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Aging and Robotization: The Duality Between Generations and Robot Adoption

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This paper examines the bilateral relationship between the robot adoption and the age characteristics of the employment. The study analyzes the reciprocal effects of robotization on different generations and presents the analysis of the effects of age groups on the robotization of countries. Based on an instrumentalization of the System GMM estimation method of a dynamic panel dataset of 28 selected countries over 2004 and 2016, the results show that the number of young workers is affected negatively from robotization, whereas there is a positive impact of robot adoption on old workers. Evidence further suggests that robotization is triggered by the density of young workers in the workforce of the country.

Keywords: Robots, Technological Progress, Aging Employment, System GMM

JEL Classifications: J24, J62

1. Introduction

The aging of society, which is a natural consequence of the decline in fertility rates and the rise in life expectancy, is one of the important problems of our century. It is also expected that this problem, especially in developed countries, will show a much faster trend in the future (Harasty and Ostermeier, 2020; OECD, 2019; IMF G20, 2019). According to ILO 2019 Labor Force Estimates, the number of old-age workers aged over 55 is expected to be equal to the quarter of the global workforce by 2030. From a macroeconomic point of view, the decline in the entry of the young workforce and the late retirement of the older workforce lead to a significant slowdown in productivity increases and also put a significant pressure on pension systems. It is also accepted that old workforce has relatively more difficulty in adopting new skills and in adapting themselves to the changing technological model in the mode of production. Considering the rapid technological progress in recent years, this brings a significant concern on the interaction between robotization and aging employment.

As in other forms of emerging technologies such as Artificial Intelligence (AI), 3D printing, Machine Learning (ML) algorithms, robots are dehumanizing the production process. As robots become more sophisticated and fulfill not only manual routine tasks but also cognitive tasks, the effect of excluding workforce from production process is also increasing. Giving rise on the declining labor demand, unemployment pressure led by robot adoption on the workforce is not felt equally for all demographic groups. Series of studies shed light on the observation that young entrants are the most negatively affected group among the workforce (Chiacchio et al. 2018, Muro et al. (2019), Dauth et al., 2019, Sachs and Kotlikof, 2012; Sachs et al., 2015; Berg et al. 2015). This shows that the increase in the use of robots boosts the aging of the workforce.

Although the world is at the beginning of the adaptation of digital and 'smart' technologies, their widespread acceleration puts these technologies at the center of global attention. In 2018, the 20 largest companies are technology companies (Stoller, 2018; UNCTAD, 2019). On the other hand, OECD (2017a) finds that the amount of investments in private equity exclusively for AI start-ups increased by 3% from 2011 to 2018, and in the first half of 2018, AI start-ups attracted nearly 12% of private equity investments in the world. As a sub-segment of digital technologies[1], robots attract more and more public and private investments each year. The World Robotics Report 2021, published by International Federation of Robotics (IFR), shows that there are nearly 3 million robots are operating in factories worldwide as of 2021. Considering the international competitiveness that robots provide to countries, especially in the manufacturing industry, this rapid increase trend is not surprising. Many studies (UNCTAD, 2019; Olsen and Hemous, 2014; Acemoğlu and Restrepo, 2017) reveal that robots mitigate productivity slowdowns and have the potential to lead to output increases and support shifts in the technological ladder. Thereby, robotic adaptation has become an important area for countries in terms of technological competitiveness (Bal and Erkan, 2019; Bongomin et. al 2020). Given these challenges, the effect of the aging of the workforce on robot adoption is becoming an important research area.

Accordingly, a reverse causality is expected between the aging workforce and robotization. This expectation is based on empirical findings that the older generation's adaptations to catching, learning and applying new technologies are relatively low (Parrotta et. al 2012; Meyer, 2011, Nishimura et. al 2002). The direct impact of the aging workforce on robots is that robots can primarily be considered as products of the human capital and that's why the level of robots reflects the accumulation of technical skills reflects the level of skill and knowledge in that country (Schubert and Andersson, 2015).

The interaction between robots and the aging workforce, despite its current value and great significance, is relatively understudied in the literature. The main purpose of this paper is to fill this gap and its contributions are as follows: Firstly it tries to understand the link between

[1]Other sub-segments are sorted as follows: The Internet Of Things (IoT), Cloud Computing, Photonics and light technologies, Blockchain, Modeling simulation and gaming, Quantum computing, Big data analytics, Artificial intelligence (AI) (OECD, 2016)

robotization and different generations. Specifically I follow these research questions (I) empirical and theoretical evidence in the literature indicates that robots replace human labor; so how does this substitution effect change between generations? (II) As one of the main drivers of economic growth, robotization offers countries an important competitive power. In this robotization race, in which direction and to what extent does the age-related demographic structure of the workforce of the countries affect robotization?

Secondly, to observe the interaction between robotization and aging workforce, the paper applies dual-way causal observation by using Generalized Method of Moments method based on the dynamic characteristics of the panel dataset from 28 different countries for the period covering 2004 and 2016.

The main findings of the paper can be summarized as follows: (i) The impact of robots on the workforce differs significantly across generations. Each additional robot usage leads a 5.3 percent drop, on average, in young employment over our sample of countries. On the other hand, a positive effect is observed for old workers, with an increase causes an increase of 1.76 percent on old employment. (ii) Reversing the direction of these effects, the evidence reveals that aging is negatively associated with the development of robotization technologies: while young workers have a positive effect on the advance of robotization, older workers have a negative effect.

2. Literature Review

2.1 Robotic impact on working age groups

Broadly stated, literature asserts that the impact of robots on labor is two-fold: Firstly, an increase in robots leads to an increase in GDP per capita and generates new jobs, primarily by providing an increase in productivity and profitability. This positive effect, referred as a *productivity effect* by Acemoğlu and Restrepo (2019), reveals the key role of technology improvements in productivity leaps, from the times of steam engine to Fordist production mode and to ICT in the 21st century (IMF, 2019). Secondly, as relative prices of robots fall over time thanks to cost reductions, production enterprises opt towards a replacement of human labor for a given degree of substitutability (Autor et al., 2006; Acemoglu and Autor, 2011; Brynjolfsson and McAfee 2014, Acemoğlu and Restrepo 2016, Graetz and Michaels, 2015, Arnzt et al. 2015, Olsen and Hemous, 2016, Prettner and Holger, 2017). This negative effect is the *displacement effect* narrated in Acemoğlu and Restrepo (2019). Notwithstanding, the impact of robotization on the the pathways of human labor employment depends on which of these colliding effects (productivity effect vs. displacement effect) will be dominant.

Most studies in the literature focus on the robot-employment relationship. This leads us to ask the following question that had been rarely posited in the literature: "Who, among the working classes, will be most affected by robot expansion?” In the relevant literature, the responses of this question rise in the direction that robot adaptation is one of the main drivers of demographic change (Graetz and Michaels, 2015). This demographic change shows a skill-biased change (Freeman and Soete, 1994; Autor et al.,2006; Goos et al., 2014; Bernman et al., 1994; Autor et al., 1998; Morrison and Siegel, 2001) in one aspect and a gender-based change (Autor et al., 2003) in another aspect. On the other hand, it has a significant impact on the aging workforce, which can also be seen as a natural consequence of aging societies. Chiacchio et al. 2018 for instance reports that the increase in robots per thousand workers causes an unemployment effect in the range of 0.16-0.20 points on the workforce, and thus, robotic effect is stronger on younger workers. More recently, Education Commission[2] claims that the young generation in the world is at high risk due to the accelerating automation, which has a higher labor substitution power previous stages of technological progress (OECD, 2012). Muro et al. (2019) indicates that in the near future, automation and AI will affect mostly men and young workers. A similar study conducted for Brazil, as country with relatively high rates of unemployment, provides empirical evidence highlighting that while 60% of the employees are negatively affected by robots, it will be the youngest ones (16-24 years old) who feel this effect the most (Lima et. al, 2021).

Additional studies (Dauth et al., 2019; Battisti and Gravina, 2021) reveal that young people will experience relatively more negative effects from robots. This is mainly explained as the decrease in the number of new jobs as a result of robots substituting labor in the service and goods production process outweighing the growth effect. From the OLG perspective, this impact is explained through savings channel: Because savings, which are the only source of investments in OLG economy, decrease as a result of falling labor demand; this reduces investments and ultimately restricts capital accumulation (Sachs and Kotlikof, 2012; Benzell et al., 2015; Berg et al. 2015). Therefore, robots that replace human labor in OLG economies drag the economy into long-term immiserization. The similar long-term immiserization is conceptualized by Rifkin (1995) decades ago. In Rifkin's world of economy, this immunization is defined as 'workless world', in which existing workforce is under a danger of automation.

2.2 Aging workforce impact on robot adoption

The aging of the workforce is mostly attributed to the skill content of robot adoption. In this context adoption of robots or in general smart technologies is embodied with human capital. World Bank defines human capital as the accumulation of productive knowledge, skills, and health in a society. Accordingly, there's close relationship between application and production of technological innovation. Thus adoption of robots requires new and advance skills and knowledge, cognitive performances, and also ability to adapt rapid innovations. There are some studies providing empirical evidence that why aging of workforce is negatively correlated with

[2] The International Commission On Financing Global Education Opportunity

advance technology adoption. Meyer, 2011 shows that technological adaptation becomes less likely as the workforce ages for German private sector. Koning and Genderblom, 2006 finds a similar result for the wholesale and printing industry, showing that the old employees had less ability to use smart technologies than the youngers as the reason for this. Schubert and Andersson supports this negative age impact on smart technologies by using Sweden industrial data based on Community Innovation Survey. The similar negative age impact on IT capital is found in Japanese industries between 1980 and 1998 by Nishimura et al. (2002) as a direct result of IT data's complementary relationship with complex skills and abilities.

From another point of view, there are also some studies claiming that aging workforce has a potential to trigger robot adaptation. In their seminal study, Acemoğlu and Restrepo (2021) put forward that aging workforce associated with adopting automation by leading shortage of middle-age workforce who take on mostly routine tasks. There are also studies showing that the aging of the workforce will lead to significant costs and productivity losses (Gordon, 2016). Robots here take a role mitigating the productivity losses coming from growing population of old workforce (Lanzafame, 2021; Park, et . al, 2020). Moreover, aging workforce is found to be associated with lower innovative activities leads less robot adoption (Basso and Jimeno, 2020; Gordon, 2012; Aksoy et al., 2019).

3. Methodology, data and descriptive trends

3.1 Data and descriptive trends

The data consists of a panel annual observations for 28 countries in a sample period 2004-2016. Industrial robot data is taken from the International Federation of Robotics (IFR), which reports the operational stock of robots under the assumption of an average service life of 12 years with an immediate withdrawal from service afterwards (IFR, 2018). Covering 90% of the world robot market, IFR collects robot data from suppliers via annual surveys and publishes yearly. IFR defines industrial robots according to International Organization for Standardization (ISO 8373:2012) as "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (International Organization for Standardization, ISO)[3].

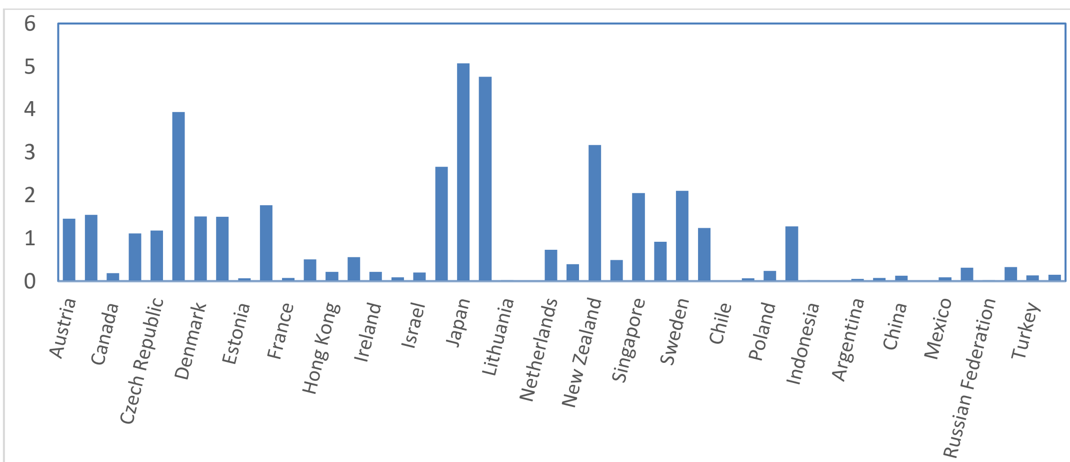
In some studies, robot data is considered as a robot per thousand workers (Acemoglu and Restrepo, 2019, Chiacchio et al. 2018, Graetz and Michaels, 2015). However, following Dauth et al. (2017) and Carbonero et al. (2018), we preferred to use it as a robot stock value to avoid the problem of collinearity between robots and employment.

[3] For the long version of ISO Definition, see https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en).

As a general definition, employment is defined as those from working-age populations, who are engaged in on economic activity for pay or get profit in a reference period. I use International Labor Organization (ILO) "Employment rate by sex and age" data to analyze the employment impact of robots by age ranges. ILO defines employed people as those in one of the following categories: "i) paid employment (whether at work or with a job but not at work); or ii) self-employment (whether at work or with an enterprise but not at work)" (see ILO yearly indicators, 1947-2019). Following the ILO classification, I define two age groups: (i) young workers: 15 to 24 years; (ii) old workers: 25 and over.

In this study a variable called "Robot Density" is generated to compare the number of robots per thousand employees between countries (Figure 1). This indicator simply provides the information about the robot-intensive levels of countries. Germany, Japan, Italy and Korea, which are also the leading countries in the number of robot stocks, are ranked as the countries with the highest robot intensiveness. In countries such as New Zealand, Slovakia and Finland, where there are relatively low number of workers due to low level of population, the robot density shows relatively high level.

Figure 1. Robot Density (robots per 1000 employees), 2016.



Source: Autor's calculation using IFR (2018) data

In this paper I use control variables to enhance causal relationship between our main variables. Following Carbonero et al. (2018) and Graetz and Michaels (2015), value added (VA) as a percentage of GDP is used as an industrial development and economic growth indicator and obtained from World Bank Open Data. World Bank merges value added data with OECD national accounts and provides the percentage GDP including construction. In addition, following Graetz and Michaels (2015) I use share of labor compensation (LCost) to capture the labor's share of income. Penn World Table version 9.1 provides the share of labor compensation in GDP data in current national prices with an extended series covered the period since 1950.

To observe the age impact on robot adoption I use additional explanatory variables to capture the effects of productive capacities and ease of adaptation of robots in the economy. Dynamic data for this purpose comes from UNCTAD's Productive Capacities Index (PCI), which includes eight indexes to measure the productive capacities of 193 economies. The level of human capital is captured by *Human Capital Index*; the efficiency and the ease of investment and also the regulatory conditions are adapted from *Institutions*; and the ease of doing business is given by Private Sector Index. Lastly I use the Structural Change Index to include the rate and possibility of the transition of labor and capital to those sectors with higher productivity. In order to control for unobserved time variations I also add a dummy variable where each year is distinguished with a dummy variable, $year_t$.

3.2 Methodology

In the extant literature, three approaches are commonly used to understand economic relations empirically: Cross-country analysis, time series analysis and panel data analysis. Compared to cross-country analysis and time series analysis, the use of panel data provides important advantages in understanding the economic relations, which are generally dynamic in nature. Having N cross sectional units and T time periods, panel data allows more sample variability and more degrees of freedom (Baltagi, 2005).

An economic relationship becomes dynamic by taking the lagged value of the dependent variable, i.e.;

$$y_{i,t} = \alpha y_{i,t-1} + X'_{i,t}\beta + \vartheta_{i,t}$$

where $\vartheta_{i,t} = \mu_i + \varepsilon_{i,t}$. In this dynamic specification, with dependent variable $y_{i,t}$ and dependent variable $X'_{i,t}$, $\vartheta_{i,t}$ represents the sum of unobserved time-invariant heterogeneity (μ_i) and idiosyncratic error term ($\varepsilon_{i,t}$).

The inclusion of lag dependent variable poses significant problems in estimating the model with OLS, FE and GLS estimators. In OLS estimation, both $y_{i,t}$ and $y_{i,t-1}$ are a function of $\vartheta_{i,t}$. So following the OLS estimation approach gives biased and inconsistent outcomes. In addition to Fixed Effect (FE) model suffering from a large loss of degrees of freedom, it yields biased and inconsistent outcomes. The FE regression forms with averaging over time and having the differences give respectively;

$$\overline{y}_i = \alpha \overline{y}_{i.-1} + \overline{X'}_i \beta + \overline{\varepsilon}_i$$

$$y_{i,t} - \overline{y}_i = \alpha\left(y_{i,t-1} - \overline{y}_{i.-1}\right) + \beta\left(X'_{i,t} - \overline{X'}_i\right) + \left(\varepsilon_{i,t} - \overline{\varepsilon}_i\right)$$

With FE estimator, although μ_i is canceled out in the model, $\left(y_{i,t-1} - \overline{y}_{i.-1}\right)$ is still correlated with the error term$\left(\varepsilon_{i,t} - \overline{\varepsilon}_i\right)$. A similar problem occurs with random effect GLS estimator. Since $\left(y_{i,t-1} - \overline{y}_{i.-1}\right)$ is correlated with$\left(\vartheta_{i,t} - \overline{\vartheta}_{i.-1}\right)$, the inconsistency and bias problems are not solved via GLS estimator.

To overcome the inconsistency and bias problems, System-GMM (Generalized Method of Moments) method is applied based on the dynamic characteristics of the panel data. System-GMM method developed by Arellano and Bond (1991), Arellano and Bond(1995), Blundell and Bond (1998) and popularized by Holtz-Eakin et al. (1998).Either differenced-GMM or system-GMM is used most commonly for estimating standard dynamic panel data models. Both are developed for: (i) Small (T) and large panels (N), (ii) the models with dynamic dependent variable, and (iii) not strictly exogenous independent variables (Roodman, 2009).

What distinguishes the system-GMM from the others is that system-GMM is often argued as the best identification method in dealing with the dynamic nature resulting from the impact of explanatory variables on the dependent variable, i.e. *endogeneity bias*, heteroskedasticity and autocorrelation within the error terms (Roodman, 2009; Baum, 2006).

In contrast to efficiency features of the results it provides, a major weakness of the GMM method is that it uses too many instruments, which may lead to missspecification. This problem is resolved by choosing a high *p-value* of the Hansen test following Roodman (2009) and using the restriction method with Stata's 'collapse' option (Sağlam, 2021). GMM coefficient levels are expected to be at a level between the coefficients found from OLS and Fixed Effect estimation results (Bond, 2002 pp: 158-159), therefore I also report Ordinary Least Squares (OLS) and Fixed Effect (FE) estimates for completeness.

Following Jun and Lim, 2020, I construct a dynamic dual equation system as follows;

$$\ln\left(\mathrm{Emp}_{\mathrm{Young}}\right)_{\mathrm{i,t}} = \alpha \ln\left(\mathrm{Emp}_{\mathrm{Young}}\right)_{\mathrm{i,t-1}} + \beta_1 \ln(Robot)_{i,t} + +\beta_2 \ln\,(\mathrm{VA})_{i,t} + \beta_3 (lnLCost)_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

$$\ln\,(\mathrm{Emp}_{\mathrm{Old}})_{\mathrm{\,i,t}} = \alpha(\mathrm{Emp}_{\mathrm{Old}})_{\mathrm{\,i,t-1}} + \beta_1 \ln\,(Robot)_{i,t} + \beta_2 \ln\,(\mathrm{VA})_{i,t} + \beta_3 (lnLCost)_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

$$\ln\,(\text{Robot})_{\,\text{i,t}} = \alpha\ln\,(\text{Robot})_{\,\text{i,t}-1} + \beta_1 \ln\,(\text{Emp\_Young})_{i,t} + \beta_2 \ln\,(\text{VA})_{i,t} + \beta_3 (lnLCost)_{i,t} + \beta_4 (KGrowth)_{i,t} + \beta_5 \ln\,(HK)_{i,t} + \beta_6 \ln\,(\text{Inst})_{i,t} + \beta_7 (lnPrivate)_{i,t} + \beta_4 (Structure)_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

$$\ln\,(\text{Robots})_{\,\text{i,t}} = \alpha\ln\,(\text{Robots})_{\,\text{i,t}-1} + \beta_1 \ln\,(\text{Emp\_Old})_{i,t} + \beta_2 \ln\,(\text{VA})_{i,t} + \beta_3 (lnLCost)_{i,t} + \beta_4 (KGrowth)_{i,t} + \beta_5 \ln\,(HK)_{i,t} + \beta_6 \ln\,(\text{Inst})_{i,t} + \beta_7 (lnPrivate)_{i,t} + \beta_4 (Structure)_{i,t} + year_t + (\emptyset_i + \varepsilon_{i,t})$$

where $i = 1,2, \dots, N$ indicates countries and $t = 1,2, \dots, T$ indicates year.

For the dynamic specification $\text{Emp}_{\text{Young}}$, and Emp_{Old} refer to young and old employment, where the robot stock is captured by $\text{Robot}_{\text{i,t}}$. Value Addded (VA) and share of labor compensation (LCost) are explanatory variables, where $\emptyset_{\text{i}}$ is time-invariant individual fixed effect and ε is the usual error term. For the specification estimating the impact of employment on robots, the explanatory variables KGrowth, HK, Inst, Private and Structure refer to capital growth, human capital, institutions, and private and structural indexes respectively. Moreover, in order to smooth data, I use natural logarithms.

3 Estimation results

Tables 1-4 show the estimation results for the interaction between robots and two different working age groups for 28 countries spanning over a thirteen-year period. The results show that while the adoption of robots affect young generations more negatively, it is the young workers who trigger the robot adaption. This explicitly reveals an important paradox, especially for countries with both aging populations and rapid robotization**.**

Table 1 presents Arellano-Bond (AB) two-step system GMM (GMM) results for causality among old workers and robots. The first and the second column reports the Fixed Effect (FE) and Ordinary Least Square (OLS) estimations for completeness. The empirical evidence is presented by GMM results at the third column. The coefficient of stock of robots is positive and significant. In this analysis the lagged robot stock variable is also used to provide robust estimate. Although there are studies that argue that using lagged dependent values have a potential to produce biased results, this possibility is avoided by the GMM method eliminating autocorrelation problem (Wilkins, 2018). The lagged dependent of robot stock is negative and significant showing that while the immediate effect of robots on older workers is positive, this effect turns negative as robot adaptation continues. Moreover, the impact of labor cost can be defined as high and positive and also significant.

Table 1. Estimation results: Number of old workers

	OLS	FE	SYS GMM 2
L1.Emp_Old			0.3417 (0.005)*
lnRobot	-0.0031 0.286	0.0347 (0.000)*	0.0176 (0.099)***
L1.Robot			-0.0141 (0.049)**
lnVA	0.0133 0.726	0.5470 (0.000)*	0.0387 0.227
lnLCost	0.3916 (0.000)*	0.5361 (0.000)*	0.2586 (0.049)**

First and second are coefficient levels and probability levels respectively
Number of groups: 28, Number of instruments: 22
Two-Step GMM/AR(2): 0.861; Two-Step Hansen test: 0.433
*, **, *** represents the significance at 1%, 5%, 10% respectively

The same estimation procedure is repeated for young workers (Table 2). According to AB two-step GMM estimates, the impact of robots on young workers is negative and significant. This result reveals that a one-unit increase in robots has a greater negative impact on youth than its own increase. Contrary to the analysis made on old workers, young workers who join the workforce in the next period are positively affected as robot adaptation increases.

Table 2. Estimation results: Number of young workers

	OLS	FE	SYS GMM 2
L1.Emp_Young			0.9971 (0.000)*
lnRobot	0.0016 0.32	-0.0212 (0.000)*	-0.0537 (0.000)*
L1.Robot			0.0488 (0.000)*
lnVA	-0.0064 0.762	0.2970 (0.000)*	0.0148 (0.094)***
lnLCost	-0.1914 (0.000)*	0.2569 (0.000)*	-0.0262 0.473

First and second are coefficient levels and probability levels respectively
Number of groups: 28, Number of instruments: 25
Two-Step GMM/AR(2): 0.446; Two-Step Hansen test: 0.738
*, **, *** represents the significance at 1%, 5%, 10% respectively

When we combine the lagged independent variable coefficient analyzes for young and old workers, an implication supporting the growth effect of robot adaptation emerges. According to this inference, the growth effect generates new jobs for the next period's young workers, while routine tasks are taken over by the robots from the old workers.

Tables 3 and 4 present the other side of the coin -that is the impact of working age groups on robot adoption. The coefficient of employment of old workers is negative and significant (Table 3). Consistently human capital has positive and significant impact on robot adoption. This empirical evidence could be explained by the skill-biased characteristic of robot adoption. The empirical evidence reported by Schubert and Andersson, 2014 indicates the negative impact of average age of employees on robot adoption due to the old workers who has outdated technological knowledge. Combining with the previous evidence, it can be also be claimed that this limited technological knowledge of old workers triggers an employment turnover (Schubert and Andersson, 2014) and this explains why young workers are positively affected by robots over time, despite the immediate negative impact.

Table 3. Estimation results: Stock of robots and number of old workers

	OLS	**FE**	**SYS GMM 2**
L1.lnRobot			0.8920 (0.000)*
lnEmp_Old	-4.2640 (0.000)*	0.6822 0.291	-3.0496 (0.032)**
lnVA	2.2698 (0.000)*	0.6834 0.294	0.4270 0.203
lnLCost	1.7554 (0.056)***	0.3323 0.701	0.7110 0.1430
lnKGrowth	-3.2690 (0.000)*	-1.2033 (0.000)*	0.0086 0.971
lnHK	11.9112 (0.000)*	-8.7840 (0.000)*	1.9057 (0.084)***
lnInst	-5.3589 (0.000)*	-0.1406 (0.011)*	-0.5274 0.370
lnPrivate	-12.5956 (0.000)*	-0.0292 0.9880	-0.8149 0.622
lnStructure	13.4772 (0.000)*	3.6208 (0.002)*	1.1515 (0.113)***

First and second are coefficient levels and probability levels, respectively
Number of groups: 28, Number of instruments: 27
Two-Step GMM/AR(2): 0.231; Two-Step Hansen test: 0.604
*, **, *** represents the significance at 1%, 5%, 10% respectively

Table 4 shows the impact of young workers' employment on robot adoption. The coefficient of the employment of young workers is positive and significant.

Table 4. Estimation results: Stock of robots and number of old workers

	OLS	**FE**	**SYS GMM 2**
L1.lnRobot			0.9604
			(0.000)*
lnEmp_Young	6.8164	-1.9326	1.6841
	(0.000)*	(0.066)***	(0.088)***
lnVA	2.2574	0.3382	0.2210
	(0.000)*	0.606	0.111
lnLCost	1.5395	-0.0211	0.2194
	(0.009)*	0.980	0.4370
lnKGrowth	-3.2708	1.0615	0.1209
	(0.000)*	(0.000)*	0.436
lnHK	11.5490	2.3025	0.3086
	(0.000)*	0.0640	0.562
lnInst	-5.4132	2.6265	-0.4986
	(0.000)*	(0.031)**	(0.006)*
lnPrivate	-12.1862	0.1680	0.8297
	(0.000)*	0.9330	0.301
lnStructure	13.4883	0.7420	0.1654
	(0.000)*	(0.040)*	0.7590

First and second are coefficient levels and probability levels respectively
Number of groups: 28, Number of instruments: 27
Two-Step GMM/AR(2): 0.195
Two-Step Hansen test: 0.566
*, **, *** represents the significance at 1%, 5%, 10% respectively

3. Concluding Comments and Policy Implication for Further Research

The effect of the aging of the workforce on the economy is a burgeoning field of labor economics. One of the leading issues is the dynamic pathways of age distributions of the demographic characteristics of the workforce across countries. The potential effects of these structural phenomena on robotization is also a leading focus of attentions in the existing literature. So, in the race of countries to catch up with the fourth industrial revolution, the role of the age structure of the workforce is the first subject of this research.

In order to cast the problem in a more dialectic fashion this paper further includes a two-way analysis. While countries improve robotic technologies, I examine the robotization effects on different age groups.

Panel data for 28 countries from 2004 to 2016 is used to conduct empirical analyses, which drew conclusions as follows: (i) Robotization has a significant and negative impact on young working generation; (ii) old workers are affected positively from robot adoption, and (iii) the effect of young employees on robotization is positive.

Obviously, (i) and (ii) together reveals an important paradox. Countries with relatively younger workforces are more competitive in robotization, but as the time passes the increasing rate of robotization excludes young labour from the market. It is estimated that tens of millions of jobs will be lost due to smart technologies in future economies. Correspondingly, there is the possibility of a significant risk of income inequality, especially for low-skilled workers and the economies this group dominates. Studies show that the negativity of robots on young labour arises mostly from the unbalanced situation where the displacement effect exceeds the creation of new jobs. Considering that robots are developing more and more rapidly, it becomes clear that this negativity can be eliminated by creating more new jobs. Thereby, the young labour force should have high skills according to these new jobs' requirements. For this reason, it is important that education be adjusted according to these skills and make it fair for access to the wider population. On the other hand, controlling the use of robots and introducing new taxes for this are among the methods. Through all these possible methods, this paradox could be evaluated as a potential subject for further studies.

Besides its threat to youth employment, undoubtedly robotization as technological progress is a challenge for countries that they cannot ignore in global competition. Robotization provides an important advance in green transformation, which is being adapted against climate change by allowing the same production and consumption level using fewer resources and energy. This makes the use of robots advantageous not only in industry but also in the agriculture and services sector. Therefore analyzing the effects of robotization on various economic sectors is a valuable topic for further studies.

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