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Economic Effects of Industrial Automation in Aging Workforces

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Abstract

With the advent of rapid advances in medicine and technology, as well as declining fertility rates, the portion of older workers participating in the world's greatest economies is increasing. The lessened physical and mental capabilities of older workers, as well as the dwindling number of young workers, can have adverse economic consequences if left unaddressed. Economists agree that this aging has caused an uptick in the implementation of industrial automation as part of an effort to combat these consequences, but its effectiveness in doing so remains a topic of debate. Some scholars argue that automation is able to overcompensate for the challenges caused by an aging workforce, resulting in a net positive gain for economic indicators like GDP per capita and labor productivity, while others contend that the efforts of automation alone are not enough to fully counter the adverse implications of aging. This paper attempts to gain a clearer idea of the extent to which automation alleviates the consequences of aging workforces by performing regressions of GDP per capita and labor productivity on the number of artificial intelligence patents per million people employed–which is used as a proxy for industrial automation–as well as the ratio of old workers to young workers. Ultimately, it is ascertained that industrial automation as measured by artificial intelligence patent data positively affects GDP per capita and labor productivity, albeit to a lesser extent in countries whose workforces are aging particularly quickly.

Introduction

As a result of declining fertility rates and increased longevity due to advancements in medicine and technology, the share of older workers is increasing in many countries. A high ratio of old to young workers can cause adverse economic effects if left unaddressed, due to the lessened physical and mental capabilities of older workers compared to their younger counterparts. A 10% increase in the fraction of the population ages 60+ results in a 5.5% decrease in GDP per capita, and a 3.4% decrease in GDP per hour worked (Maestas, Mullen, & Powell, 2022).

Many economists agree that the aging workforce has led to a greater implementation of industrial automation to compensate for the resulting economic challenges (Acemoglu & Restrepo, 2021; Basso & Jimeno, 2020; Heylen & Jacobs, 2021; Jimeno, 2019), but whether or not automation has managed to sufficiently do so remains a subject of contention. Some economists are of the opinion that automation is able to overcompensate for the adverse economic effects of aging, resulting in a net positive change for certain economic metrics such as GDP per capita (Acemoglu & Restrepo, 2017; Acemoglu & Restrepo, 2021; Prettner, 2016) and labor productivity (Abeliansky & Prettner, 2023; Acemoglu & Restrepo, 2021). Other scholars believe that automation by itself cannot fully compensate for the consequences of aging as measured by the aforementioned indicators (Angelini, 2023; Basso & Jimeno, 2020; Heylen & Jacobs, 2021; Jimeno, 2019; Maestas, Mullen, & Powell, 2022), or that it may result in unwanted side effects for human workers such as a decrease in labor share (Heylen and Jacobs, 2021) or increased inequalities in wage, welfare (Heylen and Jacobs, 2021), labor income, wealth, and consumption (Stähler, 2020). In summary, there is a debate among economists over whether or not industrial automation in itself is a sufficient solution for the economic consequences of aging.

To gain a clearer understanding of the implications of automation in aging economies, this paper will attempt to answer the following question: Does increased implementation of industrial automation in countries with aging workforces lead to relative increases in GDP per capita and labor productivity? This study may inspire greater development of industrial automation and other forms of labor-reducing technology for their benefits. It will also hopefully give insight on the potential role of these developments in allowing older workers to retire earlier, countering the adverse economic consequences of an aging workforce in providing automated substitutes for their labor.

By performing linear and panel regressions of GDP per capita and labor productivity on the number of artificial intelligence patents per million employed–a proxy for industrial automation–and the ratio of the portion of the workforce aged 65+ to the portion aged 15-64, it is ultimately revealed that industrial automation benefits GDP per capita and labor productivity, albeit less so in especially rapidly aging countries. *Section 2* will introduce the datasets used in these investigations. *Section 3* will outline the regression specifications used. *Section 4* will perform the regressions in order to analyze the aforementioned data and state the resulting findings. *Section 5* will discuss potential shortcomings of this research. Finally, *Section 6* will summarize the main points of the paper and suggest directions for further research.

Origin of Datasets

Data from OECD.Stat was used in the subsequent analysis. The first dataset used was the “LFS by sex and age” dataset within the “Labour

Force Statistics" section of OECD.Stat, which was utilized for information on yearly employment for different countries, both aggregate and separated by age group. This dataset was also previously used by Heylen and Jacobs (2021).

As the data from the International Federation of Robotics, used by Abeliansky and Prettner (2023), Acemoglu and Restrepo (2017), Acemoglu and Restrepo (2021), Basso and Jimeno (2020), and Venturini (2021), is not available free of purchase, patent data from the "Patents - total and specific technology domains (OECD)" dataset in the "Patents Statistics" section of OECD.Stat was used instead as a proxy for the implementation of industrial automation. This can be assumed to be a reasonable proxy, as the number of patents filed in a particular field is correlated with a country's dedication to advance in and integrate elements of that field. Data from the IP5 patent families was used in order to obtain the most comprehensive statistics possible, while the patents were categorized by their applicants' countries of residence as opposed to the inventors' countries to most accurately measure the interest in a given type of patent by the companies in a given country. Furthermore, the priority date of the patents was used, as they are the only dates with available data for the patent types used in this paper. The technology domain from which patent data was drawn was "Technologies related to artificial intelligence," as it provided the most accurate representation of industrial automation among the categories available. Additionally, artificial intelligence has previously been modeled as a form of automation (Aghion, Jones, & Jones, 2017).

Finally, data on countries' yearly GDP, population, and GDP for every hour worked was obtained from the "Level of GDP per capita and productivity" dataset within the "Productivity and ULC - Annual, Total, Economy" section of OECD.Stat, and was taken in United States dollars with constant prices and 2015 PPPs to avoid inaccurate results due to currency variation and inflation.

Methodology of Data Analysis

In a similar fashion to Acemoglu and Restrepo (2017), Acemoglu and Restrepo (2021), and Jimeno (2019), the aging of a country's workforce was measured by the change in the ratio of the amount of people in a group older than a certain threshold to the amount of people in the group younger than the threshold. Since this paper deals with the issue of aging workforces in particular, only employed people were considered. Workers ages 65 years or older, the typical threshold for senior citizens, were considered "old." Since OECD.Stat contains data on workers as young as 15 years old, workers between the ages of 15 and 64, inclusive, were considered "young." The change in the ratio of workers aged 65 or older to workers aged between 15 and 64 in a given country was used to measure the rate of aging of that country.

Akin to the concept of “robot density” used by Acemoglu and Restrepo (2021), the number of artificial intelligence patents in a given year for a given country was divided by the total employment, in millions, of the same country in the same year. This eliminated cross-country differences in workforce size that could have skewed the patent data in favor of more populous countries and resulted in a disproportionate view of the integration of industrial automation.

The commonly cited economic indicators of GDP per capita and labor productivity (typically defined as a country’s GDP divided by the total hours worked in that country during the same time period) were used as metrics for economic success. GDP per capita was measured as a given country’s GDP divided by its population, while labor productivity was represented using data from the “GDP per hour worked” subject in the “Level of GDP per capita and productivity” dataset.

To determine the geographic range of the data that was used, the 43 countries in the data table with the smallest list of countries, “GDP per hour worked,” were used as a baseline. The earliest year from which data was pulled was 2002, as it is the first year for which nearly all 43 countries have complete employment data, the datasets with the sparsest statistics. Colombia and South Africa were removed from the dataset due to missing various employment data points up until 2007, as moving the earliest year up to 2008 would not have provided enough data points for accurate analysis. This was because employment data contributed to the calculations of aging, which was an independent variable in the analysis. The latest year from which data was pulled was 2016. The data table which ends the earliest is the “Technologies related to artificial intelligence” data table, which contains data up until 2017. However, many of the 2017 statistics are significantly lower than their 2016 counterparts, suggesting incompleteness. Thus, 2016 was used as the final year for analysis.

It should be noted that Korea is missing “GDP per hour worked” data up until 2010. It was not excluded, however, since productivity is a dependent variable and Korean data could therefore still be used for analysis regarding GDP per capita and could easily be ignored for analysis regarding productivity before 2011. Thus, the final aggregate dataset that was analyzed comprised 41 countries from 2002-2016 and contained statistics for the ratio of old to young workers, the ratio of artificial intelligence patents to employment in millions, GDP per capita, and productivity as they were defined above for each combination of country and year (save for the aforementioned exceptions regarding Korea).

In order to ascertain the relationship between industrial automation and GDP per capita or labor productivity within aging countries, linear and panel regressions were performed using the programming language R on the aforementioned datasets.

To most comprehensively capture the scope of the data in the linear regressions, the change of each relevant variable from 2002 to 2016 was used. The two independent variables were the change in the ratio of artificial intelligence patents to millions employed for each country, as well as the degree of aging for each country (again, defined as the change from 2002 to 2016 in the ratio of workers aged 65+ to workers aged 15-64). Two linear regressions were performed; one with the change in GDP per capita for each country as the dependent variable, and the other with the change in labor productivity (again, defined as GDP per hour worked) as the dependent variable.

As each variable can be analyzed for every combination of country and year in the panel regressions, the raw forms of the variables were used. The dependent variables were the ratio of artificial intelligence patents to millions employed, as well as the ratio of workers aged 65+ to workers aged 15-64. Two panel regressions were performed; one with GDP per capita as the dependent variable, and the other with productivity (again, defined as GDP per hour worked), as the dependent variable.

Results

	Dependent variable:			
	GDPPerCapita *OLS*	Productivity *OLS*	GDPPerCapita *panel linear*	Productivity *panel linear*
	(1)	(2)	(3)	(4)
PatentsEmployment	817.533***	1.083***	492.898***	0.617***
	(241.099)	(0.304)	(64.526)	(0.075)
Aging	14,099.910	-38.123	30,303.610***	-4.551
	(36,880.120)	(46.667)	(11,324.210)	(13.174)
PatentsEmployment:Aging	-16,387.490	-14.956	-2,693.403***	-3.666***
	(9,966.926)	(13.285)	(1,026.577)	(1.266)
Constant	6,236.451***	7.681***		
	(732.550)	(0.923)		
Observations	41	40	615	606
R^2	0.285	0.334	0.130	0.125
Adjusted R^2	0.227	0.279	0.041	0.033
Residual Std. Error	3,857.017 (df = 37)	4.858 (df = 36)		
F Statistic	4.915*** (df = 3; 37)	6.024*** (df = 3; 36)	27.754*** (df = 3; 557)	25.988*** (df = 3; 548)
Note:				*p<0.1; **p<0.05; ***p<0.01

TABLE 1: Associations of proxy for industrial automation and economic indicators via linear and panel regression

Table 1 contains the resulting coefficients from the linear and panel regressions performed with ratio of artificial intelligence patents to millions employed and degree of aging as the independent variables, and GDP per capita or labor productivity as the independent variables. Detailed analysis of these values is below.

Below are the results of the linear regression with change in GDP per capita as the dependent variable.

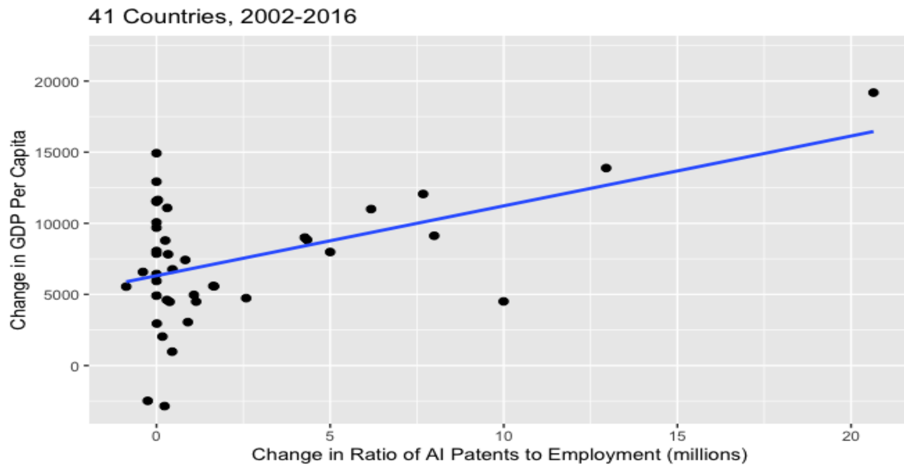

FIGURE 1: Graph for linear regression of GDP per capita on proxy for industrial automation

Figure 1 displays a graphical representation of the relationship between GDP per capita and ratio of artificial intelligence patents to millions employed. The coefficient on the independent variable for the change in the ratio of artificial intelligence patents to millions employed is 817.533, meaning that an additional artificial intelligence patent filed during the aforementioned 14-year period within a country is correlated with an additional $817.533 increase in GDP per capita in that same country during the same time frame. The p-value of this variable is much lower than the traditionally held significance level of 0.05. Thus, these datasets provide ample evidence to prove a positive association between change in the ratio of artificial intelligence patents to millions employed and change in GDP per capita from 2002 to 2016.

Additionally, the coefficient on the variable for the interaction between the degree of aging and the change in the ratio of artificial intelligence patents to millions employed is -16387.490. This means that for each additional increase of 0.01 in the previously defined old-to-young ratio between 2002 and 2016, the coefficient of the change in the ratio of artificial intelligence patents to millions employed will decrease by 163.87. Although the p-value is larger than 0.05, which alone suggests there is a plausible chance this relationship may not exist, a negative correlation between aging and the benefit of automation on GDP per capita is later affirmed in the corresponding panel regression. A possible reason for this large p-value is the comparatively small number of data points used in the linear regression. Thus, interpreting the coefficient as representing a valid relationship, between countries that had similar changes in the ratio of artificial intelligence patents to millions employed over the 14-year period, countries that aged more rapidly typically received smaller boons in GDP per capita from industrial automation.

Finally, it is also worth noting that the coefficient on the independent variable for the change in the aforementioned old-to-young ratio is 14099.910, which means that each additional increase of 0.01 in the ratio of workers ages 65+ to workers ages 15-64 during the aforementioned 14-year period is associated with a $140.999 increase in GDP per capita during the same time frame. Although the p-value is much larger than 0.05, which alone suggests that there may be no real relationship, a positive correlation between aging and GDP per capita is later affirmed in the corresponding panel regression. Again, this large p-value may be caused by the comparatively small number of data points in the linear regression. Interpreting the coefficient as representing an existent relationship, it is unlikely that a greater increase in the old-to-young ratio causes a greater increase in GDP per capita given previous research which establishes that an aging workforce has adverse implications on a country's economic performance with regards to this metric (Maestas, Mullen, & Powell, 2022). Rather, a greater increase in GDP per capita likely causes a greater increase in the old-to-young ratio as more affluent countries are able to develop more sophisticated forms of technology and medicine, increasing longevity.

Next are the results of the linear regression with change in labor productivity as the dependent variable. Note the absence of Korea, as it is missing the necessary "GDP per hour worked" data for 2002.

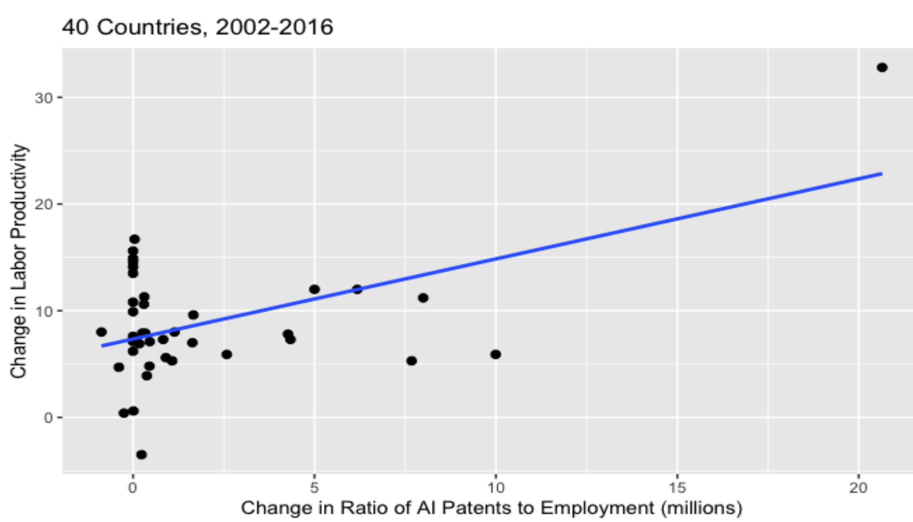

FIGURE 2: Graph for linear regression of labor productivity on proxy for industrial automation

Figure 2 displays a graphical representation of the relationship between labor productivity and ratio of artificial intelligence patents to millions employed. The coefficient on the independent variable for the change in the ratio of artificial intelligence patents to millions employed is 1.083, meaning that an additional artificial intelligence patent filed during the aforementioned 14-year period within a country is correlated with an additional 1.083 increase in productivity in that same country during the same time frame. In other words, an additional artificial intelligence patent filed is associated with an additional $1.083 increase from a country's GDP in 2002 divided by the total hours worked in that country in 2002, to the country's GDP in 2016 divided by the total hours worked in that country in 2016. The p-value of this variable is much lower than 0.05. Thus, these datasets provide ample evidence to prove a positive association between change in the ratio of artificial intelligence patents to millions employed and change in labor productivity from 2002 to 2016.

Additionally, the coefficient on the variable for the interaction between the degree of aging and the change in the ratio of artificial intelligence patents to millions employed is -14.956. This means that for each additional increase of 0.01 in the previously defined old-to-young ratio between 2002 and 2016, the coefficient of the change in the ratio of artificial intelligence patents to millions employed will decrease by 0.150. Although the p-value is much larger than 0.05, which alone suggests there is a plausible chance this relationship may not exist, a negative correlation between aging and the benefit of automation on labor productivity is also later affirmed in the corresponding panel regression. Again, a possible reason for this large p-value is the comparatively small number of data points used in the linear regression. Thus, interpreting the coefficient as representing a valid relationship, between countries that had similar changes in the ratio of artificial intelligence patents to millions employed over the 14-year period, countries that aged more rapidly typically received smaller boons in GDP per hour worked from industrial automation.

Below are the results of the panel regression with GDP per capita as the dependent variable.

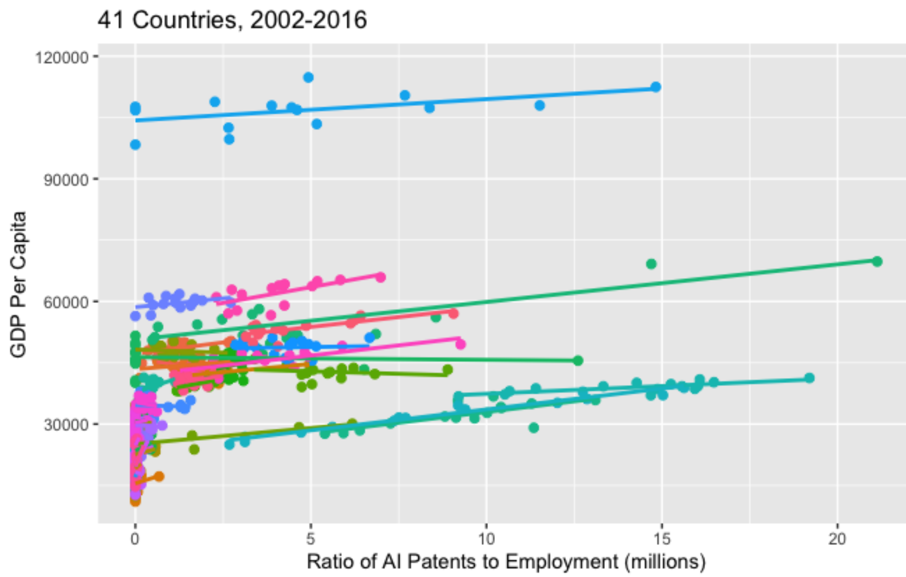

FIGURE 3: Graph for panel regression of GDP per capita on proxy for industrial automation (grouped by country)

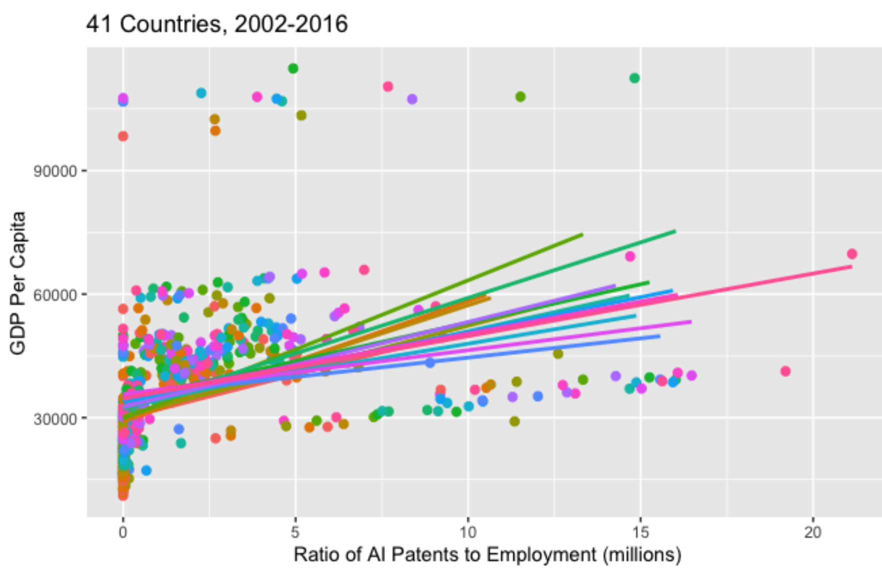

FIGURE 4: Graph for panel regression of GDP per capita on proxy for industrial automation (grouped by year)

Figure 3 displays a graphical representation of the relationship between GDP per capita and ratio of artificial intelligence patents to millions employed with data points and trend lines color coded for individual countries. Figure 4 displays the same information, but with data points and trend lines color coded for individual years. The coefficient on the independent variable for the ratio of artificial intelligence patents to millions employed is 492.898, meaning that each additional artificial intelligence patent per million people employed within a country is correlated with an additional $492.898 in GDP per capita in that same country. The p-value of this variable is much lower than 0.05. Thus, this dataset provides ample evidence to prove a positive association between the ratio of artificial intelligence patents to millions employed and GDP per capita.

Additionally, the coefficient on the variable for the interaction between the old-to-young ratio and the ratio of artificial intelligence patents to millions employed is -2693.403. This means that for an increase of 0.01 in the previously defined old-to-young ratio, the coefficient of the ratio of artificial intelligence patents to millions employed will decrease by 26.934. In other words, between countries with similar ratios of artificial intelligence patents to millions employed, countries with an older workforce will typically have undergone a smaller boon to GDP per capita from industrial automation. The p-value, which is less than 0.05, proves the robustness of this relationship.

Finally, it is also worth noting that the coefficient on the independent variable for the aforementioned old-to-young ratio is 30303.610, meaning that an increase of 0.01 in the ratio of workers ages 65+ to workers ages 15-64 in a country is associated with an increase of $303.036 in that country's GDP per capita. Using similar reasoning as used along with the corresponding linear regression, this relationship likely indicates that higher GDP per capita results in an older workforce since countries that are thriving economically are able to invest more in medicine and technology to ultimately extend the lifespans of citizens. The p-value of this variable is much lower than 0.05, so these datasets provide ample evidence to prove a positive association between the old-to-young ratio and GDP per capita.

Below are the results of the panel regression with labor productivity as the dependent variable. Note the absence of data points for Korea between 2002 and 2010, as it is missing the necessary "GDP per hour worked" data for those years.

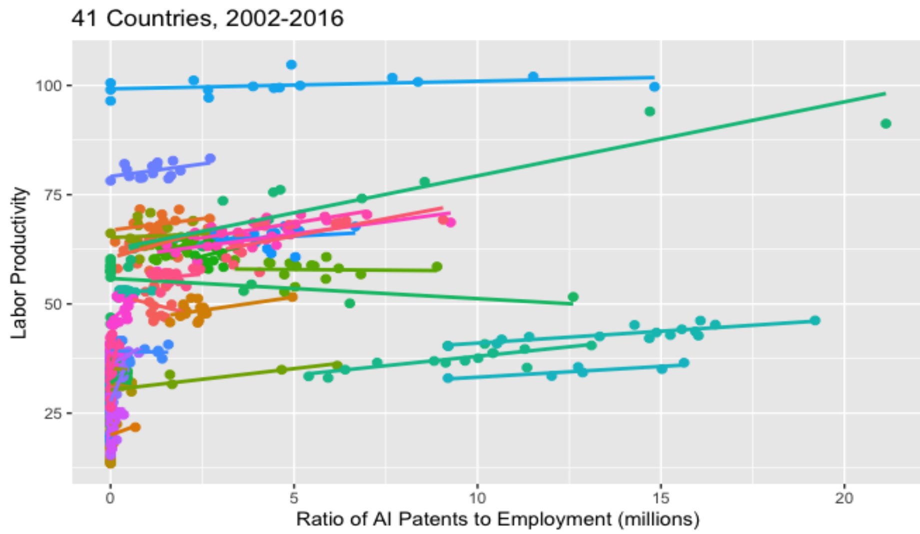

FIGURE 5: Graph for panel regression of labor productivity on proxy for industrial automation (grouped by country)

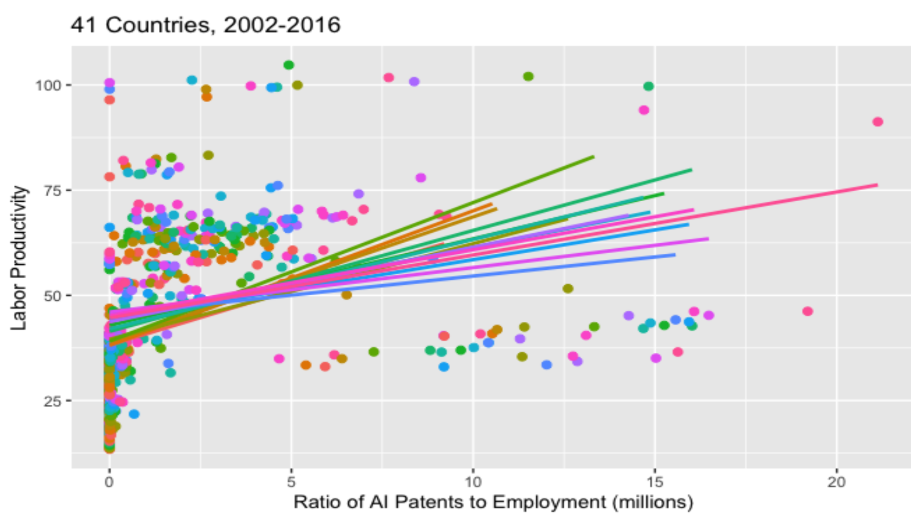

FIGURE 6: Graph for panel regression of labor productivity on proxy for industrial automation (grouped by year)

Figure 5 displays a graphical representation of the relationship between labor productivity and ratio of artificial intelligence patents to millions employed with data points and trend lines color coded for individual countries. Figure 6 displays the same information, but with data points and trend lines color coded for individual years. The coefficient on the independent variable for the ratio of artificial intelligence patents to millions employed is 0.617, meaning that each additional artificial intelligence patent per million people employed within a country is correlated with an increase of 0.617 in productivity in that same country.

In other words, an additional artificial intelligence patent filed per million workers in a country is associated with a $0.617 increase in that country's GDP divided by the total hours worked in that country. The p-value of this variable is much lower than 0.05. Thus, this dataset provides ample evidence to prove a positive association between the ratio of artificial intelligence patents to millions employed and labor productivity.

Additionally, the coefficient on the variable for the interaction between the old-to-young ratio and the ratio of artificial intelligence patents to millions employed is -3.666. This means that for an increase of 0.01 in the previously defined old-to-young ratio, the coefficient of the ratio of artificial intelligence patents to millions employed will decrease by 0.037. In other words, between countries with similar ratios of artificial intelligence patents to millions employed, countries with an older workforce will typically have undergone a smaller boon to labor productivity from industrial automation. The p-value, which is less than 0.05, proves the robustness of this relationship.

As for the question of which of the two types of regressions–linear and panel–is best suited to answer the original research question, the panel regressions likely provide a stronger case for several reasons. First, the panel regressions control for variables that vary across countries and not time or vice versa, eliminating potential distortion in the results from unobserved variables such as countries' individual economic policies or periods of unusual economic conditions in large parts of the world. Second, the lower p-values of the variables in the panel regressions more adequately support robust relationships. The p-values of the independent variables in the panel regressions are several magnitudes smaller than their counterparts in the linear regressions, while the p-values of the interaction variables in the linear regressions fall above the statistical significance level of 0.05.

Despite the shortcomings of the linear regressions, both regression types ultimately support the same conclusion: implementing industrial automation has a positive effect on GDP per capita and labor productivity. Although the data analysis itself only confirms a correlation, a causal relationship can be reasonably assumed due to the potential of automation to more accurately and efficiently replicate physical human labor. Furthermore, the panel regressions reveal another result: the efficacy of industrial automation in improving GDP per capita and labor productivity is hampered in countries with workforces that are especially aged. The interaction coefficients in the linear regressions support the extension of this theory to countries with workforces that are aging especially rapidly as well, but the p-values are too high to indicate significance. However, as explained above, given that the high p-values may have been caused by the comparatively small quantity of data points in the linear regressions and it is reasonable to assume that countries with especially aged workforces will experience similar economic trends compared to those with rapidly aging workforces, it can be inferred that the effectiveness of industrial automation in improving GDP per capita and labor productivity is also lessened in countries with workforces that are aging particularly quickly. One possible explanation for this finding is that nations with significantly aged or aging economies have likely already integrated a sizable amount of automation into their workforces, meaning that additional automation will produce diminishing returns due to an increasingly saturated environment. For example, a manufacturing plant in need of workers will greatly benefit from the first few robots brought in to fill the empty posts, but additional robots will eventually become superfluous when the workforce is at full capacity.

Limitations

The methods used throughout this paper ultimately produced findings that are robust, but not without caveats. The first is the usage of artificial intelligence patents to model industrial automation. Artificial intelligence does not encompass the entirety of what may be considered "automation," and patent filings do not provide an exact number for the actual quantities of robots and other forms of automation in the workplace. The second is the incompleteness of the datasets used, including the absence of "GDP per hour worked" data for Korea prior to 2011, and the fact that data on the required variables on OECD.Stat is only available for a relatively small fraction of the world's nations. The presence of this additional data may have proven the aforementioned results to be more robust, or refuted the perceived associations entirely.

The third is the possibility of confounding variables influencing the results, especially in the linear regressions where cross-country and cross-time differences were not accounted for. One potential confounding variable is the education level of the workforce in a given country. Because filing artificial intelligence patents requires significant technical expertise, a country with more educated citizens would likely have the knowledge base to produce more artificial intelligence patents. Furthermore, a well-educated population may skew towards the older end, as most graduate degrees are awarded comparatively later in life. Educated workers are also better equipped to boost economic indicators, since jobs with an education prerequisite typically produce more expensive goods. As education will likely increase artificial intelligence patents and economic indicators, it is a possibility that the perceived positive correlation between the two was simply a result of the differing education levels of countries' populations.

Another possible confounding variable is the industry breakdown of each country. A country with specialized technology industries will likely file more artificial intelligence patents due to the nature of artificial intelligence as a specialized technical field. Countries with predominantly blue collar and labor intensive industries will likely have younger workers due to physical demands, while countries with more white-collar or specialized industries can more easily accommodate workers of all ages.

Finally, specialized industries are better equipped to increase economic indicators due to the exclusivity of their products. Because a country's industry breakdown can positively affect the filing of artificial intelligence patents and economic indicators, it is also possible that the observed association between the two variables resulted from the different predominant industries in various countries.

Conclusion

Through linear and panel regressions on data from OECD.Stat, this paper revealed that implementing industrial automation does lead to increases in GDP per capita and labor productivity, but the effects are increasingly dampened for countries whose workforces are older and are aging more rapidly. These results affirm that industrial automation can compensate for aging in regard to GDP per capita and labor productivity in most scenarios but may not be an adequate solution by itself in especially aged or quickly aging nations.

This research opens itself up to future investigation in addressing the previously mentioned shortcomings. To improve the precision of the results, it would be worthwhile to use data more directly measuring automation in the workforce, rather than the artificial intelligence patents proxy used here. The usage of datasets or selection of alternate proxy variables, such as investment in automation technology, with more comprehensive information on the world's nations would also improve the robustness of the findings in reflecting the true relationships between these factors.

Identifying and incorporating additional confounding variables into the regressions will likely also contribute to increasing accuracy. To accomplish this, data surrounding education level, such as the percentage of the working population with undergraduate or graduate degrees in a given country, and on industry breakdown, such as the percentage of the working population working in blue collar, labor intensive fields like heavy industry, may be implemented into the panel regression. This will further isolate the effects of industrial automation on a country's economic growth, lessening interference from possible external factors.

One major societal concern surrounding the implementation of industrial automation has been the fact that robots may displace jobs, particularly those that are more physically intensive. The consequences of this possible implication may be remedied by the increased prosperity generated from incorporating industrial automation demonstrated in this study. Older workers may be able to retire earlier due to the role of automation in providing substitutes for their labor, and countries may be able to afford allocating a greater share of their budget towards welfare programs and social insurance.

References

Abeliansky, A. L., & Prettner, K. (2023). Automation and population growth: Theory and cross-country evidence. *Journal of Economic Behavior & Organization, 208*, 345-358. https://doi.org/10.1016/j.jebo.2023.02.006

Acemoglu, D., & Restrepo, P. (2017). Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation. *American Economic Review, 107*(5), 174-179. https://doi.org/10.1257/aer.p20171101

Acemoglu, D., & Restrepo, P. (2021). Demographics and Automation. *Review of Economic Studies.* https://pascual.scripts.mit.edu/research/demographics/

Aghion, P., Jones, B. F., & Jones, C. I. (2017). Artificial Intelligence and Economic Growth. *NBER Working Paper Series*. https://doi.org/10.3386/w23928

Angelini, D. (2023). Aging Population and Technology Adoption. *Working Paper Series of the Department of Economics, University of Konstanz*. https://ideas.repec.org/p/knz/dpteco/2301.html

Basso, H. S., & Jimeno, J. F. (2020). From Secular Stagnation to Robocalypse? Implications of Demographic and Technological Changes. *Banco de Espana Research Paper Series - Working Papers*. https://doi.org/10.2139/ssrn.3593334

Heylen, F., & Jacobs, A. (2021). Demographic change, secular stagnation and inequality: automation as a blessing?. *Working Papers of Faculty of Economics and Business Administration, Ghent University, Belgium*. https://ideas.repec.org/p/rug/rugwps/21-1030.html

Jimeno, J. F. (2019). Fewer babies and more robots: economic growth in a new era of demographic and technological changes. *SERIEs, 10*(2), 93-114. https://doi.org/10.1007/s13209-019-0190-z

Maestas, N., Mullen, K. J., & Powell, D. (2022). The Effect of Population Aging on Economic Growth, the Labor Force and Productivity. *NBER Working Paper Series*. https://doi.org/10.3386/w22452

Prettner, K. (2016). The implications of automation for economic growth and the labor share of income. *ECON WPS - Working Papers in Economic Theory and Policy*. https://ideas.repec.org/p/zbw/tuweco/042016.html

Stähler, N. (2020). The Impact of Aging and Automation on the Macroeconomy and Inequality. *Deutsche Bundesbank Discussion Paper*. https://doi.org/10.2139/ssrn.3627026

Venturini, F. (2021). Intelligent technologies and productivity spillovers: Evidence from the Fourth Industrial Revolution. https://www.researchgate.net/publication/324819823_Intelligent_technologies_and_productivity_spillovers_Evidence_from_the_Fourth_Industrial_Revolution