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 elderly workers participating in the world's greatest economies is increasing. The decreased capabilities of elderly workers, as well as the dwindling number of young workers, can have negative economic consequences if left unchecked. 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 harms 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 negative 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.

1. Introduction

As a result of declining fertility rates and increased longevity due to advancements in medicine and technology, the share of elderly workers is increasing in many countries. A high ratio of old to young workers can cause negative economic effects if left unchecked, due to the lower 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 [1].

Many economists agree that the aging workforce has led to a greater implementation of industrial automation to compensate for its economic detriments [2], [3], [4], [5], 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 negative economic effects of aging, resulting in a net positive change for certain economic metrics such as GDP per capita [2], [6], [7] and labor productivity [2], [8]. Other scholars believe that automation by itself cannot fully compensate for the consequences of aging as measured by the aforementioned indicators [1], [3], [4], [5], [9], or that it may result in unwanted side effects for human workers such as a decrease in labor share [4] or increased inequalities in wage, welfare [4], labor income, wealth, and consumption [10]. In summary, there is a debate among economists over whether or not industrial automation in itself is a sufficient solution for the harmful 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 an increased implementation of industrial automation in countries with an aging workforce lead to relative increases in GDP per capita and labor productivity? 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.

2. 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, a dataset previously used in [4]. In a similar fashion to [2], [5], [6], 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.

As the data from the International Federation of Robotics, used in [2], [3], [6], [8], [11], 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 applicants' countries of residence were used 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 automation among the categories available. Additionally, artificial intelligence has previously been modeled as a form of automation [12]. Akin to the concept of "robot density" used in [2], 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 data was also taken from the "LFS by sex and age" dataset, and eliminated cross-country differences in workforce size that could have skewed the patent data in favor of more populous countries and result in a disproportionate view of the integration of industrial automation.

Finally, the commonly cited economic indicators of GDP per capita and 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. All requisite data 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. GDP per capita was measured as a given country's GDP divided by its population, while productivity, as mentioned above, was measured using GDP per hour worked.

To determine the geographic scope of the data that was used, the 43 countries in the dataset with the smallest list of countries, the "GDP per hour worked" dataset used for productivity, 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 is because employment data contributes to our calculations of aging, which was an independent variable in our analysis. The latest year from which data was pulled was 2016. The dataset which ended the earliest is the "Technologies related to artificial intelligence" dataset, 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 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).

3. Methodology of Data Analysis

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.

4. 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

Figure 1: Table with regression results

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

Figure 2: Graph for GDP per capita linear regression

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 0.00167, which 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 163.87490. In other words, 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. However, the p-value of 0.10861, which is larger than the significance level of 0.05, suggests there is a plausible chance that this relationship may not actually exist. A possible reason for this large p-value is the comparatively small number of data points used in the linear regression, as a negative correlation between aging and the benefit of automation on GDP per capita is later affirmed in the corresponding panel regression.

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.

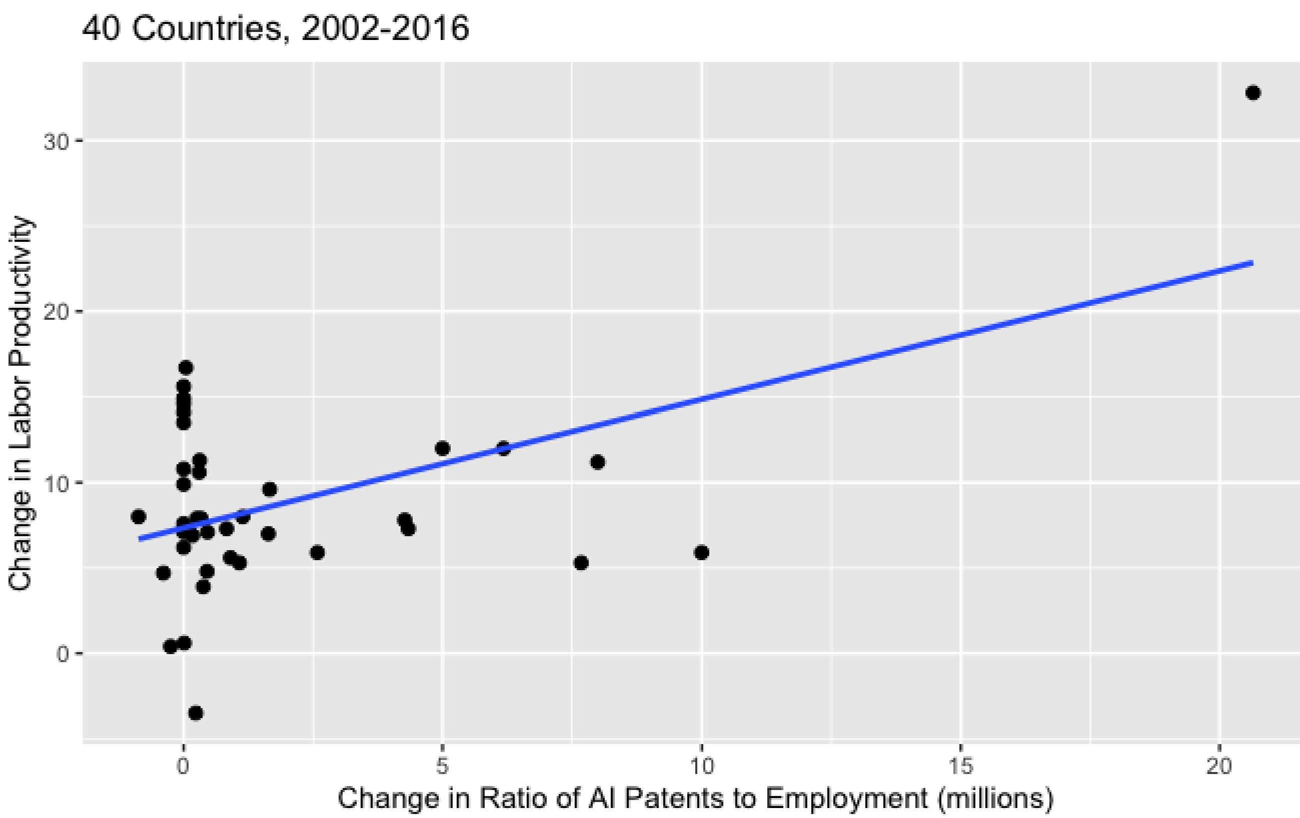

Figure 3: Graph for labor productivity linear regression

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 0.00105, which 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 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 0.14956. In other words, 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. However, the p-value of 0.26773, which is much larger than the significance level of 0.05, suggests there is a plausible chance that this relationship may not actually exist. Again, a possible reason for this large p-value is the comparatively small number of data points used in the linear regression, as a negative correlation between aging and the benefit of automation on labor productivity is later affirmed in the corresponding panel regression.

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

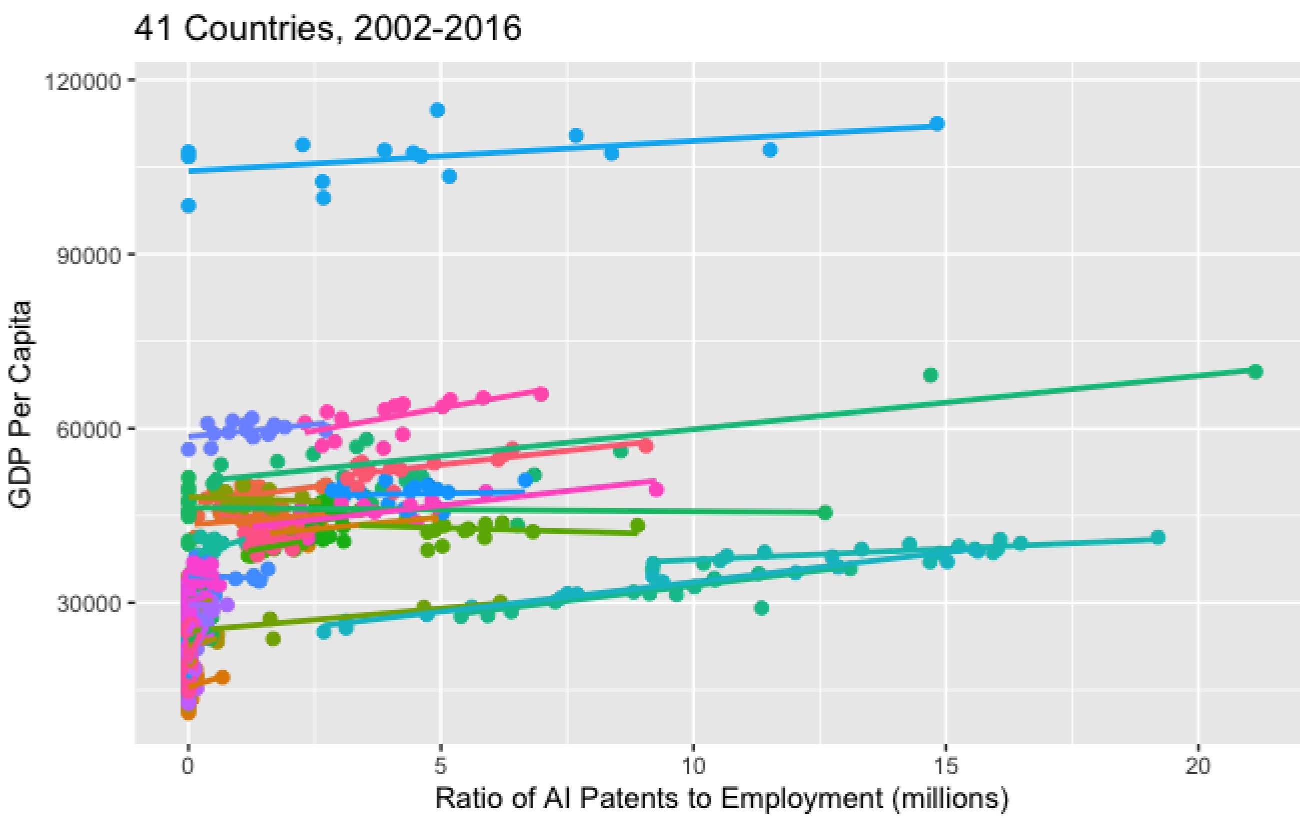

Figure 4: Graph for GDP per capita panel regression (grouped by country)

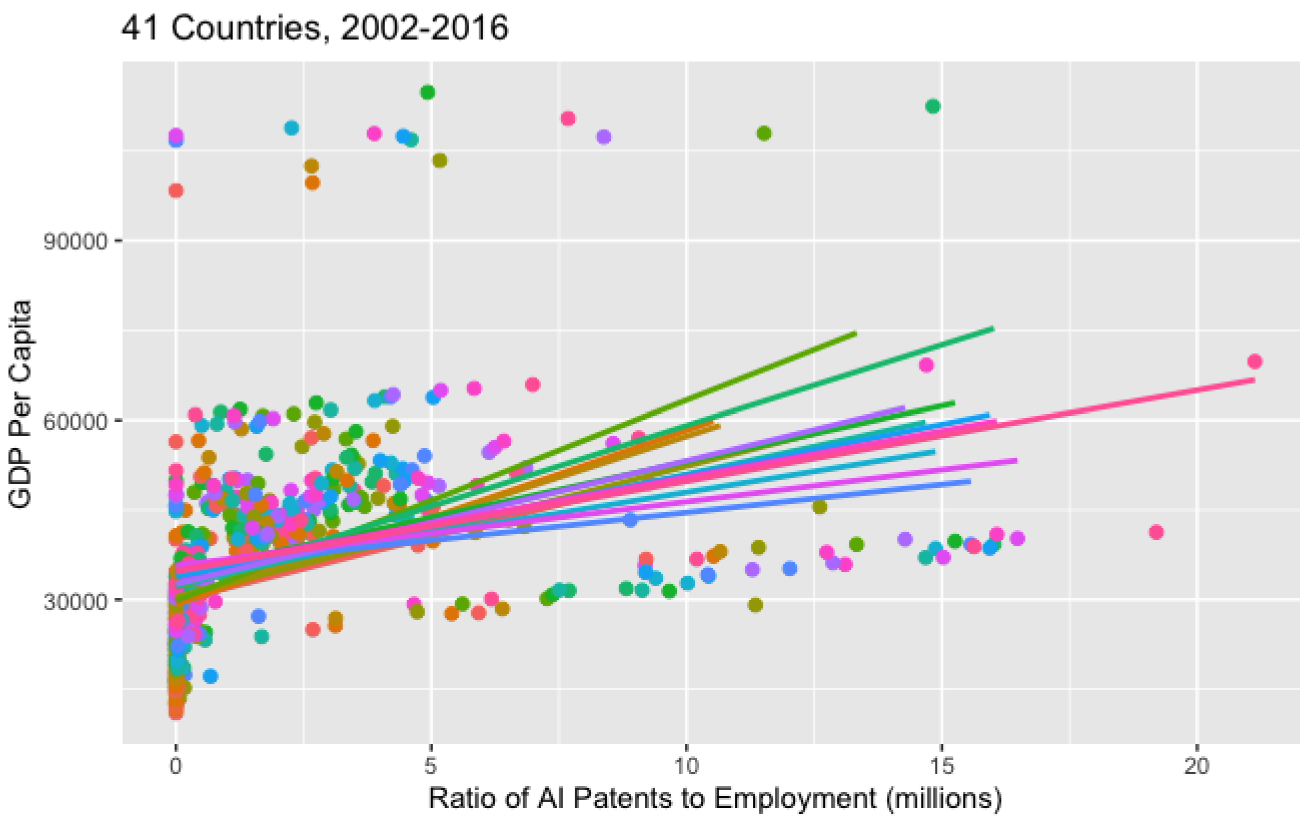

Figure 5: Graph for GDP per capita panel regression (grouped by year)

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 $9.622*10^{-14}$, which is much lower than the traditionally held significance level of 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.

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 $303.03610 in that country's GDP per capita. The p-value of this variable is 0.007670, which is much lower than the traditionally held significance level of 0.05. Thus, these datasets provide ample evidence to prove a positive association between the old-to-young ratio and GDP per capita. Although this may initially seem to contradict the previously introduced idea of an aging workforce being a hindrance to GDP per capita, this relationship likely indicates that a 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.

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 26.93403. 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 of 0.008937, which is less than the significance level of 0.05, proves the robustness of this relationship.

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.

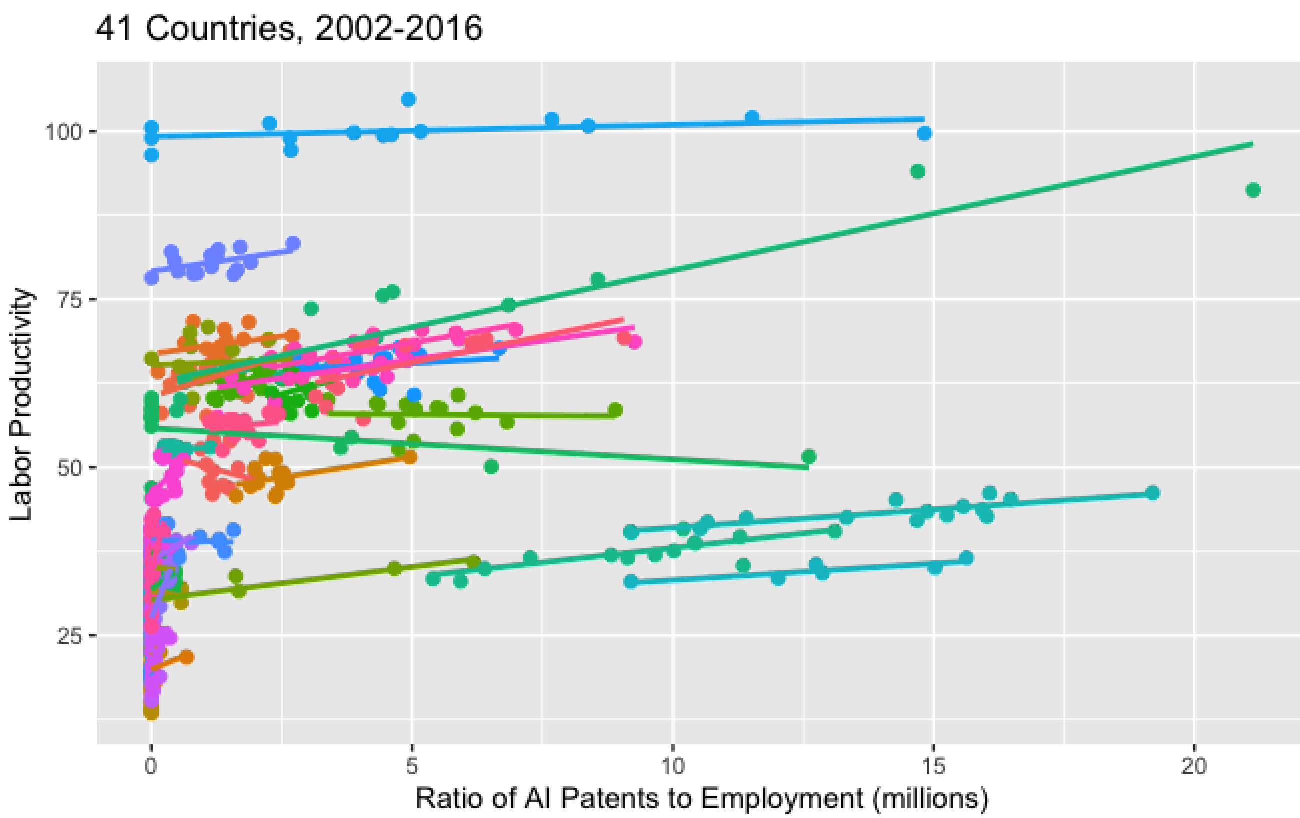

Figure 6: Graph for labor productivity panel regression (grouped by country)

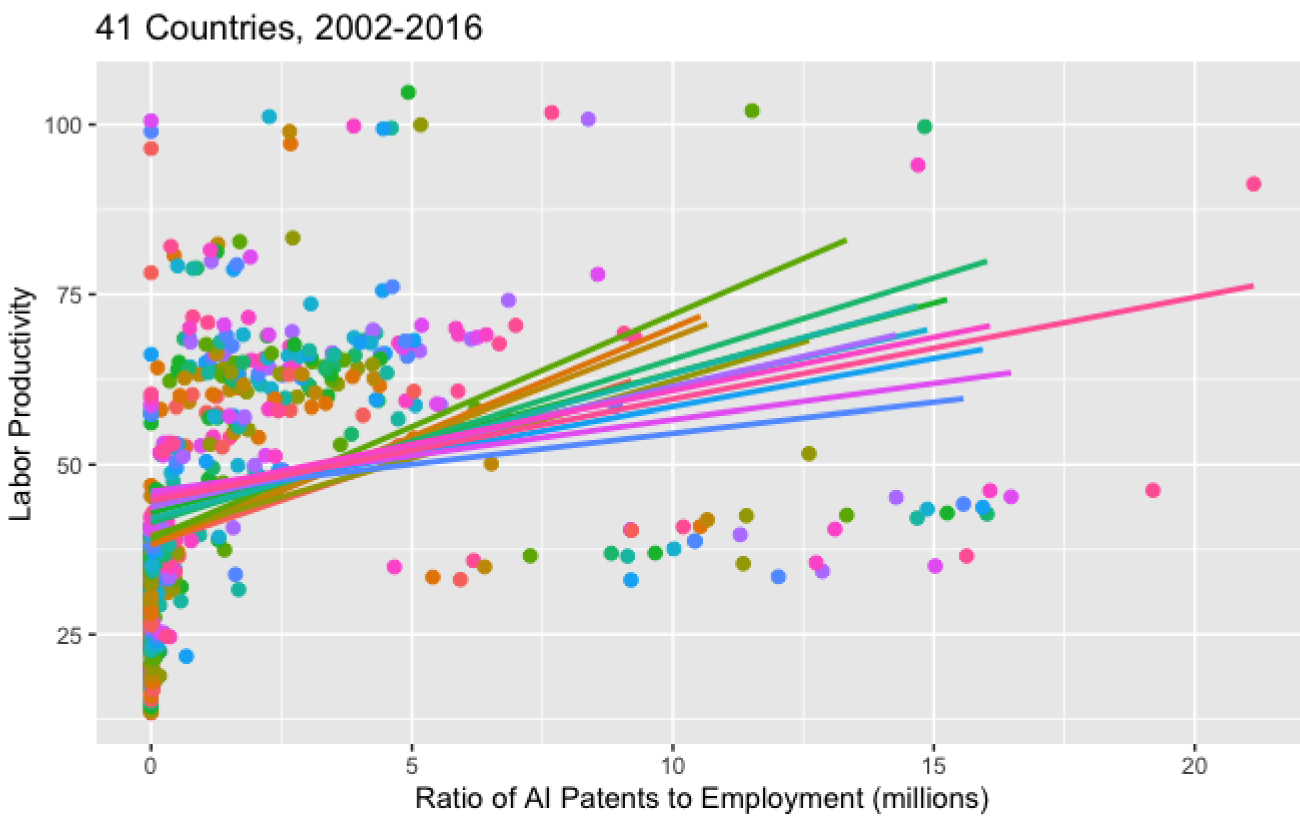

Figure 7: Graph for labor productivity panel regression (grouped by year)

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 $1.364*10^{-15}$, which is much lower than the traditionally held significance level of 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 0.03666. 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 of 0.003934, which is less than the significance level of 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 regression likely provides a stronger case for several reasons. First, the panel regression controls for variables that vary across countries and not time, or vice versa, eliminating potential distortion in the results from unobserved variables. Second, the lower p-values of the variables in the panel regression more adequately support a robust relationship. The p-values of the independent variables in the panel regression are several magnitudes smaller than their counterparts in the linear regression, while the p-values of the interaction variables in the linear regression fall above the 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 aging especially rapidly. The interaction coefficients in the linear regressions support a similar theory, but the p-values are too high to indicate significance. One possible explanation for this finding is that rapidly 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.

5. 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 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.

6. Conclusion

This paper aimed to answer the following question: Does an increased implementation of industrial automation in countries with an aging workforce lead to relative increases in GDP per capita and labor productivity? Performing linear and panel regressions on data from OECD.Stat 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. This will likely also contribute to the accuracy of these findings to identify and incorporate additional confounding variables into the regressions.

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