variance. Since there was no single factor accounting for most of the variance in the model, this test indicates that common method bias is not a problem in this sample.

To test hypotheses 1 to 5 we have used simple t-test for equality of means. All the variables had to be computed. For example, labor productivity had to be computed from revenues of that year and divided by number of employees for that year. Control variables are the company size (three groups: 1 less than 50 employees, 2 from 50 to 249 and 3 over 250 employees), product complexity (1 for simple products, 2 medium complexity products and 3 high complexity products). The sample was also divided by technological intensity according to European commission [43]: High technology (NACE 21 and 26), Medium-high technology (NACE 20, 27 to 30), Medium-low technology (NACE 19, 22 to 25), Low technology (NACE 10 to 18, 31 to 32). We have investigated all hypotheses on 4 types of robots: robots for manufacturing processes, robots for handling processes, industrial mobile robots and collaborating robots. All the calculations were performed by SPSS ver. 29.

4. Results

4.1. Descriptive results

We will first start with descriptive results of our sample. Even though we did not analyze by country rather the whole sample, here in Table **1**, we present the distribution of four types of robots by country.

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Table 1. Distribution of robots by country.

Type of robots	Spain	Croatia	Slovakia	Slovenia	Total	Share
Industrial robots for manufacturing processes	17	21	28	77	143	30.3 %
Industrial robots for handling processes	21	26	28	57	132	28.0 %
Mobile industrial robots	0	2	1	8	11	2.3%
Collaborating industrial robots	7	3	6	15	31	6.6%
Number of companies having at least one type of robot	**25**	**39**	**41**	**90**	**195**	**41.3 %**

Table 1 presents that industrial robots for manufacturing processes and industrial robots for handling processes are present in little less than third of manufacturing companies. The share of other two types of robots is, as expected, much lower. The totals in sixth column are the summation of robots. The seventh column presents share of companies that have a specific type of robot as a percentage of companies having a specific type of a robot divided by the number of companies in the dataset. However, the sixth row presents the number of companies that have at least one type of robot in each country and all together (195). We conclude that 41.3% of companies has at least one type of robot installed in their manufacturing plant.

4.2. Hypotheses testing

Hypotheses testing was be done for all four type of robots using the standard student t-test. We present the results in Table 2.

Table 2. T test for differences of means between robot's adopters and non-adopters.

T test for equality of means		Industrial robots for manufacturing processes			Industrial robots for handling processes			mobile industrial robots			collaborating industrial robots		
		N	Mean	F (Sig.)	N	Mean	F (Sig.)	N	Mean	F (Sig.)	N	Mean	F (Sig.)
LaborProducti	yes	126	17.48	4.884 (0.028)	121	24.16	1.616 (0.204)	10	26.95	0 (0.998)	26	34.06	3.028 (0.083)
vity2022	no	281	20.65		288	17.63		383	18.94		367	18.41	
LaborProducti	yes	121	13.88	7.098 (0.008)	114	21.99	1.707 (0.192)	10	25.36	0.01 (0.919)	25	28.23	1.027 (0.312)
vity2019	no	276	19.35		285	15.86		374	17.72		359	17.19	
	yes	125	71.56	4.075 (0.044)	117	71.51	12.299 (0.000)	9	61.67	0.005 (0.943)	25	84.08	13.355 (0.000)
Exports	no	260	58.88		269	59.71		362	63.82		346	62.33	
	yes	133	1.897	12.328 (0.000)	125	2.809	0.002 (0.961)	10	2.03	0.393 (0.531)	28	2.006	0.495 (0.482)
scrap rate [%]	no	290	3.267		300	2.833		398	2.885		380	2.927	
No. of	yes	138	343.22	19.568 (0.000)	127	402.4	46.718 (0.000)	11	977.64	22.129 (0.000)	29	837.21	105.968 (0.000)
emp.2022	no	290	173.8		302	151.42		400	211.24		382	185.85	
No. of	yes	125	306.85	11.569 (0.000)	117	372.22	38.435 (0.000)	10	956.3	28.424 (0.000)	25	800.32	91.149 (0.000)
emp.2019	no	282	173.39		292	146.09		383	191.87		368	176.95	
Tech to	yes	142	0.4	57.768 (0.000)	131	0.5	98.98 (0.000)	11	0.82	1.355 (0.245)	31	0.55	10.057 (0.002)
recuperate	no	298	0.2		309	0.17		408	0.25		388	0.24	
Tech for	yes	139	0.32	14.754 (0.000)	125	0.4	59.201 (0.000)	11	0.45	3.338 (0.068)	30	0.47	10.568 (0.001)
recycling and	no	298	0.22		312	0.19		409	0.25		390	0.24	

Productivity: From the second and third row we can see a statistically significant lower productivity for adopters comparing to non-adopters, but only for manufacturing robots for manufacturing processes. For the rest of robots (handling robots, mobile industrial robots and cobots) we see that the productivity is higher for adopters in comparison to non-adopters but the difference is not statisticaly significant. In all cases when we compare means for productivity from year 2019 to year 2022 we see a clear increase in labor productivity.

Exports: From the forth row we can see that exports are statisticaly significant higher for adopters in comparison to non-adopters except for mobile robots. However, this different result for

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mobile robots may be due to a small number of implemented mobile robots. As it can be seen in the whole sample of 476 manufacturing companies there are only 11 mobile robots installed.

Scrap rate: Scrap rate (fifth row) is statistically significantly lower only for manufacturing robots. This is expected because in the scrap rate it is measured only the nuber of defects in the manufacturing process. Errors in handling are usualy tracked but not in the scrap rate. Errors in handling are usualy measured in cooperation with the vendor of robots to adjust the robot for lowering occurrence of those mistakes.

Number of employees: If we look at rows 6 and 7, we can see that for all types of robots number of workers is statistically significantly higher than for non-adopters. Also if we look at average number of workers between years 2022 and year 2019 we see an increase of workers in companies that employ robots unlike non-adopters, where the average number of workers stayed the almost the same. The question of how the company size afects the use of robots will be addressed later with the use of regression analysis.

Technology to recuperate kinetic and process energy and Technology for recycling and reuse of water are considered to improve environmental impact of the company. We can see from rows 7 and 8 that all the adopters of industrial robots have a higher usage of these two technologies and they are statistically significant except for mobile industrial robots which again might be due to low number of installed mobile robots in the sample. As we saw in the theoretical part, there is still no explanation as why companies that invest in robots also invest in these green technologies. They are not forced by some legislative, but they simply invest more in sustainability as well.

4.3. Regression analysis

We have performed Two step OLS regression with two models. Model 1 has the dependent variable number of different robots installed and only control variables (company size, industry intensity, and product complexity). Model 2 has additionally independent variables Technologies to recuperate kinetic and process energy and Technologies for recycling and reuse of water. We included only control variables in the first step, and in the second step we included our independent variables as seen in Table **3**.

Table 3. Two step OLS regresion for contextal factors.

Model	Dependent variable: Number of different kinds of robots				Collinearity Statistics	
		Stand. Beta	t	Sig.	Tolerance	VIF
1	(Constant)		1.412	0.16		
	No. of employees in 3 groups	0.195	2.339	**0.021**	0.995	1.005
	Industry intensity	-0.186	-2.083	**0.039**	0.869	1.151
	Product complexity	-0.022	-0.242	0.809	0.871	1.148
2	(Constant)		2.086	0.039		
	No. of employees in 3 groups	0.063	0.763	0.447	0.877	1.14
	Industry intensity	-0.198	-2.386	**0.018**	0.867	1.153
	Product complexity	-0.041	-0.487	0.627	0.847	1.181

Technologies to recuperate kinetic and process energy	0.311	3.707	**0.001**	0.844	1.184
Technologies for recycling and reuse of water	0.203	2.55	**0.012**	0.944	1.059
Model Summary			Change Statistics		
Model	R	R Square	Δ R Square	Δ Sig. F	
1	0.266	0.071	0.05	0.02	
2	0.463	0.214	0.184	0.001	

As it can be seen from Table 3, in Model 1 contextual factors influence decision of implementing robots. If we look at company size as a contextual factor, it can be seen that larger the company, higher is the probability of implementing robots. Therefore, in Table 4 we show the distribution of robots by company's size:

Table 4. Breakdown of implementation of robots by company size.

	Small	**Medium**	**Large**
Industrial robots for manufacturing processes	21%	32%	43%
Industrial robots for handling processes	20%	27%	45%
Industrial robots: mobile industrial robots	1%	1%	8%
Industrial robots: collaborating industrial robots	4%	5%	17%

According to our Model 1 when number of robots is the dependent variable that can take value from 1 to 4 different kind of robots, company size matters. If we look at Table 4, we can see that indeed as size of the company increases so does the percentage of robots. Yes, the smaller companies have fewer robots, but contrary to suggested by literature [44], the medium sized companies have also a lot of robots contrary to findings. The main barriers for adoption of robots in SME according to [44] are lack of processes to automate. Other literature only deals with SMS readiness for Industry 4.0 or with only cobots.

From our 2-step OLS regression in Table 3 we can also see that industry intensity also matters for robot implementation. In step two where we added technologies for recuperating energy and water cleaning only the industry intensity mattered. That means that number of robots will depend on the industry intensity. Since the Standardized Beta coefficient is negative that would suggest that lower-intensity companies have installed more. Therefore, we also created Table 5 to show descriptive statistics between robot implementation and industry intensity. So far, we can only see that the highest implementation of robots is in the middle-to-low and middle-to-high intensity. We could even suggest that the relationship between industry intensity and the number of robots is inversely U-shaped, or, according to the Normal distribution, probably due to a low number of high intensity companies in the sample.

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Table 5. Number of robots by Industry intensity.

Type of robot	Low tech	Medium - low tech	Medium-high tech	High-tech
Industrial robots for manufacturing processes	17.42%	36.73%	39.05%	25.00%
Industrial robots for handling processes	29.55%	29.08%	26.67%	28.57%
Mobile industrial robots	1.52%	1.02%	5.71%	3.57%
Collaborating robots	1.52%	6.12%	14.29%	7.14%
Share of companies having at least one robot type	32.6%	46.9%	46.7%	39.3%

Product complexity and technological intensity does not matter. However, it is very interesting that some technologies correlate. Technologies to recuperate kinetic and process energy are usually bought in tandem with robots for manufacturing and mobile industrial robots, whereas Technologies for recycling and reuse of water are usually implemented in tandem with Industrial robots for handling processes. This is an interesting result since, as we showed in the theoretical part, there is still no explanation for why industrial robots go hand in hand with environmentally friendly technologies. Several authors show that robot adoption decreases CO2 emissions but that still doesn't explain why companies invest in recuperating and cleansing technologies. Both authors [45] and [46] argue that countries should impose environmental guidelines. However, both researchers are from China. Our result might mean that managers who invest into industrial robots are more proactive and because of their proactivity those technologies get implemented in tandem. But that is not something we can prove through manufacturing data. Zhang et al. [47] name the phenomenon that robotization enhances green productivity, they proved it, but also did not elaborate on why this happens.

Therefore, we performed an additional regression analysis in order to find which environmental technology is connected with which type of robot. The results are in Table 6.

Table 6. OLS regression only second step, environmental technologies as dependent variables.

Dependent variable	Technologies to recuperate kinetic and process energy				Technologies for recycling and reuse of water			
			Collinearity Statistics				Collinearity Statistics	
	Standard Beta	Sig.	Tolerance	VIF	Standard Beta	Sig.	Tolerance	VIF
(Constant)		0.001				0.475		
No. of employess in 3 groups	0.287	**0.001**	0.926	1.079	0.088	0.297	0.927	1.079
Industry intensity	0.075	0.373	0.445	2.248	0.075	0.406	0.816	1.225
complexity of the product	0.131	0.11	0.864	1.158	-0.105	0.233	0.866	1.155
Industrial robots for manufacturing processes	0.198	**0.013**	0.886	1.128	0.096	0.259	0.924	1.082
Industrial robots for handling processes	0.104	0.222	0.789	1.268	0.273	**0.003**	0.789	1.268
Industrial robots: mobile industrial robots	0.236	**0.003**	0.917	1.09	-0.136	0.108	0.928	1.078
Industrial robots: collaborating industrial robots	0.008	0.915	0.97	1.031	0.135	0.105	0.97	1.031
	R=0.514	Adjusted R Square =0.264	Sig of the model (<0.001)		R=0.385	Adjusted R Square= 0.102		Sig of the model (0.003)

Now, from Table 6 we can see that company size matters for installing technologies which recuperate energy and that they are connected with robots for manufacturing processes and mobile robots (significances are bolded). On the other hand, for implementing technologies for recuperating water, company size does not matter but they are tied to robots for handling processes.

4.4. Summary of findings

In Table 7 we present a summary of findings in one place. However, testing the H5 we found that different robots include different environmental technology. This is already a step forward to solve the mystery why robot adopters usually invest in environmental technology.

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Table 7. Summary of findings.

Hypotheses	Conclusion
H1: In companies that adopted robots we will see higher productivity than non-adopters	Partially confirmed
H2: There is no statistically significant difference in number of workers in 2022 and 2019 in companies that have industrial robots.	confirmed
H3: Adopters of industrial robots will have statistically significant lower scrap rate than non-adopters.	confirmed
H4: Adopters of industrial robots will have statistically significant higher exports than non-adopters.	confirmed
H5: Adopters of industrial robots will have statistically significant higher usage of ecological technology than non-adopters.	confirmed

4. Discussion

In the European Union, 91% of all employment corresponds to SMEs, and 68.2% of all jobs are in manufacturing. However, according to [44] SME have not embraced robotic manufacturing. Our findings show that company size is important for introduction of robots, however, also small companies have robots. As expected, medium-sized and large companies have more robots than smaller companies.

When it comes to productivity there is a large gap in the literature concerning the current state of robot adoption. Most analyses were performed on Chinese manufacturing companies on old IFR data. Reason for this large number of research done in China is that according to IFR report, China is one of the highest density robots' adopters (number of robots divided by number of employees). In Europe, only Germany stands up in robot density. Very few researches are done on European manufacturing sector [4,6,28] (France, Italy, Norway). There is much less data for less developed European countries such as Spain, Slovenia, Slovakia and Croatia. They are high exporters because their domestic market is small, so they depend on exports for growth. We showed that indeed robots increase exports and reduce scrap rate by series of t-test. Productivity raised from year 2019 to 2022, but the productivity for adopters of industrial robots for manufacturing is actually statistically significantly lower than in the non-adopters group. This might mean that that maybe those robots are just implemented and still need humans to do their work. For all other types of robots, we see that productivity is higher in the adoption group but not statistically significant. This also means that relationship between installed robots and productivity growth is not that simple. We argue that merely implementing robots will not solve issues in the company

We also tackled the question raised by [4] that the robots will decrease the number of workers. Therefore, we used data from 2019 and 2022 to compare did the number of workers decrease. If we look at rows 6 and 7 of Table **2** we can see that for all types of robots number of workers is statistically significantly higher than for non-adopters, and the number of workers even raised for robot adopters. But we cannot predict if this is just a short-term effect or will in the long run number of workers fall as also predicted by [4].

There is still the question why robots increase implementation of energy recuperating technologies and water recycling technologies. We managed to find combinations of environmental technologies and robots such as technologies to recuperate kinetic and process energy are usually both in tandem with robots for manufacturing and mobile industrial robots, whereas technologies for recycling and reuse of water are usually implemented in tandem with industrial robots for handling processes. In this way we give a contribution Zhang et al. [47] who predicted that sustainability is connected to robot adoption but could not explain why. In this work we however find direct connection of technologies for recuperating energy and manufacturing robots. The other OLS regression showed that water recycling and recuperation is connected to handling robots.

Zhang et al. [32] state that SME seldomly adopt robots, and our regression analysis confirms it, however in Table **4** we show that even small companies have robots and that the highest number of robots is in larger companies. Industry intensity also showed the importance in our analysis, therefore we displayed Table **5** showing that most robots are in the group of middle technology intensity groups. There are no other examples known to the author of distributions of robots by technology intensity. We get same mixed results by technology intensity as [48] did for Industry 4 readiness.

5. Conclusions

In this work we fill the gap in the literature on robot adoption in European countries. Most research is done by China mostly due to the fact that China has among highest robot adoption rate and the fact that they are changing from volume producer to quality producer. Even though the works researching robots were recently published, they relied on old data and looked at whole country or regions and not on the company level. We fill this gap by analyzing productivity, exports, quality, environmental technologies on company level data. For this purpose, we used subset of European Manufacturing Survey comprised by four countries Spain, Slovakia, Slovenia and Croatia.

We proved four out of five hypotheses. We did find statistically significant higher productivity for robots adopters, except for robots for manufacturing processes. We show that the number of workers did not fall due to robot introduction, in fact, the number of workers even raised. We showed that adopters of industrial robots have a lower scrap rate than non-adopters. We showed that adopters of industrial robots have higher exports.

We showed that adopters of industrial robots have higher usage of energy efficient technologies than non-adopters. We also contribute by showing that indeed implementation of robots does enhance implementation of environmental technologies and we show which environmental technologies go with which kind of robots. Technologies to recuperate kinetic and process energy are usually bought in tandem with robots for manufacturing and mobile industrial robots, whereas technologies for recycling and reuse of water are usually implemented in tandem with Industrial robots for handling processes. This is an interesting result since, as we showed in the theoretical part, there is still no explanation for why industrial robots go hand in hand with environmentally friendly technologies. Several authors show that robot adoption decreases CO_2 emissions but that still does not explain why companies invest in recuperating and cleansing technologies. Both authors [45] and [46] argue that countries should impose environmental guidelines. Our result might mean that managers who invest into industrial robots are more proactive and because of their proactivity those technologies get implemented in tandem.

Limitation of the research is that it includes only four countries, but for the questions analyzed (not country comparison) this was enough. However, there is the term productivity paradox [49] which must be further explored. It has both to do with the level of technological advancement of a country but also in the way technology is deployed. This should absolutely be further explored, by including more advanced countries in the sample.

Further research should go in including more countries but perform the analysis with robot density as a control variable and does the technology paradox only happen in poorer countries compared to more developed ones.

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