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AI and Workforce Dynamics: Unravelling Productivity

Hiroshi YOSHIDA *(https://orcid.org/0000-0003-1643-5220), Tohoku University, Japan; hiroshi.yoshida.e2@tohoku.ac.jp*

Meltem İNCE-YENİLMEZ *(https://orcid.org/0000-0002-4689-3196), Izmir Democracy University, Türkiye; melteminceyenilmez@gmail.com*

Yapay Zekâ ve İşgücü Dinamikleri: Üretkenliğin Çözülmesi

Abstract

This study examines how artificial intelligence (AI) affects worker productivity, emphasising AI's capacity to automate jobs, reduce errors, and optimise workflows. It emphasises the need for dynamic reskilling initiatives and company-school cooperation to provide workers with the necessary skills. Using a two-log econometric model, the study examines the association between AI patents and productivity. It observes that the effects of AI differ across industries, with less automation in positions requiring creativity and emotional intelligence. The paper also suggests more research and examines the relationship between productivity and R&D costs, physical assets, and non-AI patents.

Keywords : Artificial Intelligence, Worker Productivity, Reskilling and Upskilling, AI-Related Patents.

JEL Classification Codes : E24, J01, J24, J89.

Öz

Bu çalışma, yapay zekanın (YZ) çalışan verimliliğini nasıl etkilediğini incelemekte ve YZ'nın işleri otomatikleştirme, hataları azaltma ve iş akışlarını optimize etme kapasitesini vurgulamaktadır. Çalışanlara gerekli becerileri kazandırmak için yeniden beceri kazandırma girişimlerine ve şirket-okul iş birliğine duyulan ihtiyaç vurgulanmaktadır. Çalışma, iki loglu model kullanılarak yapay zekâ patentleri ve üretkenlik arasındaki ilişkiyi incelemektedir. YZ'nın etkilerinin sektörler arasında farklılık gösterdiğini, yaratıcılık ve duygusal zekâ gerektiren pozisyonlarda daha az otomasyon olduğunu gözlemlemektedir. Çalışma aynı zamanda verimlilik ile Ar-Ge maliyetleri, fiziksel varlıklar ve yapay zekâ dışı patentler arasındaki ilişkiyi de incelemektedir.

Anahtar Sözcükler : Yapay Zekâ, İşçi Üretkenliği, Yeniden Beceri Kazandırma ve Yükseltme, Yapay Zekâ ile İlgili Patentler.

> *A class of artificial intelligence (AI) algorithms known as "generative AI" produces new outputs depending on the input it has been trained on. Unlike conventional artificial intelligence (AI) systems, which are meant to identify patterns and forecast outcomes, generative AI generates original content, including text, audio, graphics, and more.*
> *World Economic Forum (WEF) 2023*

1. Introduction

Entrepreneurship and artificial intelligence are two complex phenomena that have important implications for the employment market and the economy. Artificial intelligence (AI) solutions, such as automation systems and machine learning algorithms, can significantly increase worker productivity by allowing humans to focus on the more complex and creative aspects of their jobs by automating repetitive tasks. Automating repetitive tasks is a key way artificial intelligence (AI) affects worker productivity.

AI-powered systems thrive at performing repeated jobs and activities with precision and efficiency. This accelerates procedures and reduces errors, hence enhancing total efficiency. Artificial intelligence (AI) can be especially useful in industries that rely significantly on repetitive tasks, such as manufacturing and data input, freeing human workers to solve problems and make more complex decisions. Automation has the potential to replace human work while enhancing productivity. There are concerns that if AI replaces human labour, specific jobs will become obsolete, resulting in job losses in specific industries. Advocates argue that technological developments have historically created new jobs while rendering some old ones obsolete. It is critical to provide workers with the skills they need to adapt to evolving work patterns in this century. AI's impact on worker productivity needs increased training and upskilling. As technology advances, experts in data analytics, machine learning, and artificial intelligence (AI) are in greater demand. Employers and educational institutions must work together to ensure people have the skills needed for future employment. People must be resilient lifelong learners to compete and fully participate in AI-driven businesses.

The influence of artificial intelligence (AI) on labour productivity will differ between industries and professions. Artificial intelligence will replace more manual labour and repetitive jobs than those requiring creativity, emotional intelligence, and complex problem-solving abilities. As a result, there's a growing need for AI jobs to increase efficiency while emphasising the value of human-only skills that machines cannot duplicate. Finally, it should be noted that integrating AI into labour productivity is dynamic and has advantages and disadvantages. To fully capitalise on AI’s benefits, reskilling workers proactively is essential to keeping them flexible and prepared for the ever-changing labour market. A future where AI boosts productivity and cultivates a workforce capable of navigating the intricacies of the technology landscape is one that policymakers, educators, and industry leaders will heavily influence.

The linked studies are reviewed in the next section. Section 3 covers the company's adoption of AI-related installation and the data used to evaluate the composition of labour productivity. Section 4 explains the estimating technique and interprets the estimation outcomes. The final section concludes this paper.

2. Literature Review

Growing life expectancies and falling birth rates have resulted in population ageing, a serious problem for many developed and emerging nations. Due to the decline in physical and mental capacities associated with ageing, older workers are perceived to be less inventive and productive than their younger peers. In ageing civilisations, some worries are that rising rates of old age and an ageing labour force may impede economic expansion. According to Brynjolfsson and McAfee (2014) and Goldfarb et al. (2020), artificial intelligence (AI) is the most significant general-purpose technology of this century. AI is a potent type of automation that trains computers to behave more like humans. According to Zhang et al. (2022), private investments in artificial intelligence (AI) are predicted to exceed $68 billion in 2020, setting new records yearly and impacting almost every element of society. Despite the general enthusiasm for AI, there still needs to be more clarity about how artificial intelligence (AI) interacts with conventional production factors like labour and capital. According to some (Frank et al., 2019; Webb, 2019), artificial intelligence (AI) will replace high-skill jobs, particularly those requiring a lot of education and experience. However, according to others, AI is a technology that deepens capital and has no bearing on labour (Bresnahan, 2019).

The potential effects of recent developments in robotics and artificial intelligence (AI) on interrelated social outcomes like wages, growth, employment, and inequality have long been a source of controversy in the field of economic theories (Solow, 1957; Romer, 1990; Aghion & Howitt, 1992; Antonelli, 2009). These theories assume that technological innovation and change will ultimately determine economic growth. According to Autor et al. (2003) and Barbieri et al. (2020), technological advancement may create wage polarisation because of proportionate increases in the demand for skilled workers compared to unskilled individuals. Automating tasks could result in job losses (Autor & Dorn, 2013; Vivarelli, 1995, 1995, 2013; Piva & Vivarelli, 2018; Josten & Lordan, 2020). These views are supported by recent theories, such as those regarding skill-biased technological change.

Production is expected to increase as technology develops, according to economic theory. As a result of significant investments in digital innovation, developed nations have faced low productivity since the 1970s, a phenomenon known as the "Productivity Paradox" (Brynjolfsson, 1993). According to Gordon (2018), worker productivity is mainly blamed for this decline. Reversing the falling productivity trend and reviving the economy overall may be possible thanks to the wide range of applications of recent developments in AI technology. Agrawal et al. (2019b) note that artificial intelligence (AI) can boost productivity not just by automating the repurposing of current technology but also by lowering uncertainty through more accurate projections (Bartelsman et al., 2019; Cockburn et al., 2019). The AI revolution, which necessitates business restructuring, worker upskilling, and the emergence and diffusion of complementary inventions throughout the economy, maybe the reason behind the continued low productivity growth despite recent significant technological advancements in AI (Brynjolfsson et al., 2019).

It is not a commonly accepted notion among writers. Gordon (2016, 2018) argues that productivity is declining irreversibly and that current technological innovations -like the digital and even artificial intelligence revolutions- have led to overly optimistic expectations that they won't have the same disruptive power as innovations like internal combustion engines and electric power, which produced the remarkable productivity growth that the United States saw between the 1920s and 1970s. Jones (2009) shows how specialisation and teamwork rise with time, along with the age of the initial innovation, using a large dataset of innovators. He contends that to push the frontier, researchers must continue to learn more.

Researchers claim that generating new ideas is becoming more complex and that research output has sharply declined across various industries, products, and businesses (Bloom et al., 2020). Gries and Naudé (2018) offer an alternative perspective and emphasise the possible significance of aggregate demand. Since most inventions are acquired by a few agents, automation and artificial intelligence (AI), in particular, increase inequality and decrease wages and labour share. This could lower productivity and possible economic growth. The total net employment growth for all businesses creating workers and net employment decreases for all businesses eliminating staff is the conventional job creation measure (Davis et al., 1996). Usually, industries, organisations, or companies are categorised according to corporate size, degree of internationalisation, and other factors used to create aggregations. Net job flows are the total quantity of employment created and eliminated or the difference between gross and net job flows.

For instance, in Japan, Kodama and Inui (2015) and Ando and Kimura (2015) used the previously mentioned metrics to look at how changes in net and gross domestic employment were affected by foreign direct investment. Because positions added or eliminated within a company were not included in these studies, nor the majority of previous research, it is possible that the real employment adjustment needed to be increased (Ando & Kimura, 2017; Liu, 2018; Liu & Nin, 2018). They evaluated the growth or contraction of jobs at the company level by adding up the net employment gains or losses across growing (contracting out) divisions. To get a more accurate approximation of employment adjustment by manufacturing enterprises in Japan, we opt to examine the later subset of relevant research.

Previous research demonstrates how competent workers and innovative technologies complement each other in terms of professional occupation and educational attainment. Highly skilled labourers can only implement these innovative technologies successfully and efficiently. Thus, frequently established innovative technologies and talented labourers are expected to have a favourable relationship. Nonetheless, it is well acknowledged that new technologies and unskilled labourers have a substituting effect (Machin & Van Reenen, 1998; Los et al., 2014).

Since labour productivity is a significant indicator in measuring economic development and efficiency, the statistics used in the research align with this literature. The choice of labour productivity as the dependent variable is conceptually supported by economic theories that relate possible changes in productivity to technological progress, especially artificial intelligence (AI) (Solow, 1957; Romer, 1990; Brynjolfsson et al., 2019). The body of research indicates that labour substitution and capital deepening-two intricate processes that need empirical support-are two ways AI may affect productivity. The study investigates the hypotheses derived from the literature empirically by incorporating factors such as R&D spending (Inv), non-AI patents (nonAIPt), and AI-related patents (AIPt). The theory that innovation propels productivity development is directly extended by using patent applications as a proxy for innovation (Hausman et al., 1984; Kortum & Lerner, 1998). Furthermore, the ability to distinguish between patents on artificial intelligence and those that do not permit a more thorough examination of how various technological innovations influence productivity. The econometric model, particularly the log-log formulation, is methodologically consistent with the literature. This literature emphasises how labour and capital inputs affect productivity elasticity (Baddeley & Barrowclough, 2009). This model provides empirical insights that add to the ongoing debate indicated in the literature by allowing the relationship between AI innovation and productivity to be quantified. Therefore, the main ideas and theories covered in the literature are reflected in the data construction. The study is rigorous and relevant, based on a theoretical framework established by previous research. This allows the analysis to tackle the intricate concerns raised by the interplay between productivity and AI in the context of ageing populations and economic expansion.

3. Data Construction

The variable under investigation in this analysis is labour productivity. Productivity growth quantifies the economy's efficiency in using production inputs to produce a given output. In other words, the quantity of output each employee produces correlates with labour productivity. As a result, the ratio of firm total production to labour is used to calculate labour productivity.

According to Hausman et al. (1984) and Kortum and Lerner (1998), patent applications are valuable for measuring innovation. Patents are a crucial component in measuring the progress of technologies in a nation and, perhaps more crucially, their influence on development, even though they are one of the metrics that receive the least attention from the media. In addition to reflecting a dynamic growth of knowledge and technologies that positively influence society, they first ensure financial gains through the marketing, sale, or licensing of technology. Additionally, patent applications are a sufficient measure of technological production (Griliches, 1990; Joutz & Gardner, 1996). Businesses are prepared to apply for a sizable return on their initial investments after investing considerable resources in developing a unique technology they deem to have commercial value. Companies that successfully leverage artificial intelligence to create novel products and services have a strong motivation to patent at least part of their innovations. Failing to do so may allow other businesses to freely replicate their creations or prevent the original inventor from using their ideas in the marketplace through patents (Alderucci et al., 2020). Thus, this paper uses patent applications to create information flows while following the patent literature.

Studies on the effects of creative effort and technological development have traditionally used patents. Companies are reorganising, refocusing, and downsizing their research departments to prioritise the timely and successful commercialisation of innovations and the continuous and quick advancement of existing technology (Kortum & Lerner, 2001). One possible explanation for the sharp rise in patenting might be an increase in invention and discovery.

Therefore, this paper will investigate the following hypothesis: H0: Labour productivity and enterprises engaged in AI patenting are directly related (on one side).

H_0: Labour productivity and companies that pursue AI patents are directly related.

H_1: Labour productivity and companies that pursue AI patents do not directly correlate.

To address the study question, "How does the introduction of AI-related innovations within the company influence labour productivity?" the hypothesis will be investigated using statistical inference. In all those aspects above, this paper's analysis of the number of AI advancements utilised for patenting reveals the results of R&D activities. Some other measures of R&D input include the number of workers at the beginning of each year and the total amount spent on R&D throughout the preceding for the last thirteen years. However, spending on research and development is a more comprehensive statistic than employment since it includes inputs to the process obtained from other organisations.

The number of employees (Lab), the total number of fixed assets (Asst), the number of patents connected to artificial intelligence (AIPt), the number of patents unrelated to AI (nonAIPt), the labour productivity (Prod), and the R&D investments (Inv) are the data utilised. The PATSAT database (which contains data from leading industrialised and developing countries) and the ORBIS database (the world's most powerful comparable data resource on private companies) serve as the data source. Here, the total company output to labour ratio is called labour productivity. The information is given in terms of US dollars. The years 2020 through 2023 are covered. Twenty businesses from two distinct areas are included in the statistics: Japan and the USA.

A double-log or log-log model was used for analysis. As the model shows, both sides of the equation appear to be written. In other words, the log-log specification fits both explanatory and independent variables. The model predicts that if X increases by 1%, Y should change by β1%, according to Baddeley and Barrowclough (2009). Thus, the coefficients reflect the complexity of the variables Y and X. The unknown effect of changing a single variable can be determined through regression analysis. Stated differently, a regression model calculates how much Y will change when Xn changes by one percentage point. The dependent variable in this model is the natural logarithm of the labour productivity of an occupation. Knowledge enhancement was used to determine the dependent variable. An important explanatory variable is the number of AI license applications as it measures a firm’s artificial knowledge development. Therefore, the econometric model is:

$$Y_{it} = \alpha_i L^{\beta}{}_{it} C^{\gamma}{}_{it} K^{\delta}{}_{it}\, e^{\sigma}{}_{it} \quad (1)$$

In this case, the variables output, labour input, physical capital stock, and knowledge stock are represented by L, C, K, and Y. β, γ, and δ are the parameters that characterise labour elasticity. In this instance, the variables Yit, Lit, Cit, and Kit symbolise the output, labour input, physical capital stock, and knowledge stock. α is a constant efficiency parameter that varies across firms but is constant over time. The parameters β, γ, and δ are the output elasticities concerning labour, capital, and knowledge. The efficiency parameter αi remains consistent and distinct across time in any business. Time-variant entities are related to an efficiency metric called σit. Applying log to the equation's two sides yields:

$$\text{Log } Y_{it} = \text{Log}\alpha + \beta \text{ Log}L_{it} + \gamma \text{Log}C_{it} + \delta \text{Log}K_{it} \quad (2)$$

The estimating equation that results when both sides of the equation are divided by labour and the resultant equation is differentiated twice in a row to eliminate the parameter α is as follows:

$$\frac{Yit}{Lit} = \frac{\alpha L_{\text{it}}^{\beta} C_{\text{it}}^{\gamma} K_i^{\delta} t}{L_{it}} \quad (3)$$

$$\text{Log } \left(\frac{Yit}{Lit}\right) = \text{Log } \alpha + (\beta - 1) \text{ Log } L_{it} + \gamma \text{ Log } C_{it} + \delta \text{ Log } K_{it} \quad (4)$$

Since $\frac{Yit}{Lit}$ represents labour productivity, we define it as p_{it}:

$$p_{it} = \text{Log } \alpha + (\beta - 1) \text{ Log } L_{it} + \gamma \text{ Log } C_{it} + \delta \text{ Log } K_{it} \quad (5)$$

To tackle the problem of the constant parameter α α across businesses over time, we separate the labour input equation, L_{it}. To remove bias, this is rewritten to account for the firm-specific constant α, which is not directly visible. What results from the initial differentiation is:

$$\Delta p_{it} = (\beta - 1)\ \Delta \text{Log } L_{it} + \gamma\ \Delta \text{Log } C_{it} + \delta\Delta \text{ Log } K_{it} \quad (6)$$

Here, Δ represents the change from one time period to the next, effectively capturing the growth rates of the variables. To account for the dynamic nature of productivity, we introduce a lagged dependent variable p_{it-1}, which represents the labour productivity of the previous period:

$$p_{it} = (1 + \boldsymbol{\psi})\ pit_{-1} + (\beta - 1)\ \Delta l_{it} + \gamma \Delta c_{it} + \delta \Delta k_{it} + \mu_i + \varepsilon_{it} \quad (7)$$

The variables p_{it}, Δl_{it}, Δc_{it}, and Δk_{it} denote labour productivity, labour input growth, fixed capital growth, and knowledge stock change, respectively. ε_{it} is the typical error term, while μ_i represents the fixed impact of the idiosyncratic person and time-invariant company. To address productivity, the shift from Equation (2) to Equation (7) entails dividing the output by labour, differentiating to eliminate firm-specific constants, and adding lag variables to account for dynamic impacts. This yields an estimating equation that, especially in the context of AI-related breakthroughs, can more precisely reflect the relationship between productivity and the various inputs.

Within the framework of this research, it is conceivable that the companies under observation -particularly those in the same geographical area, like Japan or the USA- are impacted by comparable technical advancements, market dynamics, or governmental policies. Horizontal cross-sectional dependence between enterprises may result from these variables. A time series' ability to maintain its statistical characteristics across time -such as its mean, variance, autocorrelation, etc.- is called stationarity. Spurious regression results, meaning the estimated connections between variables appear significant when they are not, can be caused by non-stationary data. It is critical to verify that the time series data (such as labour productivity, patent volume, and R&D investments) are stationary because the dataset covers several years (2020-2023). This is especially crucial when employing log-log models since non-stationary series can lead to inaccurate conclusions and misleading coefficients.

4. Empirical Findings

A balanced panel of data on businesses from two distinct locations is used in the model, and the data spans the years 2020-2023. The dataset has no missing values, so it is *balanced*. To keep things simple, the analysis that follows will use the columns that are supplied by the dataset:

- Region: The three distinct regions in which the businesses operate are shown in this column.
- Firm: The name of the observed firm is suggested in the column Firm.
- Year: The information gathered between 2020 and 2023 is recorded in this column.
- Prod: The labour productivity, or production, is the dependent variable.
- Lab: Labour denotes the total number of workers.
- AIP_t: Pat contains the total number of patents about AI.
- $nonAIP_t$: This measures the total number of patents unrelated to AI.
- Invest: Invest comprises all R&D investments.
- Asst: Asset denotes the company's total amount of fixed assets.

So, the study question is:

- What impact does the company's adoption of AI-related advances have on worker productivity?

Table: 1
Description of Variables

Name	Variable
Region	Region
Firm	Firm Name
Year	Year
Prod	Labour Productivity
Labour	Number of Employees
AIPt	AI-related patents
NonAIPt	non-AI-related patents
Inv	R&D investment
Turnover	Physical Capital Stock
Firmcode	group(firm)
RegionID	group(region)
YearID	group (year)

Table: 2
Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
regionID	363	2,091	0,831	1	3
firmcode	363	17	9,535	1	33
yearID	363	6	3,167	1	11
Lprod	363	-0,806	1,159	-6,063	1,552
Llabour	363	4,592	1,204	0,704	7,169
lAIpt	363	4,721	0,428	3,434	5,969
NonAIpt	363	-0,324	0,425	-1,839	0,789
Linv	363	2,316	1,823	-2,056	6,588
Lturnover	363	1,495	1,297	-2,244	5,052

In the analysis, a pooled OLS is performed first. Pooled OLS requires fewer factors to handle. Suppose exogeneity means that the expected value of the disturbance is zero. In that case, if the disturbance is uncorrelated with any regressors, and/or the variance of the error terms is constant concerning the free variable (symmetry), then fixed effect or Rendon effect models are most likely appropriate. It also shows no autocorrelation; the barriers are not correlated. For this reason, the Hausman test is used to verify exogeneity. The presence of non-correlation and symmetry is tested using various statistical methods. The White Breusch Pagan test determines the presence of unusual ancestry. The Durbin-Watson test is used to examine non-independent relationships.

When there is no need to consider individual effects or significant variability in the data, pooled OLS is an effective method for estimating the common effects across all cross-sections and periods. Based on the summary statistics, it can be inferred that the average impact of labour productivity is determined by pooling ordinary least squares (OLS). Variables like labour productivity (Lprod), labour productivity (Llabour), AI-related patents (lAIpt), and non-AI-related patents (NonAIpt) vary between firms and periods. When the data do not show significant heterogeneity or individual effects that need to be considered, pooled OLS effectively predicts the common effects across all cross-sections and periods. A helpful first model to comprehend the average impact of these variables on labour productivity is provided by pooled ordinary least squares (OLS). This is because the summary statistics indicate that variables like labour productivity (Lprod), labour (labour), AI-related patents (lAIpt), and non-AI-related patents (NonAIpt) vary across firms and periods.

5. Linear Regression

The outcome includes several noteworthy facts. The R2 number, also called R-squared, indicates the proportion of the dependent variable's fluctuation that the independent variable can explain (Gujarati, 2006). The model's independent variables account for 48% of the variation in labour productivity. This model estimates data from 363 observations. There appears to be a significant correlation between the response variable and the predictors, as indicated by the 45.8 F-statistic predictive power. The data analysis indicates the model's importance. The regression model's p-value indicates the statistical significance of the model (Prob> F). Greene (2008) states that it ascertains whether R2 deviates from zero.

With a p-value of less than 0.05, a statistically significant relationship between X and Y is demonstrated. P-values with two tails test the hypothesis that each coefficient diverges from 0. A p-value of less than 0.05 is needed to rule out the null hypothesis. The model estimating procedure will have a 95% significance level. The analysis shows a statistically significant link between labour productivity and the independent variables. To find the t-values, divide the standard errors associated with the coefficients. The t-values indicate a variable's significance in the observed model. As all the variables suggest, the dependent variable is significant in this instance; however, the independent variables in this model account for labour productivity. There appears to be a significant correlation between the response variable and the predictors, as indicated by the 45.8 F-statistics predictive power.

The null hypothesis that the coefficient varies from zero is rejected if the t-value exceeds 1.96 (at the 0.05 confidence level). The correlation between the independent variables and (Y) is shown in the coefficient column. The model indicates that labour productivity and employee count have a negative relationship. Labour productivity rises by 0.473% for every 1% decline in the workforce (ceteris paribus). In contrast, there is a positive correlation between total labour productivity and the amount of AI-related patents, total asset turnover, and R&D spending.

Table: 3
Linear Regression

lprod	Coef.	St.Er.	t-value	p-value	[95% Conf	Interval]	Sig
Ilabour	-0,473	0,176	-8,89	0	-0,548	-0417	***
LAIpt	0,618	0,438	5,27	0	0,26	0,958	***
LNonAIpt	0,457	0,289	4,07	0	0,313	0,651	***
Linv	0,361	0,024	10,27	0	0,354	0,472	***
Lturnover	0,214	0,179	4,98	0	-0,417	-0,164	***
Constant	-2,48	0,547	-3,98	0	-3,541	-1,329	***

Mean dependent var	-0,813	SD dependent var	1,063
R-squared	0,428	Number of obs	363
F-test	45,800	Prob > F	0,000
Akaike crit. (AIC)	957,126	Bayesian crit. (BIC)	971,275

**** p<.01, ** p<.05, * p<.1*

The autocorrelation test is run using the Durbin-Watson statistics. If autocorrelation is present, it may lead us to conclude that predictors are important when they are not by undervaluing the standard error. An autocorrelation test is applied to the residuals of a statistical regression study using the Durbin Watson (DW) statistic. We may be led to feel that predictors are significant when they are not by autocorrelation, which undervalues the standard error. The first-order correlation, or one with a one-unit lag, is the kind of serial correlation the Durbin-Watson test searches for. For the Durbin-Watson test, the following are the hypotheses:

H_0 = first-order autocorrelation does not exist.

H_1 = first-order correlation exists.

According to Hsiao (2003), a value of two denotes the absence of autocorrelation in the sample. The Durbin-Watson statistics range from one to four. Values ranging from zero to less than two signify positive autocorrelation. The closer a value is to zero, the stronger the association is in reality. Autocorrelation is negative when the value is between 2 and 4. An adverse autocorrelation is present in this instance. Therefore, using an FE or RE model will be more reasonable.

Under the assumption of homogeneity amongst enterprises, the Pooled OLS model offers a generalised estimation of relationships between variables. Nevertheless, it ignores variations in firm-specific attributes that could impact output. However, to account for this heterogeneity, the FE and RE models show that firm-specific characteristics like size, age, and R&D activity impact productivity. Because the Pooled OLS model does not consider firm-specific effects, autocorrelation tests using the Durbin-Watson statistic indicate that the model may be biased towards missing variables. The Pooled OLS model's residuals have positive autocorrelation, which implies that the predictors' importance may have been overestimated. The FE and RE models overcome this problem by accounting for firm-specific variability and yield more accurate estimates. The RE model is recommended since the p-value for comparing the FE and RE models is more than 0.05, indicating no significant coefficient difference. When changes between firms are uncorrelated with the predictors, this model is adequate for handling those variations. As such, it provides a more realistic representation of the effect of firm-specific variables on productivity than the Pooled OLS model, including size, age, and R&D activities.

The panel models in the analysis do not include time and/or firm (industry) dummies. Since size, age, and R&D activities are the primary sources of variation in this study, it is understandable that a concentration on firm-level factors would lead to this omission. The study tries to investigate subtle correlations. However, including time or firm dummies would have absorbed the variance related to these firm-specific factors or generated multicollinearity. Furthermore, adding dummies would have decreased the number of degrees of freedom that could be estimated, which could have reduced the model's statistical strength. In addition, the choice not to utilise dummies is consistent with the theory that productivity outcomes are influenced mainly by firm-specific characteristics as opposed to temporal or industry-wide impacts. The fixed effects (FE) and random effects (RE) models show that these firm-specific characteristics considerably impact productivity. The business variability is best reflected when dummies are removed from the picture. That is why time and firm dummies are not included in the models: the analysis focuses on comprehending the inherent heterogeneity among firms and how factors like firm size, age, and R&D on artificial intelligence affect productivity.

Table: 4
Fixed Effect

lprod	Coef.	St.Er.	t-value	p-value	[95% Conf	Interval]	Sig
llabour	-0,628	0,039	-16,10	0	-0,765	-0,59	***
lAIpt	0,463	0,034	13,61	0	0,273	0,421	***
lnonAIat	0,317	0,055	0,58	0	0,242	0,444	***
lturnover	0,139	0,038	4,82	0	0,088	0,209	***
linv	0,375	0,05	7,5	0	0,279	0,437	***
Constant	-0,281	0,219	-1,16	0,246	-0,732	0,189	

Mean dependent var	-0,683	SD dependent var	968,000
R-squared	0,549	Number of obs	363
F-test	84,107	Prob> F	0,000
Akaike crit. (AIC)	-217,319	Bayesian crit. (BIC) DW statistics	-245,466 1,87

**** p<.01, ** p<.05, * p<.1*

The outcomes analysis indicates significance for the multiple regression model. A 95% confidence level of less than 0.05 is shown by the Prob>F of 0.000. As X increases by one percentage point, the regressors' coefficients show how much Y changes. Every variable shows statistical significance in this case. To further refute the null hypothesis that each coefficient deviates from zero, the t-statistics must be more than 1.96 (with a 95% confidence level). The variable's significance increases with a larger t-value. Except for labour, all model variables have high t-values. In addition, the Durbin-Watson value of 1.87, nearly equal to 2, indicates that the residuals show little to no indication of positive autocorrelation. However, it is somewhat less than 2, suggesting a possible weak positive autocorrelation that isn't significant enough to cause alarm immediately.

Table: 5
Random Effect

lprod	Coef.	St.Er.	t-value	p-value	[95% Conf	Interval]	Sig
llabour	-0,57	0,037	-15,41	0	-0,719	-0,519	***
lAIpt	0,318	0,029	10,96	0	0,185	0,396	***
lnonAIpt	0,307	0,048	6,40	0	0,218	0,417	***
lturnover	0,119	0,027	4,41	0	0,069	0,185	***
linv	0,286	0,025	11,44	0	0,225	0,407	***
Constant	-0,304	0,194	-1,57	0,204	-0,816	0,195	

Mean dependent Var	-0,785	SD dependent Var	968,000
Overall r-squared	0,217	Number of obs	363
Chi-square	409,318	Prob> chi2	0,000
R-squared within DW statistics	0,537 1,82	R-squared Between	0,217

Again, the model is significant if Prob>chi2 is less than 0.05 at the 95% confidence level. Every variable indicates statistical significance with p-values less than 0.05. They also have high t-values. The Random Effects Model's Durbin-Watson statistic of 1.82 is near 2, indicating that autocorrelation is not very high. However, the number is marginally less than 2, suggesting that the residuals have a small positive autocorrelation.

Given that the p-value of>0.05 is insufficient to rule out the null hypothesis that there is no significant difference between the FE and RE coefficients, the random effect model is the best fit. You may remember that in every situation when there is a possibility that variations across entities would have an impact on the dependent variable, the random effects estimator is employed. Put differently, labour productivity may be impacted by changes within firms.

- The number of patents covering artificial intelligence has a beneficial impact on labour productivity. This shows that integrating AI breakthroughs within the organisation increases worker productivity. In other words, the more resources a corporation devotes to AI, the higher its labour productivity and potential economic worth.
- The number of patents unrelated to artificial intelligence significantly impacts labour productivity. However, its influence is less than that of AI patents. Put differently, increasing worker productivity is more closely correlated with advancements in artificial intelligence.
- Considering the correlation between productivity and physical capital stock, it seems that investments in manufacturing facilities, namely in ICT, can increase labour productivity and, consequently, industry productivity overall.
- The evidence indicates that R&D investments increase labour productivity. Thus, encouraging firms to spend more on research and development can raise employee productivity. The collaboration emphasises how crucial it is for companies to focus more on expanding and improving their R&D departments.
- Labour productivity and staff count have an inverse relationship. When productivity increases, fewer personnel are required. The production and displacement impacts discussed in the preceding chapter could help explain this outcome.

6. Conclusions

The results offer critical new perspectives on the intricate connection between employee productivity and technological advancements, especially about artificial intelligence. The study validates the favourable impact of technical improvements, particularly those linked to artificial intelligence, on labour productivity inside enterprises, which aligns with previous literature. Companies actively engaging in AI research will likely have higher productivity gains among their workforce. Specifically, the results show a statistically significant positive association between the number of AI-related patents and employee productivity.

According to Agrawal et al. (2019a) and Brynjolfsson et al. (2019), AI can increase productivity through several methods, such as automation, optimisation, and more precise decision-making. This conclusion is consistent with their theoretical propositions. A second argument favouring investing in both physical capital and artificial intelligence is the favourable association between labour productivity and R&D spending on tangible capital stocks. The claims made by Solow (1957) and Romer (1990) that technical innovation and capital deepening are important factors influencing economic development and productivity are also supported by this. The study also discloses several subtleties that set it apart from earlier research. Although prior research (Graetz & Micheals, 2018; Alderucci et al., 2020) usually indicates that artificial intelligence (AI) has a favourable effect on productivity, it frequently needs to distinguish between advances related to AI and those not. By focussing only on AI-related patents, this analysis shows that these innovations significantly influence labour productivity more than non-AI-related breakthroughs. This finding is significant because it highlights the unique contribution that artificial intelligence makes to productivity growth, a contribution that may need to be clarified in more general studies of technical innovation.

Possible explanations for these results include AI's transformative character, which automates repetitive jobs and improves workers' ability to make decisions, resulting in more productive and effective use of resources. Additionally, companies that invest in AI-related advancements might be more progressive and flexible, which would help them better use new technology to increase productivity. On the other hand, the disruptive potential of non-AI discoveries might not be as great as that of AI technology, leading to less notable productivity gains. Companies investing in AI and physical capital will likely see more significant productivity gains, underscoring the significance of a comprehensive approach to technological innovation. The study focused on R&D spending on tangible capital stocks and its positive correlation with productivity.

In conclusion, this study adds to the body of knowledge about the beneficial effects of artificial intelligence (AI) on productivity while offering fresh perspectives on the relative significance of discoveries versus those unrelated to AI. The results show that organisations should prioritise AI-related R&D while also considering the additional role that physical capital investment plays in maximising productivity advantages.

7. Suggestions for Future Research

Several limitations in this paper suggest areas for future investigation. The model only considers companies that submitted at least one AI-related patent between 2020 and 2023. This kind of sample may be chosen as the most desirable because AI patents are a sign of technological proficiency; as a result, sample selection may have influenced the results. More research might be done by analysing the data on a more significant sample of companies, including those that never patent and those that only patent in fields unrelated to artificial intelligence.

The absence of a widely accepted definition of artificial intelligence is another limitation that most scientific studies about the field of AI share. Since this study only looks at current definitions of AI, it makes sense to expand it to include a more thorough description to apply the results to automation and robotics. The author suggests conducting a qualitative investigation to enhance the research process further and offer a deeper comprehension of the subject.

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