

Impacts of industrial robot usage on international labor markets and productivity: Evidences from 22 OECD countries

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Abstract. This paper examines the impact of the number of industrial robots on employment, minimum wage, and productivity by using the panel pooled mean group estimator method in the context of the Creative Destruction hypothesis of Schumpeter and the Technological System of Freeman with Dosi both in the long and short term for 22 OECD countries (Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Japan, Korea, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, Turkey, the UK, and the US). The study covers the period of 2006-2017. This article is one of the few empirical studies on industrial robots. According to the panel cointegration analysis results, it is concluded that the number of industrial robots has a positive long-term impact on employment and productivity. Meaningless result has been found in relation to the impact on minimum wage.

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1. INTRODUCTION

In this study, the relationships between employment, productivity, minimum wage, and the number of industrial robots are examined by using the panel pooled mean group estimator method in the context of the Creative Destruction hypothesis of Schumpeter and the Technological System of Freeman with Dosi. One of the essential economic targets of countries is to increase their exports. Thus, policymakers aim to increase employment and productivity. Schumpeter mentions the effects of new production techniques on the economy in his Creative Destruction hypothesis. The Creative Destruction hypothesis states that if a country does not become an innovator, then it will lose its international competitiveness. Innovation may take place if new production techniques are employed (Schumpeter, 1939 & Schumpeter, 1942). Freeman et al. (1982 & 2000) and Dosi (1982 & 2000), both being influenced by Schumpeter's Creative Destruction Theory, explain the impact of technological development on employment via the technological system

approach. According to this approach, development of each new technological system is a process. In this process, employment is affected differently at various stages. In the first stage of technological innovation, employment is created on a small scale and for skilled labour only. At the advanced stage, employment is increased to a greater extent due to production expansion. Currently, population of developed countries is decreasing aging at the same time. Robots present a solution to the shortage of young skilled labour. Robots have been gradually employed in manufacturing as a new production technique. Many companies now prefer to use robots to increase productivity as compared to traditional labour.

Industrial robots are employed in many branches, such as food production, automotive sector, and electronics. Industrial robots provide a variety of benefits. Robot systems have a flexible structure. In other words, the same robot system can be used for different aims. They increase productivity by approximately 50% (MHI, 2018), and the initial investment costs are recovered within one year on average, with a production cost advantage of approximately 60%. Robotic production reduces the error rate to a minimum while increasing the quality and the rate of production (IHA, 2015).

In this study, long-term and short-term impacts of industrial robotics are analysed in relation to employment, productivity, and minimum wages. This is a more comprehensive study as compared to those already available in the related literature. This study will illustrate that productivity and employment in developed countries increase with the utilization of industrial robots. The results of the analyses are given with explanations. This is a pioneering study; to the best of our knowledge, there are no studies in literature that would have the same theme, method, countries, and time period. Key hypothesis is formulated as follows: The use of industrial robots increases productivity and employment, but decreases the minimum wage.

2. LITERATURE REVIEW

Industrial robotics is a relatively new topic. Therefore, there are few studies related to the impact of industrial robotics. Some of these studies include Howell (1985), who states that robots lead to job loss among unskilled and blue-collar labours while increasing employment of skilled or white-collar labours. Ebel (1987) indicates that industrial robots cause job loss for unskilled labours and hazardous job workers. Moreover, the study by Carbonero et al. (2001) shows that the use of robots affects employment negatively; the negative impact of robots is higher in developed countries than in emerging countries. However, Qureshi and Saijad (2014) indicate that industrial robots' use has both positive and negative impacts on employment and motivation. They determine that the use of robots is inevitable in the health care sector, especially in conditions hazardous to human workers. They also conclude that robotics will increase in the service sector in the coming years.

On the contrary, Graetz, and Michaels (2015) state that there is no significant correlation between employment and robots in developed economies. While Marr (2016) indicates that as the use of robots increases in the west, unskilled minimum-wage workers, primarily in East Asian countries, will lose their jobs due to production shifting back to developed western countries such as the United States (US) and the European Union. De Canio (2016) states that manufacturing wages decline as the use of robots increases in the US. Dauth et al. (2017) state that robots do not cause severe unemployment and that the job losses which do occur in the manufacturing sector are balanced by new jobs in the service sector.

Acemoglu and Restrepo (2017) express that one robot per thousand workers affects the US employment to population ratio negatively by 0.37 percentage points. IFR (2017) states that as the use of robots increases, demand for skilled high-wage workers increases while demand for medium or unskilled low-wage workers decreases. The study by Chiacchio et al. (2018) shows that one robot per thousand workers negatively affects the EU employment to population ratio by 0.16-0.20 percentage points while

raising productivity in EU economies. Cho and Kim (2018) indicate that the current use of robots does not yet negatively affect employment.

De Backer et al. (2018) explains that there is a definite link between investment in robotics and employment within multinational enterprises in developed economies. Vermeulen et al. (2018) state that potential unemployment due to robots is counterbalanced with new employment opportunities in other sectors. Ramaswamy (2018) states that the use of robots does not necessarily cause loss of employment as a rule, but unskilled workers have a higher risk of losing employment than skilled workers. Studies by Schlogl and Sumner (2018) show that robots do not lead to unemployment nationwide, at least in the short and medium terms. Furthermore, they state that employment increases in the service sector and contributes to a decrease in wage stagnation.

In the literature, employment, productivity, and minimum wage are analysed separately. This is a weakness characteristic of existing studies. Furthermore, current studies interpret the impact of industrial robots almost solely as positive. However, there is not a consensus among all researchers as to the negative and positive impacts on employment and wages.

3. METHODOLOGY

The panel cointegration method is used in this study. Panel data units (countries, firms, households, and individuals) bring together cross-sectional observations in a certain period (Greene, 2012, pp. 383-384). Panel data is based on time-series observations. There are two dimensions, time-series, and section. The panel data analysis has a hierarchical structure. This hierarchical structure can be explained as follows (Hsiao, 2006, pp. 1-6):

1. The panel data method is suitable for solving complex behavioural models.
2. If the panel data model is appropriately configured, it can solve problems related to regression results.
3. Panel data is a suitable method for controlling the set dynamics.
4. The panel data method provides the opportunity to determine the correct model parameters.

An ordinary panel data model is written as follows:

$$Y_{it} = \alpha_{it} + \beta_{kit} X_{kit} + u_{it}, \quad i = 1, + \dots, N; t = 1, \dots, T \quad (1)$$

Y is the dependent variable in the model. X_k represents an independent variable, α is a constant parameter, β is slope parameter, u is an error term, and i represents individuals, households, firms, and countries. T represents time concepts such as day, month, and year (Tatoğlu, 2012, p. 4).

In the first stage, the panel unit root test is applied. Researchers use unit root tests frequently because unit root tests can determine the stationarity of data. Breitung, Hadri, Im-Pesaran and Shin, Levin, Lin & Chut, Fisher, and Harris-Tzavalis are unit root tests commonly used by researchers. Sometimes unit root tests can give different results. Therefore, Mishra et al. (2009) recommend applying the Breitung unit root test because the Breitung test gives more realistic results when compared to many unit root tests for small samples in the tests where Monte Carlo simulation is performed (Breitung, 1999; Moon et al., 2006; Hlouskova & Wagner, 2006). Therefore, the Breitung unit root test is used in the study.

In the second stage, the panel cointegration test is applied. Panel cointegration tests aim to examine the long-term relationship between panel data series. Several tests are applied to examine the long-term relationship between the panel series, such as Kao, Pedroni, and Westerlund. The Pedroni test is based on residues from static relationships. However, since the cross-sectional correlations with the Westerlund test

can be easily calculated, the Westerlund panel cointegration test is used. The Westerlund panel cointegration test's main features are as follows (Tatoğlu, 2012, p. 240):

- 1) Unbalanced panels and units allow unequal series lengths.
- 2) Resistant critical values can be obtained if there is a correlation between units.
- 3) It allows for heterogeneity in short and long-term parameters of the error correction model.
- 4) It is based on four statistics.

In the third stage, the Hausman test is performed. The Hausman test is applied to examine long-term homogeneity and to choose whether the pooled mean group estimator or the mean group estimator is appropriate. After the Hausman test, the pooled mean group estimator test is applied. Pesaran, Shin, and Smith recommend the pooled mean group estimator. Because the pooled mean group estimator includes both pooling and average. This predictor also permits long-term homogeneity (Pesaran et al., 1998, pp. 1-2). The pooled mean group estimator test generates the error correction model and provides the estimation of both short-term and long-term parameters. The pooled mean group estimator test consists of a mean group estimator and a combination of a fixed-effects estimator. Both constant and slope parameters can vary according to the units in the mean group estimation, while the slope parameters are constant in the fixed effect estimator, the fixed parameters vary according to the units (Tatoğlu, 2012, p. 243).

4. DATA TYPE AND SOURCES

In this study, data from 22 OECD countries (Austria, Belgium, Czechia, Denmark, Finland, France, Germany, Hungary, Italy, Japan, Korea, Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, Turkey, the UK, and the US) are used. The study aims to examine the impact of the number of industrial robots on employment, productivity, and the minimum wage in the 22 OECD countries. In this study, the relevant data covers the period of 2006-2017 because there is data available for these OECD countries for this specified period. The article is one of the few empirical studies related to industrial robots. All observations are constant and annual. Employment, minimum wage, and productivity data sources were obtained from the OECD data sources. Industrial robotics data was taken from the International Federation of Robotics. The unit of data related to the minimum wage was determined in US Dollars.

5. EMPIRICAL RESULTS AND DISCUSSION

The panel cointegration method is used in the study. Employment, minimum wage, and productivity are initially examined separately. Employment, minimum wage, and productivity are dependent variables. E, W, and P represent dependent variables that are employment, minimum wage, and productivity, respectively. The number of industrial robots is the independent variable and is represented by R. The study aims to determine the impact the number of industrial robots has on employment, minimum wage, and productivity. For this purpose, the relationships between employment, minimum wage, productivity, and the number of industrial robots are analysed separately by using the panel pooled mean group estimator method for the 22 OECD countries.

Table 1

Results of the breitung unit root test

Test Variables	Breitung Test		First Differences	Breitung Test	
	Statistic	P-value		Statistic	P-value
R	2.1675	0.9849	ΔR	-2.5326**	0.0057
E	0.5693	0.7154	ΔE	-5.8737**	0.0000
W	2.2241	0.9960	ΔW	-2.6374**	0.0042
P	-0.3702	0.3556	ΔP	5.4102**	0.0000

** : Statistically significant at 5%.

The Breitung unit root test is applied to determine the stationarity of the variables. As a result of the application, R, E, W, and P variables are not stationary. Therefore, ΔR , ΔE , ΔW , and ΔP variables are obtained by taking the first difference of R, E, W, and P variables (Table 1).

Table 2

Results of the westerlund's (2007) cointegration test

Variables	Statistics	Gt	Ga	Pt	Pa
E	Values	-10.466	-12.378	-16.832	-8.571
	Z- Values	-44.705	-4.377	-9.945	-4.210
	P- Values	0.000**	0.000**	0.000**	0.000**
W	Values	-2.099	-2.599	-99.681	-86.366
	Z- Values	-1.335	3.289	-92.763	-69.223
	P- Values	0.091*	1.000	0.000**	0.000**
P	Values	-3.487	-5.336	-1.1e+03	-781.734
	Z- Values	-8.733	1.577	-1.1e+03	-776.390
	P- Values	0.000**	0.943	0.000**	0.000**

** : Statistically significant at 5% level

* : Statistically significant at 10% level

Westerlund ECM panel cointegration test is performed to test whether there is a long-term relationship between R, E, W, and P variables. E, W, and P are dependent variables, while R is an argument. Z-values, panel-variance ratio statistic values (Pa, Pt), group mean-variance ratio statistic values (Ga, Gt), and probability values are given. According to E, W, and P results, hypothesis H_0 is rejected in statistics other than Ga (p values). A long-term relationship is found between E, W, P dependent variables, and R independent variable (Table 2).

Table 3

Results of the hausman test

Variables	E	W	P
Results			
Prob>chi2	0.1885	0.4188	0.3909
Results	PMG	PMG	PMG

The Hausman test is used to determine if the pooled mean group estimator method or mean group estimator method should be used. Results of “prob> chi2” are 0.1885, 0.4188 and 0.3909 respectively. In other words, the results of “prob> chi2” bigger than 0.05 (Table 3). Therefore, the pooled mean group estimator method is preferred.

Table 4

Results of the PMG test

Variables		E		W		P	
		Coef.	P> z	Coef.	P> z	Coef.	P> z
General Long Period		0.424	0.000**	0.0117	0.212	0.125	0.000**
Austria	ec	-0.003	0.971	---	---	-0.060	0.602
	RD1.	.049	0.450	---	---	-.012	0.499
	cons	-.002	0.994	---	---	.245	0.569
Belgium	ec	.013	0.754	-.802	0.001	-.220	0.008**
	RD1.	-.011	0.517	-.006	0.448	-.000	0.979
	cons	-.070	0.669	7.933	0.001	.846	0.007
Czechia	ec	-.100	0.082**	.005	0.980	.012	0.927
	RD1.	.021	0.313	-.028	0.310	-.012	0.367
	cons	.384	0.169	-.036	0.986	-.024	0.958
Denmark	ec	-.142	0.132	---	---	-.464	0.000**
	RD1.	.171	0.000**	---	---	-.080	0.000**
	cons	.446	0.184	---	---	1.795	0.000
Finland	ec	-.040	0.456	---	---	-.013	0.910
	RD1.	.031	0.233	---	---	-.006	0.800
	cons	.113	0.562	---	---	.069	0.878
France	ec	-.137	0.008**	-.959	0.000	-.059	0.210
	RD1.	.031	0.615	-.003	0.751	-.016	0.008**
	cons	.650	0.055	9.42	0.000	.230	0.183
Germany	ec	-.095	0.162	---	---	-.025	0.424
	RD1.	.004	0.871	---	---	-.066	0.000**
	cons	.464	0.228	---	---	.106	0.324
Hungary	ec	-.061	0.161	.210	0.102	.045	0.752
	RD1.	-.000	0.960	.016	0.400	.011	0.424
	cons	.268	0.194	-1.83	0.107	-.155	0.780
Italy	ec	-.117	0.033**	---	---	-.127	0.014**
	RD1.	.020	0.445	---	---	-.060	0.000**
	cons	.553	0.099	---	---	.466	0.012
Japan	ec	-.126	0.014**	1.323	0.079	-.176	0.099*
	RD1.	-.000	0.981	-.020	0.850	-.037	0.024**
	cons	.614	0.102	-12.50	0.080	.584	0.104
Korea (South)	ec	-.024	0.409	.009	0.938	-.145	0.270
	RD1.	.040	0.008**	-.017	0.542	-.029	0.206
	cons	.107	0.427	-.049	0.966	.492	0.269
Netherlands	ec	-.147	0.001**	-.398	0.070	.089	0.528
	RD1.	-.013	0.677	-.010	0.328	-.009	0.697
	cons	.553	0.038	3.964	0.070	-.322	0.546
Norway	ec	.010	0.856	---	---	-.152	0.001**
	RD1.	.006	0.815	---	---	-.018	0.172
	cons	-.060	0.775	---	---	.643	0.001
Poland	ec	-.098	0.076*	-.053	0.435	-.061	0.610
	RD1.	.003	0.885	-.020	0.361	.004	0.738
	cons	.528	0.121	.537	0.384	.250	0.584
Portugal	ec	-.137	0.027**	-.182	0.208	-.104	0.397
	RD1.	.031	0.470	.026	0.396	-.037	0.201
	cons	.565	0.078	1.721	0.203	.415	0.392
Romania	ec	---	---	-.197	0.150	---	---
	RD1.	---	---	-.028	0.405	---	---
	cons	---	---	1.114	0.122	---	---
Slovakia	ec	.009	0.834	.076	0.446	.074	0.445
	RD1.	-.017	0.297	.006	0.467	.000	0.994
	cons	-.028	0.870	-.637	0.471	-.267	0.475
Spain	ec	-.160	0.023**	-.484	0.083	.038	0.773
	RD1.	.027	0.504	-.001	0.986	-.007	0.754
	cons	.696	0.073	4.598	0.082	-.135	0.781
Sweden	ec	-.069	0.098*	---	---	-.268	0.006**
	RD1.	.059	0.018**	---	---	-.058	0.001**
	cons	.210	0.209	---	---	1.017	0.005
Turkey	ec	.017	0.665	.050	0.763	.026	0.655
	RD1.	.066	0.000**	-.000	0.993	-.012	0.546
	cons	-.088	0.694	-.433	0.777	-.011	0.957

UK	ec	-.128	0.066 *	.001	0.083	.082	0.303				
	RD1.	.044	0.280	-.021	0.030 **	-.011	0.324				
	cons	.610	0.133	-.010	0.995	-.283	0.336				
US	ec	-.128	0.015 **	-.214	0.139	-.498	0.000 **				
	RD1.	.057	0.006 **	-.068	0.085 *	-.028	0.002 **				
	cons	.688	0.093	2.062	0.135	1.676	0.000				
**:				Statistically significant at 5% level							
				*:				Statistically significant at 10% level			

According to the pooled mean group estimator test results, R independent variable impacts both E and P dependent variables in the long-term positively. However, W is statistically negligible. In the long term, the use of industrial robots increases by 1%; the E increases by 0.42%. Moreover, the usage of industrial robots increases by 1%; the P increases by approximately 0.13% in the long term (Table 4). In other words, the use of industrial robots affects employment positively because the population of developed countries will not increase notably will have an elderly population. This will cause the demand for young labours to increase. Thus, employment will increase in these countries. Robots do not need days off and can work more than 8 hours a day. As a result, robots can increase productivity in countries in the long-term. The error correction estimator parameters of ec are negative and are significant for employment in Czechia, France, Italy, Japan, Netherlands, Poland, Portugal, Spain, Sweden, the UK, and the US. Parameters of ec are negative and significant for productivity for Belgium, Denmark, Italy, Japan, Norway, Sweden, and the US (Table 4).

RD1 represents short-term impacts. According to the results of employment in the short-term, industrial robots' use positively affects employment in Denmark, South Korea, Sweden, Turkey, and the US. While the use of industrial robots negatively affects the short-term in the UK and the US, it negatively affects the minimum wage. Moreover, industrial robots' use negatively affects productivity in the short-term in Denmark, France, Germany, Italy, Japan, Sweden, and the US (Table 4).

CONCLUSION

This study is dependent on the data available from 2006-2017 for 22 OECD countries to illustrate the impact that the number of industrial robots has on employment, minimum wage, and productivity for the period 2006-2017. The pooled mean group estimator method is applied. The result of the analysis shows that industrial robots' use positively affects both the long-term employment and productivity of the 22 OECD countries. These results are consistent with Schumpeter's Creative Destruction hypothesis and the Technological System of Freeman with Dosi.

According to the short-term results, industrial robots' use positively impacts employment in Denmark, South Korea, Sweden, Turkey, and the US. However, in the short-term, industrial robots' use has a negative impact on minimum wage in the UK and the US while productivity is impacted in Denmark, France, Germany, Italy, Japan, Sweden, and the US negatively.

According to this analysis, industrial robots' use positively affects both employment and productivity in the long-term. Therefore, in the last several years many developed countries have been investing heavily in robotics due to their aging populations. This situation is especially true in Japan, China, and European countries. These countries are aware that an aging and elderly population without cheap young labour will lead to a decrease in manufacturing and productivity. So, while China currently has the cheapest workforce globally, it is securing its economic future by investing in robotics. As the population ages, the standard of living has increased, rising steadily since the 1970s. Chinese labours have demanded and gained new worker's rights such as vacations, a higher minimum wage, and insurance. All these factors have increased manufacturing costs when using traditional labours. Likewise, South Korea aims to become a world leader in the robotics industry and currently has a higher robot density than Japan. The South Korean government plans to invest billions of US Dollars in the next ten years to establish new industries dependent on robotics.

Germany is Europe's most automated country and highest investor in robotics. Eastern European countries such as Slovenia (ranking 16th), Slovakia (ranking 17th), and Czechia (ranking 20th) are increasing their use of robotics for their growing automotive industries. Slovenia currently ranks as the most successful among Balkan countries in terms of implementing robotics in its manufacturing.

If European countries want to protect their export characteristics in other sectors, especially in automotive, against China and other Asian countries, they should support robotic R&D centers, university-industry cooperation, and companies engaged in robot production via grants, low-interest credit opportunities. Also, as robot use will increase in industry and other fields in the coming years, European countries should encourage universities to provide training in the robot field so that people who will work in robot production and maintenance can be trained.

In conclusion, developed countries are investing in robotics to establish new industries and strengthen existing ones. These countries are set to raise employment and productivity in the long-term. The target of these developed countries is compatible with the results of this study.

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