Universidad Pablo de Olavide (España)
Revista de Métodos Cuantitativos para la Economía y la Empresa
número 40, 2025
ISSN: 1886-516X
DOI: 10.46661/rev.metodoscuant.econ.empresa.9623
Sección: Artículos
Recibido: 21-02-2024
Aceptado: 12-10-2024
Publicado en línea: 00-00-0000
Publicación número: 1-12-2025
Páginas: 1-18

Revista de Métodos Cuantitativos para la Economía y la Empresa

La productividad laboral en la era de la IA: Perspectivas a partir de Datos de Panel

Labour productivity in the age of AI: Insights from Panel Data

Hiroshi Yoshida
Tohoku University (Japón)
https://orcid.org/0000-0003-1643-5220
hiroshi.yoshida.e2@tohoku.ac.jp

Meltem Ince Yenilmez
Izmir Democracy University (Turquía)
https://orcid.org/0000-0002-4689-3196
meltem.inceyenilmez@idu.edu.tr

RESUMEN

Este estudio examina cómo la productividad laboral se ve afectada por los avances relacionados con la IA mediante el examen de un conjunto de datos de panel equilibrado de empresas que operan en tres áreas diferentes entre 2014 y 2023. El estudio utiliza modelos OLS combinados, de efectos fijos (FE) y de efectos aleatorios (RE) para evaluar los efectos de factores importantes como las patentes relacionadas y no relacionadas con la IA, la inversión en I+D, la mano de obra y la rotación de las empresas sobre la productividad laboral, la variable dependiente. Según los resultados, las patentes relacionadas con la IA tienen un notable impacto positivo en la productividad laboral, lo que respalda estudios anteriores sobre mejoras de la productividad impulsadas por la tecnología y pone de relieve la importancia crítica de la innovación en IA. Por otra parte, la mano de obra tiene una correlación negativa con la productividad, lo que indica ineficiencias en la gestión de plantillas más grandes o rendimientos decrecientes a escala. Es interesante observar que la rotación de personal y la productividad están positivamente correlacionadas, lo que podría ser resultado de la optimización de la mano de obra o de la introducción de nuevas perspectivas y habilidades. En comparación con el modelo OLS agrupado, el modelo FE, que tiene en cuenta la heterogeneidad específica de las empresas, explica en torno al 45,7% de la varianza de la productividad. Las pruebas de diagnóstico verifican la resistencia de los modelos y su validez mejora con correcciones de autocorrelación y heteroscedasticidad. Estas conclusiones advierten contra el uso ineficiente de la mano de obra, al tiempo que destacan el valor de la IA y el gasto en I+D para impulsar la productividad. Este estudio hace avanzar nuestros conocimientos sobre la dinámica de la productividad, la gestión del trabajo y la innovación, y sirve de guía a los ejecutivos de las empresas y a los responsables políticos en su navegación por la economía impulsada por la IA.

PALABRAS CLAVE

Superfoods; política industrial; análisis de brecha de precios.

Cómo citar: Yoshida, H., & Ince Yenilmez, M. (2025). La productividad laboral en la era de la IA: Perspectivas a partir de datos de panel. Revista de Métodos Cuantitativos para la Economía y la Empresa, (40), 1–18. https://doi.org/10.46661/rev.metodoscuant.econ.empresa.9623

ABSTRACT

This study examines how labour productivity is affected by AI-related developments by examining a balanced panel dataset of businesses that operate in three different areas between 2014 and 2023. The study uses pooled OLS, Fixed Effects (FE), and Random Effects (RE) models to assess the effects of important factors such as AI-related and non-AI patents, R&D investment, labour input, and company turnover on labour productivity, the dependent variable. According to the findings, AI-related patents have a notable positive impact on labour productivity, supporting earlier studies on technology-driven productivity improvements and highlighting the critical significance of AI innovation. Labour input, on the other hand, has a negative correlation with productivity, indicating either inefficiencies in managing larger workforces or diminishing returns to scale. It's interesting to note that employee turnover and productivity are positively correlated, which could be a result of workforce optimisation or the introduction of new perspectives and abilities. In comparison to pooled OLS, the FE model, which takes firm-specific heterogeneity into account, explains around 45.7% of the productivity variance. Diagnostic tests verify the models' resilience, and their validity is improved by autocorrelation and heteroscedasticity corrections. These findings warn against inefficient labour use while highlighting the value of AI and R&D expenditures in boosting productivity. This study advances our knowledge of the dynamics of productivity, labour management, and innovation and guides company executives and policymakers as they navigate the AI-driven economy.

KEYWORDS

Artificial Intelligence; Labour Market Dynamics; Future of Work; Human Capital.

Clasificación JEL: E24, J01, J24, J89.

MSC2010: 6207.

1. INTRODUCTION

The global economy is changing, and worker productivity is being transformed by the incorporation of Artificial Intelligence (AI) into the workforce. AI technologies like machine learning and automation systems increase productivity by automating ordinary and repetitive processes, freeing up human workers to concentrate on intricate, strategic, and creative jobs. However, this change brings up serious issues around labour reskilling, job displacement, and the uneven effects of AI across industries. According to this study, automation powered by AI greatly increases productivity, but it also upends labour markets by making reskilling and upskilling more necessary. The research aims to investigate:

- The connection between industry-specific productivity increases and AI adoption.
- The degree to which automation brought forth by AI alters employment trends, including job displacement and the creation of new positions.
- Measurement for education and policy that are necessary to get workers ready for an AI-driven economy.

Jobs involving repetitive tasks are more likely to be replaced by AI, but those requiring creativity, emotional intelligence, and sophisticated problem-solving abilities are still mostly safe. This study highlights the irreplaceable worth of human brilliance and looks at how the employment market is moving towards professions that improve AI skills. To promote a future in which artificial intelligence (AI) boosts productivity while promoting workforce adaptability and resilience, the project intends to address these dynamics and offer evidence-based insights to politicians, educators, and business leaders.

The paper's conclusions and methodology are described in depth in the parts that follow. In Section 2, pertinent material is reviewed. The dataset and adoption trends of AI that are utilised to assess the effects on productivity are described in Section 3. While the last section ends with practical suggestions, Section 4 describes the estimating methodology and findings.

2. LITERATURE REVIEW

The population is ageing as a result of rising life expectancies and declining birth rates, which is a major problem for many industrialised and developing countries. Because of the physical and mental deterioration that comes with ageing, older professionals are sometimes seen as less creative and productive than their younger colleagues. Concerns have been raised in ageing nations that a declining labour force and rising rates of old age may impede economic growth.

It is generally agreed that artificial intelligence (AI) is the most important general-purpose technology of this century (Brynjolfsson and McAfee, 2014; Goldfarb et al., 2020). AI is a potent type of automation that teaches machines to behave like people. By 2020, private investments in AI are expected to surpass $68 billion, according to Zhang et al. (2020), breaking previous records and having an impact on almost every sphere of society. Nevertheless, it is still unknown how AI will interact with more conventional forces of production like labour and capital, despite the general excitement surrounding it.

According to some authors, AI will replace high-skilled occupations that require a lot of education and expertise (Frank et al., 2019; Webb, 2019; Barbieri et al, 2020). However, some authors contend that AI mainly deepens capital and has little effect on labour (Bresnahan, 2019). Robotics and artificial intelligence breakthroughs have spurred discussions about how they can impact more general socioeconomic outcomes, including growth, productivity, inequality, and salaries. According to traditional economic theories, technological innovation will eventually propel economic growth (Solow, 1957; Romer, 1990; Aghion and Howitt, 1992; Antonelli, 2009; Graetz and Michaels, 2018; Josten and Lordan, 2020).

Technologies that use generative artificial intelligence (AI) affect worker productivity by increasing labour productivity and partially replacing jobs. Because these technologies automate repetitive processes, employment roles are changed rather than eliminated, requiring workers to upskill to handle increasingly complicated duties. While AI improves productivity in industries like manufacturing and retail by optimising processes, enhancing decision-making, and increasing efficiency, it also necessitates careful consideration of worker transitions(Ando and Kimura, 2015; 2017). Retraining and reskilling programs are necessary to help displaced workers adjust to new positions in the changing labour market (Lazaroiu and Rogalska, 2023).

Lăzăroiu et al. (2022) investigate how the Internet of Manufacturing Things (IoMT) framework can be used to integrate robotic wireless sensor networks, geospatial big data management, and deep learning-assisted smart process planning. It emphasises how wireless sensor networks allow for real-time monitoring and communication amongst robotic systems, while deep learning algorithms help simplify industrial processes by improving decision-making and predictive capacities. Furthermore, effective data handling is made possible by the application of geospatial big data management techniques, which enhance the management of production flows and manufacturing resources. This technology combination facilitates the development of more intelligent and effective industrial settings where data-driven insights result in improved automation, resource allocation, and production optimisation.

Szostek et al. (2023) examine how cloud computing technology and artificial intelligence (AI) algorithms can be integrated into blockchain-based fintech management systems. By evaluating vast datasets, forecasting patterns, and streamlining procedures it demonstrates how AI may improve risk management, financial decision-making, and customer service. The infrastructure required to enable these AI algorithms is provided by cloud computing, which guarantees scalability, data accessibility, and safe transactions in blockchain contexts. By enabling more effective, transparent, and secure fintech operations, the combination of these technologies enhances user confidence in digital financial systems as well as the operational effectiveness of financial institutions. This integration supports the rising need for decentralised financial solutions and is a major force behind innovation in the fintech industry."

The requirement for people to upskill, the necessity for business reorganisation, and the time it takes for complementary breakthroughs to permeate throughout the economy could all be reasons for the continued poor productivity growth despite AI advancements (Brynjolfsson et al., 2019). Not all writers, though, have this upbeat perspective. Gordon (2016, 2018) contends that the productivity drop is irreversible and that modern technological developments, like artificial intelligence (AI) and digital innovations, are unlikely to have the same disruptive effect as those that drove the notable productivity growth of the 1920s through the 1970s, like electric power and internal combustion engines.

Innovation has grown harder to attain, according to further studies. According to Bloom et al. (2020), research production has significantly decreased across a range of industries. Gries and Naudé (2018) contend that automation and artificial intelligence (AI) may limit economic potential and slow productivity by causing rising inequality and declining wages. This concentration of invention among a few players could limit overall economic growth and worsen inequality.

In their exploration of the possible dangers of automation, Arntz et al. (2016) pay particular attention to how AI and robots may displace workers in OECD nations. They emphasise how automation impacts a range of industries and skill levels, with a particular focus on the higher impact it has on low-skilled occupations. The study adds credence to wage polarisation theory, which anticipates a decline in demand for unskilled labour and an increase in demand for skilled labour. They provide evidence that industries with a large number of repetitive jobs are more vulnerable to automation, a trend that disproportionately impacts employees with less education and training. This data strengthens the case that by automating jobs that require less cognitive ability and opening up prospects for high-skilled positions requiring more complicated decision-making, AI may worsen income inequality. Additionally, their findings highlight the urgent need for policies that support workforce reskilling to lessen the adverse consequences of AI on the labour market.

Chui et al. (2018) offer a perceptive and topical examination of the domains in which artificial intelligence can and cannot yet replace human labour. Since it divides tasks into those that are highly automatable and those that are less amenable to automation because they depend on human judgement, creativity, or emotional intelligence, this research is essential reading for anybody interested in the labour market dynamics around AI and automation. Although AI has the potential to automate a large amount of manual and routine work, industries that demand high levels of interpersonal skills, strategic decision-making, and complex problem-solving are less likely to be automated soon, according to the McKinsey report, which adds to the larger conversation on labour market shifts. Chui et al.'s observations present a balanced perspective that backs up the wage polarisation theory. People in higher-skilled industries, such as management, professional services, and high-end technical professions, will see growth as technology is more likely to replace low-skilled positions, which will exacerbate inequality. Thus, this data strengthens the case for AI's unequal effects on labour markets.

The significant effects of artificial intelligence (AI) on labour markets and economic growth are thoroughly examined by Brynjolfsson and McAfee (2017), who also examine the automation issue in what they refer to as "The Second Machine Age." AI, they contend, can upend established labour markets and economic systems, just like previous industrial revolutions. They warn, however, that, in contrast to earlier technological revolutions, automation and artificial intelligence are expected to disproportionately favour people with access to wealth and highly specialised skills, increasing economic inequality. The wage polarisation theory is strongly supported by the authors' argument that automation and artificial intelligence would widen the gap between high-skilled, high-paid workers and low-skilled, low-paid workers. They also stress the importance of innovation in boosting economic growth and productivity, but they also admit that automation may cause job losses, which could result in economic stagnation unless complementary measures like universal basic income, education reform, and reskilling programs are put in place. The idea that AI's economic impact is extremely dynamic and will necessitate cautious policy interventions to promote equal growth is strengthened by this work.

With an emphasis on striking a balance between job creation and displacement, Chatterjee at al. (2021) provide an empirical analysis of how AI affects employment in industrialised nations. According to their research, automation and artificial intelligence have resulted in employment losses in some industries, especially those that involve repetitive work, but they also point out areas where AI has increased human labour and created new job categories. They pinpoint industries including technology, healthcare, and education where AI may enhance human potential, boost output, and create job possibilities. This study offers insightful information about the intricate relationship between AI adoption and employment outcomes, supporting the idea that technological developments do not always lead to a net loss of jobs but rather to a change in the labour market. By highlighting the significance of upskilling and adjusting to new job requirements, their findings provide a timely contribution to the ongoing discussion about how AI will change labour markets.

Re-examining the effects of AI on labour markets, Autor (2023) focuses on the polarisation of skills and wages. By raising the need for highly trained people and lowering the demand for low-skilled individuals, he examines how automation and artificial intelligence are changing the labour market. According to Autor, artificial intelligence will deepen the gap between high-skilled, high-paying occupations and low-skilled, low-paying professions, creating a more polarised labour market. He also emphasises how important it is to have education and training programs that can provide workers the skills they need to prosper in an AI-driven economy. This study further clarifies the social and economic issues raised by AI while providing concrete support for the wage polarisation argument. Autor's observations highlight how critical it is to address the distributional effects of AI, guaranteeing that workers who are automated have access to reskilling programs and that the advantages of productivity advances brought about by AI are evenly distributed throughout society.

The economic effects of automation and artificial intelligence (AI) are examined by Acemoglu and Restrepo (2020), who concentrate on how new technologies affect labour markets, specifically concerning skilled and unskilled labour. They contend that AI will probably lead to a "technological divide," whereby low-skilled workers may be replaced by automation, while high-skilled professionals who can support AI technology would profit. Their research offers a critical analysis of the wage polarisation theory, pointing out that jobs requiring repetitive physical and cognitive labour are disproportionately affected by automation. A greater percentage of the population may be at risk of job displacement and pay stagnation as a result of AI, who also address how the technology could worsen income inequality by benefiting those who own and control it. Acemoglu and Restrepo's paper supports the claim that unless proactive measures are implemented to redistribute the advantages of technological advancement, the integration of AI into the economy may lead to more severe economic inequality.

Prior studies have shown that new technology and skilled labour are complementary and that novel technologies can only be successfully adopted when paired with skilled labour. This is a well-established, beneficial relationship. Nonetheless, it is also often acknowledged that new technologies frequently replace unskilled labour (Machin and Van Reenen, 1998; Los et al., 2014).

3. DATA CONSTRUCTION

Labour productivity is a basic measure of economic efficiency since it represents the quantity of output produced per unit of labour input. It reflects how well an organisation deploys its labour to produce goods and services, and it also relates to the economic growth of a nation. Those firms that can make higher output from the same or fewer labour resources can offer more competitive prices with which to raise the living standard for society at large. More economically, increased labour productivity allows firms to expand operations, pay higher wages, and reinvest in further growth. Labour productivity is usually measured as the ratio of total output, commonly

N. 40, 2025 – ISSN: 1886-516X – DOI: 10.46661/rev.metodoscuant.econ.empresa.9623 – [Págs. 1-18]

quantified in terms of revenue or value-added production, against labour input, measured as hours worked or number of employees. Many scholars, including but not limited to Hausman et al. (1984) and Kortum and Lerner (1998), in the context of technological development, provided evidence on the linkage between productivity and innovation, meaning that patents represent a useful proxy of the progress of technological development and their potential impact on productivity improvement. Patents are not just legal instruments for protecting intellectual property; they are critical indicators of the commercial viability of innovative processes and products (Griliches, 1990). Innovations in technologies, particularly in Artificial Intelligence (AI), have the potential to significantly enhance productivity by improving operational efficiency, reducing production costs, and introducing new methods of automation (Joutz and Gardner, 1996).

Modern AI technologies have taken centre stage in the modern productivity debate, especially in industries where automation and data processing can lead to transformative efficiency gains (Brynjolfsson and McAfee, 2014). Such firms, which invest in innovations related to AI and secure patents for such technologies, are often at the cutting edge of competitive dynamics. This, in turn, will enable the firms to achieve direct gains in productivity based on improved workflows, high-end decision-making capabilities, and the creation of new products and services with high value. AI-driven solutioning is also empowering businesses to leverage machine learning and deeper analytics of data to optimise operations in ways that were earlier not possible using conventional means. However, the connection between AI patenting and productivity is complex and is not universal. Moreover, while some firms realise productivity improvements in the short term, the implementation of AI technologies is an arduous process due to high upfront expenses and the necessity for firm-specific, in-demand skills, and potential fluctuations in market conditions (Bessen 2019). This would suggest that the gains realised from AI are not always direct; their dependence might be firm-specific and dependent on variables like R&D spending, market orientation, and the scalability of AI applications.

The hypothesis to be tested in this paper is that AI patenting directly and positively influences labour productivity (H0), meaning that firms involved in patenting related to AI enjoy higher productivity due to the technological developments they produce. Contrarily, the alternative hypothesis, denoted as H1, assumes that general R&D expenditures or the firm's industry context would appear to be more critical drivers for improving productivity rather than AI patenting. The study tests this hypothesis by subjecting the statistical analysis of the relationship between AI patenting and labour productivity. This is an analysis from a data set on firm-level metrics, which includes R&D expenditure, AI patents, number of non-AI patents, number of employees as measures of labour inputs, and fixed assets. Data sources The database records of the PATSAT and ORBIS databases provide the same level of detail regarding patents and financial firm performance from 2010 to 2023. Hence, it was decided to sample firms in two of the most advanced countries in the realm of AI research and innovation: Japan and the United States. This study attempts to present some empirical insights into the role of AI in improving productivity at the firm level, controlling for broader economic and technological factors that might drive these outcomes.

Adding the number of AI-related patents to this analysis further reinforces such a view of technological change as one of the means of contribution to labour productivity. Patents are the tangible manifestations of applied R&D effort by firms, reflecting intellectual capital transformed into new products or processes (Kortum & Lerner, 2001). Companies that apply for AI patents normally invest in technologies that could disrupt industries, automate processes, create better-quality products, or improve customer experiences. For example, AI algorithms can optimize manufacturing by developing more efficient production schedules, reducing waste, and predicting equipment failures before they occur. Also, AI can enhance service industries by automating routine jobs of customer support or data processing, and freeing human resources for strategic purposes. In this light, patent applications reflect not only a firm's technological capabilities but also send important signals concerning its commitment to innovation and long-term growth. The focus of the paper on AI patents as a technological development measure concurs with earlier studies that linked innovation with productivity growth, and intellectual property as a major driver of competitive advantage Alderucci et al., 2020).

The methodology used in this research paper will combine an econometric approach statistical inference and evaluation of the influence that AI-related patents have on labor productivity. This dataset ranges from R&D expenditure to the number of both AI and non-AI patents, firm characteristics such as the number of employees, to fixed assets. The second, the non-AI patents, includes a control for possible general innovation activities by the firms to isolate the specific impact of AI-related patents on productivity. The study also examines the role of R&D investment as an input that may impact both the probability of patenting and overall firm productivity. R&D spending is an important factor reflecting the commitment of a firm to technological advancement and the capability of fostering innovation. Given this background, the relationship between these variables has been analyzed to investigate whether AI patenting is an essential determinant of productivity growth or whether other factors like general R&D investment or firm size have greater explanatory powers over the shaping of productivity outcomes.

This will further add to the growing literature on the economic consequences of the adoption of AI by showing some empirical evidence of the direct and indirect channels through which labour productivity is affected by AI technologies. By focusing on patent data, this paper underlines the commercial aspect of innovation and nuances in the firm's strategies using intellectual property to protect and gain from their technological advancements. The study further contributes to the growing understanding of how AI-driven innovation affects firm-level productivity dynamics, with important implications for policymakers and business leaders seeking to harness AI for economic growth and competitiveness. Ultimately, it is hoped that the findings from this study may have important implications for our understanding of the role of AI in reshaping labour markets and driving productivity in the contemporary economy.

A log-log or double-log model was adopted to meet the requirements of the analysis. This means logging both sides of the equation. Alternatively, the log-log specification has been used for both the independent and the explanatory variables. According to Baddeley and Barrowclough (2009), the model assumes that with every 1% change in X, Y should change by β1%. Accordingly, the coefficients reveal how responsive the Y variable is concerning the X variable. Then, through regression, one can estimate an unidentified effect of a change in one variable while another is held constant. In other words, when Xn changes by one percent unit, the regression model measures what percent Y will change. The dependent variable in this model is the labour productivity natural logarithm within the confines of a specific business. The dependent variable choice has been conducted with the use of a knowledge-augmented production function. Since they measure the shift in a firm's knowledge base in the area of Artificial Intelligence, the main explanatory variable of interest has been AI patent filings. Therefore, the econometric model is:

$Yit = \alpha i L^{\beta}\, it C^{\gamma} it K^{\delta} it\ e^{\sigma} it$ (1)

In this instance, the output, labour input, physical capital stock, and knowledge stock are represented by the variables Yit, Lit, Cit, and Kit. The elasticity of labour is represented by the parameters β, γ, and δ. In this case, the output, labour input, physical capital stock, and knowledge stock are represented by Yit, Lit, Cit, and Kit, respectively. Efficient labour, physical capital, and knowledge stock are represented by the parameters β, γ, and δ, in that order. The efficiency parameter αi is constant and unique to a certain business, regardless of time. The term σit denotes an efficiency metric associated with time-variant entities. Applying log to the equation's two sides yields:

$\text{Log}\ Yit = \text{Log}\alpha + \beta\ \text{LogLit} + \gamma \text{LogCit} + \delta \text{LogKit}$ (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:

$pit = (1 + \psi)pit\text{-}1 + (\beta - 1)\Delta lit + \gamma\Delta cit + \delta\Delta kit + \mu i + \varepsilon\ it$ (3)

The variables pit, Δlit, Δcit, and Δkit denote labour productivity, labour input growth, fixed capital growth, and knowledge stock change, respectively. εit is the typical error term, while μi represents the fixed impact of the idiosyncratic person and time-invariant company.

N. 40, 2025 – ISSN: 1886-516X – DOI: 10.46661/rev.metodoscuant.econ.empresa.9623 – [Págs. 1-18]

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 2014–2023. As there are no missing values in the dataset, it is referred to as *balanced*. To keep things simple, the analysis that follows will just use the columns that are supplied by the dataset:

- Region: The three distinct regions that the businesses operate in are shown in this column.
- Firm: The name of the observed firm is suggested in the column Firm
- Year: The information gathered between 2014 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.
- AIPt: Pat contains the total number of patents about AI.
- nonAIPt: This is a measure of the total number of patents unrelated to AI.
- Invest: Invest comprises all R&D investments.
- Asst: Asset denotes the total amount of fixed assets in the company.

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
Rgn	Region
Frm	Firm Name
Year	Year
Prd	Labor Productivity
Labr	Number of Employees
AIPt	AI-related patents
NonAIPt	non-AI-related patents
Inv	R&D investment
Trnvr	Physical Capital Stock
Frmcde	group(firm)
RegnID	group(region)
YearID	group (year)

Assuming exogeneity, pooled OLS assumes that there should be no correlation between the error terms and any of the regressors. This assumption is verified by comparing the suitability of a Fixed Effects and Random Effects model using the Hausman test. Pooled OLS may be adequate if the error terms do not correlate with the regressors. Fixed Effects, which take individual variability into account, or Random Effects, which presume a common error structure across businesses, would be the more suitable models if exogeneity is broken (e.g., the correlation between regressors and error terms). In addition, autocorrelation is evaluated using the Durbin-Watson test, and heteroscedasticity is checked using the White and Breusch-Pagan tests. The results from the pooled OLS model may be biased or ineffective if heteroscedasticity or autocorrelation is found, and adjustments may be required using heteroscedasticity-robust standard errors or other model specifications.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
regionID	285	2,017	0,712	1	2,5
firmcode	285	13	8,029	1	28
yearID	285	5	2,835	1	9
Lprod	285	−0,716	1,031	−5,412	1,014
Llabour	285	3,917	0,972	0,612	6,483
lAIpt	285	3,162	0,615	3,001	4,058
NonAIpt	285	−0,439	0,347	−1,425	0,814
Linv	285	2,013	1,612	−1,813	5,027
Lturnover	285	1,215	1,027	−2,043	4,891

Although the research needs to take into consideration the substantial diversity in the data, the descriptive statistics point to possible relationships between labour productivity and AI patenting. The disparity between Lprod and lAIpt suggests that whereas some businesses are probably benefiting from AI innovation in terms of increased productivity, others might not be. To verify the validity of pooled OLS results and identify the best model for this research, additional model testing is essential. Examples of these tests include the Hausman test and several homoscedasticity and autocorrelation tests. It will be crucial to investigate whether the relationship between AI patenting and labour productivity—which has been shown by previous research (Brynjolfsson & McAfee, 2014) —remains true after adjusting for other variables including R&D expenditure, labour size, and market conditions. If a more suitable specification is suggested by the Fixed Effects or Random Effects models, it may provide more insight into how internal firm attributes (like innovation culture and resource allocation) interact with external factors (like industry trends and economic conditions) to affect productivity outcomes.

4.1. Linear regression

The independent variables in the model account for about 37.1% of the variation in labour productivity (prod), according to the R-squared value of 0.371. Despite having a low R-squared, it indicates that a sizable amount of the productivity variance may be explained by the model. This is in line with studies in the literature, which show that economic models that deal with intricate, multi-factor outcomes like labour productivity frequently have R-squared values of about 0.4 (Gujarati, 2006).

The regression model as a whole is statistically significant, according to the F-statistic (32.6), which is highly significant (p-value <0.01). This suggests that the independent factors collectively predict labour productivity in a meaningful way. The model's significant explanatory power is demonstrated by the high F-statistic, which implies a strong correlation between the predictors and the response variable. The regression model's significance at the 1% level is confirmed by the p-value (Prob>F = 0.000), which adds to the evidence that the model is trustworthy overall and that the calculated coefficients have meaning.

N. 40, 2025 – ISSN: 1886-516X – DOI: 10.46661/rev.metodoscuant.econ.empresa.9623 – [Págs. 1-18]

llabour (-0.386) has a strongly significant t-value of (-7.71) and a negative coefficient. This implies that a decline in labour productivity is linked to an increase in labour input (as indicated by labour force size). This may suggest that businesses with larger workforces can encounter diminishing returns to scale, which is a common occurrence in labour economics and could be caused by inefficiencies or overstaffing (Greene, 2008). The AI patent coefficient (LAIpt) is positive and significant (t-value = 4.15), suggesting that companies with more AI patents have higher labour productivity (LAIpt = 0.579). This outcome is consistent with research indicating that technological advancements, especially artificial intelligence (AI), can greatly increase productivity through process simplification, automation, and the development of more effective work procedures (Brynjolfsson & McAfee, 2014).

The positive coefficient for non-AI patents (LNonAIpt) (0.428) shows that even patents in non-AI fields have a beneficial impact on worker productivity. This aligns with the widespread belief that technological innovation, whether or not it involves artificial intelligence, can boost productivity by bringing new goods, procedures, or methods to the company (Griliches, 1990). This observation is supported by the importance of the t-value of 3.41.

The R&D investment coefficient (Linv) is likewise positive and statistically significant (t-value = 8.92). This implies a productivity increase for businesses that spend on R&D, especially in technology. As R&D expenditures enable the creation of new technologies and procedures that can directly increase labour productivity and operational efficiency, this is to be expected (Joutz & Gardner, 1996). The significant coefficient highlights how crucial R&D is to promoting productivity driven by innovation.

According to the positive coefficient for firm turnover, businesses with higher employee turnover rates also typically have higher levels of productivity. This could indicate a dynamic staff with regular introductions of new ideas and skills, or it could indicate efforts at workforce optimisation and restructuring that increase productivity. This finding, however, necessitates more research because high turnover may also result in increased expenses for hiring and training.

When comparing models, the Bayesian Information Criterion (BIC = 813.294) and the Akaike Information Criterion (AIC = 813.076) show how well the models fit together; lower values indicate a better match. The model's fit appears to be reasonable without going overboard, as indicated by the relative closeness of these values.

The linear regression model's findings demonstrate that many variables have a significant impact on labour productivity, including labour input, R&D investment, patents (both AI and non-AI), and turnover. The favourable correlations between R&D spending and AI patents are especially significant since they demonstrate how important innovation is to raising productivity. However, given the inverse link between productivity and labour input, businesses must effectively manage their labour resources to prevent diminishing returns. All things considered, the model shows how technological innovation—especially artificial intelligence (AI)—is crucial for raising labour productivity, but it also shows that turnover and R&D expenditure are significant contributing variables.

Table 3: Linear regression

lprod	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
llabour	−0,386	0,148	−7,71	0	−0,455	−0,321	***
LAIpt	0,579	0,403	4,15	0	0,183	0,815	***
LNonAIpt	0,428	0,201	3,41	0	0,286	0,532	***
Linv	0,318	0,005	8,92	0	0,217	0,448	***
Lturnover	0,207	0,156	3,92	0	−0,357	−0,103	***
Constant	−2,13	0,498	−2,95	0	−3,024	−1,007	***

lprod	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Mean dependent var		−0,674	SD dependent var			1,063	
R-squared		0,371	Number of obs			253	
F-test		32,600	Prob> F			0,000	
Akaike crit. (AIC)		813,076	Bayesian crit. (BIC)			813,294	

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

The autocorrelation test is run using the Durbin-Watson statistic. 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 that the Durbin-Watson test searches for. For the Durbin-Watson test, the following are the hypotheses:

H0 = first-order autocorrelation does not exist.

H1 = first-order correlation exists.

According to Hsiao (2003), the Durbin-Watson statistics have a range of one to four, where a value of two indicates that there is no autocorrelation in the sample. Positive autocorrelation is indicated by values between 0 and less than 2. In actuality, the correlation increases with the value's proximity to zero. A value between 2 and 4 indicates a negative autocorrelation. There is a negative autocorrelation here. Consequently, a FE or RE model will be more appropriate.

Table 4: Fixed Effect

lprod	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
llabour	−0,628	0,017	−6,474	0	−0,738	−0,57	***
lAIpt	0,463	0,009	9,448	0	0,275	0,407	***
lnonAIat	0,317	0,047	6,7446	0	0,203	0,399	***
lturnover	0,139	0,018	7,7222	0	0,069	0,201	***
linv	0,375	0,007	10,714	0	0,192	0,415	***
Constant	−0,281	0,226	−1,243	0,246	−0,615	0,163	
Mean dependent var		−0,513	SD dependent var			063	
R-squared		0,457	Number of obs			253	
F-test		81,178	Prob> F			0,000	
Akaike crit. (AIC)		−208,012	Bayesian crit. (BIC)			−214,007	

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

This number shows that the independent variables in the model account for approximately 45.7% of the variation in labour productivity (lprod). Since the Fixed Effects model takes indivi-

N. 40, 2025 – ISSN: 1886-516X – DOI: 10.46661/rev.metodoscuant.econ.empresa.9623 – [Págs. 1-18]

dual variability into account, which the simpler model does not, it appears to be a better fit for the data than the pooled OLS model (R-squared = 0.371).

The high F-statistic (81.178) suggests that the model is statistically significant and that there is a strong correlation between labour productivity and the predictors. The model's explanatory capacity is not the result of chance, as confirmed by the p-value for the F-test (0.000), which supports the validity of the regression. Every independent variable is highly statistically significant ($p < 0.01$), indicating that each component is relevant concerning labour productivity. Labour (-0.628) The Labour input and labour productivity have a significant inverse relationship, as seen by the negative coefficient for labour (labour input) and the t-value (-6.474). This implies a tendency for productivity per worker to decrease in companies with larger manpower. As a well-known economic theory, this could be because of declining returns to labour or inefficiencies in managing larger workforces (Greene, 2008).

The positive and highly significant lAIpt coefficient is 0.463. This finding suggests that labour productivity tends to rise for companies that produce more AI patents. AI patents are a reflection of technology developments that can increase productivity per worker by streamlining procedures, cutting expenses, and improving efficiency. This result is consistent with studies by Chui et al. (2018) and Brynjolfsson & McAfee (2014), which indicate that AI may play a significant role in increasing business productivity.

The coefficient for non-AI patents, or lnonAIpt, is likewise positive and significant, suggesting that patents generally add to labour productivity, even when they are not related to AI. This demonstrates the wider contribution of innovation to increased productivity, since technical developments can result in more effective corporate operations in a variety of sectors (Griliches, 1990). The positive coefficient for employee turnover (0.139) indicates that increased labour productivity is linked to higher employee turnover. High turnover might be expensive for hiring and training new employees, but it can also introduce fresh perspectives, ideas, and techniques that could boost productivity and spur creativity (Pfeffer, 1998). This research highlights how complicated turnover is and how, depending on the situation, it can have both beneficial and detrimental impacts.

R&D investment has a positive and statistically significant coefficient. This demonstrates that businesses who spend money on R&D get an increase in worker productivity. R&D investments stimulate technical innovation, which boosts business competitiveness, improves product quality, and streamlines manufacturing processes (Joutz and Gardner, 1996). This variable's high significance highlights how crucial consistent investment in innovation is to long-term productivity development.

Although the constant term is negative, it is not statistically significant ($p = 0.246$), suggesting that, when all other variables are held constant, the baseline productivity does not deviate significantly from zero. This finding has no bearing on how the model should be interpreted because, after controlling for other variables, it probably captures the average production level among the enterprises in the dataset.

The correlations between labour productivity and important factors, including labour input, AI and non-AI patents, employee turnover, and R&D expenditure, are more accurately estimated by the Fixed Effects model. The findings demonstrate how important technology advancement, especially artificial intelligence (AI), and research and development expenditures are in boosting worker productivity. The necessity of effective workforce management is further supported by the inverse relationship between labour input and productivity. Overall, by taking individual variability into account, the Fixed Effects model enhances our knowledge of labour productivity dynamics, and the results corroborate the idea that investment and innovation are essential to raising productivity in the contemporary economy. These insights could be further refined in the future with the use of panel data models, particularly regarding the contribution of unobserved factors to productivity.

The results of a Random Effects (RE) model are shown in Table 5, providing information about the relationship between labour productivity (lprod) and its explanatory variables: investment (linv), turnover (lturnover), AI-related productivity (lAIpt), non-AI productivity (lnonAIpt), and labour input (llabour). Compared to Fixed Effects (FE), the RE model offers a more comprehensive view of the dataset since it can account for both within-group and between-group variation.

Table 5: Random Effect

lprod	Coef.	St.Err.	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**	253
Chi-square	409,318	**Prob > chi2**	0,000
R-squared within	0,537	**R-squared between**	0,217

At the 1% level, the labour input (llabour) coefficient is statistically significant (p-value = 0) and negative (-0.57). This finding implies that labour productivity declines as labour input increases. As labour input rises, the marginal contribution of more labour decreases, possibly as a result of overutilization or inefficiency. This strong negative relationship is consistent with the concept of diminishing returns to labour. The very significant positive coefficient (0.318) for AI-related productivity (p-value = 0) indicates that labour productivity is positively impacted by advances in the usage of AI technology. This result lends credence to the idea that AI improves productivity, streamlines procedures, and raises output levels per worker. Additionally, the non-AI productivity coefficient is significant (p-value = 0) and positive (0.307). Even though this effect's magnitude is marginally less than that of AI productivity, it nevertheless emphasises the significance of conventional productivity-boosting elements even in the presence of sophisticated AI systems.

There is a positive and significant correlation between higher production and larger turnover, as indicated by the coefficient of 0.119. This finding might indicate that turnover boosts labour productivity, perhaps as a result of a move towards more lucrative or fruitful endeavours. With a statistically significant (p-value = 0) coefficient of 0.286, investment has the biggest beneficial effect on production. This research highlights how important capital expenditure is for boosting productivity, especially when it comes to improvements in machinery, technology, or infrastructure. Although statistically insignificant, the constant is negative, suggesting that factors not included in the model might not have a substantial baseline impact on the sample's labour productivity.

With an aggregate R-squared value of 0.217, the independent variables account for about 21.7% of the variation in labour productivity. The model appears to be more effective at explaining productivity differences within groups than between them, as indicated by the higher within-group R-squared (0.537). The significance of chi-squared Confirming the model's overall explanatory power, the Chi-square statistic (409.318) is highly significant (p-value = 0).

The findings show how labour productivity and its variables have a complex connection. Productivity is negatively impacted by labour input, although efficiency gains are largely driven by technical and capital advancements. The fact that AI-related productivity factors have a greater influence than non-AI components shows how modern technologies have the power to drastically alter productivity landscapes. Furthermore, the relevance of investment and turnover highlights how crucial resource allocation and dynamic market adjustments are to raising labour output. All things considered, the RE model offers solid insights into the factors that influence labour productivity, promoting wise capital and technology investments while warning against excessive reliance on labour inputs. For businesses and politicians looking to maximise productivity in modern economic contexts, the findings are crucial.

5. CONCLUSIONS

This paper advances our knowledge of the relationship between labour productivity and technological progress, especially artificial intelligence. It emphasises how crucial R&D expenditures, capital investments, and AI patents are to the expansion of productivity. But the results also highlight issues, such as the possible loss of jobs due to automation, which calls for a well-rounded approach to strategy and policy. Businesses and governments can take advantage of technological advancements while reducing related risks by putting these suggestions into practice. To further improve tactics, future studies should examine industry-specific subtleties and longitudinal effects.

The study's conclusions have important theoretical and practical ramifications, influencing policy and strategic corporate choices as well as how labour productivity dynamics are understood. An extended conversation addressing these points is provided below:

PRACTICAL IMPLICATIONS

Encouragement of AI Adoption: The significance of incorporating cutting-edge technologies within businesses is highlighted by the positive correlation between labour productivity and AI-related patents. By offering tax breaks, subsidies, or innovation grants, policymakers could encourage businesses to spend money on AI R&D. Companies can use these findings to their advantage by integrating AI technologies to improve productivity and operational efficiency.

Strategic R&D Investments: The solid correlation between labour productivity and R&D expenditures highlights the necessity of consistent investment in innovation. Businesses should put a high priority on research and development (R&D) to create innovative technology, and governments might help by providing financing for research projects and encouraging partnerships between the public and private sectors. These expenditures will also aid in closing regional disparities in industrial production.

Reevaluating Workforce Strategies: The inverse relationship between labour productivity and staff size points to a displacement effect, in which advances in technology lower the demand for labour. This raises questions about staff reorganisation even if it might help businesses cut costs. Businesses must concentrate on upskilling and reskilling initiatives to move employees into positions that use new technologies and prevent job losses.

Sector-Specific Policy Development: The development of sector-specific policies is crucial, considering the unique productivity impacts of both AI and non-AI-related patents. In order to optimise the productivity gains from the use of AI, industries with high potential for innovation, like manufacturing and information technology, should receive appropriate assistance.

Enhancing Capital Stock: The study shows that productivity is greatly increased by investing in tangible capital stock. The need for businesses to update their infrastructure and make investments in cutting-edge equipment, especially in ICT, is highlighted by this study. Public-private partnerships or low-interest loans should be made available by policymakers to encourage such investments.

THEORETICAL IMPLICATIONS

Enhancing Innovation-Productivity Models: By measuring the relative impact of AI-related innovations in comparison to non-AI innovations, the study adds to the expanding corpus of research on the productivity effects of AI. According to the findings, productivity models that take into account the character and emphasis of innovation may provide more complex insights.

Recognising Technological Spillovers: The greater impact of patents on AI underscores the technologies' longer-term capacity to boost productivity. Potential avenues for future theoretical research include examining how AI technologies spread across industries and how they affect overall productivity.

Augmentation vs. Labour Displacement: The inverse link between staff numbers and labour productivity encourages more research into striking a balance between augmentation and labour displacement. Although AI increases productivity, theoretical models should take into account how advances in technology shift work across skill levels and affect labour market dynamics.

R&D and Innovation's Dynamic Effects: The results confirm that productivity is fuelled by both AI-related and non-AI advancements. In principle, this is in line with Schumpeterian growth theories that emphasise the contribution of innovation and creative destruction to economic advancement. The findings also suggest that models that account for the delayed effects of R&D expenditures on productivity are necessary.

BUSINESS AND POLICY RECOMMENDATIONS

Policy

To concentrate resources and skills in high-potential sectors, create innovation clusters focused on AI.

Adopt labour policies that offer displaced workers retraining opportunities in addition to unemployment benefits.

Business

Create research and development facilities devoted to AI and increase funding for the creation of exclusive AI technology.

To take use of research expertise and provide creative solutions, form alliances with academic institutions.

Future Research

Examine how industry type and business size affect the way AI affects productivity.

To determine how the advantages of adopting AI change over time, do longitudinal research

Stakeholders can more effectively leverage AI and innovation's potential while navigating issues related to workforce adjustments and investment priorities by addressing these theoretical and practical ramifications. This strategy promotes a well-rounded path to long-term productivity and economic success.

LIMITATIONS OF THE STUDY

This study offers insightful information about the connection between labour productivity and AI-related developments, although it has limits. One of the main limitations is using patent data as a stand-in for innovation. Despite being commonly accepted as a measure of technological progression, patents do not account for non-patentable innovations, unofficial information transfers, or breakthroughs businesses choose not to patent for strategic reasons. In areas where patenting is less prevalent, this technique can unintentionally under-represent AI-related advances or overemphasise companies with active patenting tactics. Furthermore, the examination of AI inventions' productivity contributions may be distorted because patent data alone does not consider the innovations' quality, applicability, or real-world impact.

The study's geographic and chronological emphasis, which only includes data from 2010 to 2023 and only covers two regions—Japan and the USA—also restricts its breadth. This could limit the findings' applicability to other nations or developing markets where labour market conditions and AI adoption patterns vary greatly. Despite their robustness, the selected econometric models presume linear connections between variables, which may cause them to ignore the non-linear or interacting effects of AI on labour productivity. Furthermore, the conclusions' granularity may be limited by the use of firm-level aggregated data, which may mask differences among firm sizes or within industries. Future research may be more thorough and applicable if these constraints are addressed using larger datasets, different innovation indicators, and more extensive methodology.

SUGGESTIONS FOR FUTURE RESEARCH

Several limitations in this paper suggest areas for future investigation. The model only takes into account companies that between 2010 and 2023 have submitted at least one AI-related patent. 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 bigger sample of companies that include both 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 the field of automation and robotics. To further enhance the research process and offer a deeper comprehension of the subject, the author suggests carrying out a qualitative investigation.

REFERENCES

Acemoglu, D., & Restrepo, P. (2022). Tasks, Automation, and the Rise in U.S. Wage Inequality. *Econometrica*, *90*(5), 1973-2016. https://doi.org/10.3982/ECTA19815

Aghion, P. and Howitt, P. (1992). A Model of Growth Through Creative Destruction, *Econometrica*, *60* (2), 323-351. https://doi.org/10.2307/2951599

Alderucci, D., Branstetter, L., Hovy, E., Runge, A. and Zolas, N. (2020). Quantifying the impact of AI on productivity and labour demand: Evidence from U.S. census microdata. In Paper presented at the Allied Social Science Associations—ASSA 2020 Annual Meeting.

Ando, M. and Kimura, F. (2015). Globalisation and domestic operations: Applying the JC/JD method to Japanese manufacturing firms, *Asian Economic Papers*, *14*: 1-35. https://doi.org/10.1162/ASEP_a_00342

Ando, M. and Kimura, F. (2017). Job Creation and Destruction at the Levels of Intra-firm Sections, Firms, and Industries in Globalisation: The Case of Japanese Manufacturing Firms, *RIETI Discussion Paper Series*, 17-E-100, Tokyo: Research Institute of Economy, Trade and Industry.

Antonelli, C. (2009), The Economics of Innovation: From the Classical Legacies to the Economics of Complexity, *Economics of Innovation and New Technology*, *18*(7): 611-646. *https://doi.org/10.1080/10438590802564543*

Arntz, M., Gregory, T. & Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis. *OECD Social, Employment and Migration Working Papers*, No. *189*.

Author, D. (2023). Applying AI to Rebuild Middle Class Jobs,*NATIONAL BUREAU OF ECONOMIC RESEARCH*, Working Paper 32140, http://www.nber.org/papers/w32140

Baddeley, M. and Barrowclough, D. (2009). Running regressions: a practical guide to quantitative research in economics, finance and development Studies. Cambridge: Cambridge Univ. Press.

Barbieri, L., Mussida, C., Piva, M. and Vivarelli, M. (2020). Testing the employment and skill impact of new technologies. In K. Zimmermann (Ed.) *Handbook of labour, human resources and population economics.* Cham: Springer.

Bessen, J. (2019). Automation and jobs: when technology boosts employment, *Economic Policy, CEPR, CESifo, Sciences Po*; *34*(100),589-626. https://ideas.repec.org/a/oup/ecpoli/v34y2019i100p589-626..html

Bloom, N., Jones, C. I. and Van Reenen, J. (2020). Are ideas getting harder to find? *American Economic Review*, *110*(4): 1104–1144. https://doi.org/10.1257/aer.20180338

Bresnahan, T. (2019). Technological change in ICT in light of ideas first learned about the machine tool industry. *Industrial and Corporate Change, 28*: 331–349. https://doi.org/10.1093/icc/dty076

Brynjolfsson, E., Rock, D. and Syverson, C. (2019). Artificial Intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, and A. Goldfarb (Eds.), *The economics of Artificial Intelligence: an agenda*. Chicago: University of Chicago Press and NBER.

Brynjolfsson, E. and McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton.

Chatterjee, S., Chaudhuri, R., Vrontis, D., Thrassou, A. & Ghosh, S.K. (2021). Adoption of artificial intelligence-integrated CRM systems in agile organisations in India, *Technological Forecasting and Social Change*, *168*,120783.

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., & Malhotra, S. (2018). *Notes from the AI frontier: Insights from hundreds of use cases*. McKinsey Global Institute. http://straty.com/wp-content/uploads/2018/04/McKinsey-AI-Frontier-paper-April-2018.pdf

Frank, M.R., Autor, D., Bessen, J.E., Brynjolfsson, M. Cebrian, D.J., Deming, M., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., and Rahwan, I. (2019). Toward understanding the impact of Artificial Intelligence on labour. *Proceedings of the National Academy of Sciences of the United States of America (PNAS), 116*(14): 6531-6539. https://doi.org/10.1073/pnas.1900949116

Goldfarb, A., Taska, B. and Teodoridis, F. (2020). Could machine learning be a general-purpose technology? *Evidence from online job postings*. *52*(1): 104653 https://doi.org/10.1016/j.respol.2022.104653

Gordon, R. J. (2016). *The rise and fall of American growth: The US standard of living since the Civil War*. Princeton: Princeton University Press.

Gordon, R. J. (2018). Why Has Economic Growth Slowed When Innovation Appears to be Accelerating? NBER Working Paper 24554. *National Bureau for Economic Research*. http://www.nber.org/papers/w24554

Graetz, G. and Michaels, G. (2018). Robots at Work, The Review of Economics and Statistics, *MIT Press*, *100*(5): 753-768. https://doi.org/10.1162/rest_a_00754

Greene, W. (2008). *Econometric Analysis*. 6th Edition, Prentice-Hall. Upper Saddle River.

Gries, T. And Naudié, W. (2018). Artificial Intelligence, jobs, inequality and productivity: Does aggregate demand matter? *IZA DP* No. *12005*, Bonn. https://doi.org/10.2139/ssrn.3301777

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey, *Journal of Economic Literature*, *18*(4): 1661–707.

Gujarati, N. D. (2006). *Essentials of Econometrics* (4th ed.). United States Military Academy.

Hausman, J., Hall, B. and Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship, *Econometrica*, *52*: 909–938. https://doi.org/10.2307/1911191

Hsiao, C. (2003). *Analysis of Panel Data* (2nd ed.). Cambridge University Press.

Jones, B. F. (2009). The burden of knowledge and the 'Death of the Renaissance Man': Is innovation getting harder? *Review of Economic Studies*, *76*(1):283–317. https://doi.org/10.1111/j.1467-937X.2008.00531.x

Joutz, F. L. and Gardner, A.T. (1996). Economic Growth, Energy Prices and Technological Innovation, *Southern Economic Journal*, *62*(3): 653–66.

Josten, C. and Lordan, G. (2020). Robots at work: Automatable and non-automatable jobs. In K. Zimmermann (Ed.), *Handbook of labour, human resources and population economics*. Cham: Springer.

Kortum, S. and Lerner, J. (1998). Does venture capital spur innovation?, Discussion paper, *NBER* Working Paper No. 6846.

Kortum, S. and Lerner, J. (2001). Does venture capital spur innovation?, In *Entrepreneurial inputs and outcomes: New studies of entrepreneurship in the United States* (Advances in the Study of Entrepreneurship, Innovation and Economic Growth, Vol. 13: 1-4), Emerald Group Publishing Limited, Leeds. https://doi.org/10.1016/S1048-4736(01)13003-1

Lazaroiu, G., and Rogalska, E. (2023). How generative artificial intelligence technologies shape partial job displacement and labour productivity growth. *Oeconomia Copernicana*, *14*(3), 703–706. https://doi.org/10.24136/oc.2023.020

Lăzăroiu, G., Andronie, M., Iatagan, M., Geamănu, M., Ștefănescu, R., & Dijmărescu, I. (2022). Deep Learning-Assisted Smart Process Planning, Robotic Wireless Sensor Networks, and Geospatial Big Data Management Algorithms in the Internet of Manufacturing Things. *ISPRS International Journal of Geo-Information*, *11*(5), 277. https://doi.org/10.3390/ijgi11050277

Los, B.; Timmer, M.P. and De Vries, G.J. (2014). The demand for skills, 1995-2008. A global supply chain perspective. *OECD Economics Department Working Papers*, 1141

Machin, S. and Van Reenen, J. (1998). Technology and Changes in Skill Structure: Evidence from Seven OECD Countries, *The Quarterly Journal of Economics*, *113*(4),1215–1244, https://doi.org/10.1162/003355398555883

Pfeffer, J. (1998). Seven Practices of Successful Organisations. *California Management Review*, *40*(2), 96-124. https://doi.org/10.1177/000812561988400200l

Romer, P. M. (1990). Endogenous Technological Change, *Journal of Political Economy*, *98*(5), 71-102. https://doi.org/10.3386/w3210

Solow, R. (1957). Technical Change and the Aggregate Production Function, *Review of Economics and Statistics*, *39*, 312-320. https://doi.org/10.2307/1926047

Szostek, D.; Balcerzak, A.P. and Rogalska, E. (2023). Impact of employees' counterproductivity on interpersonal relationships in the context of company competitive potential: Application of SEM methodology for Poland, *Journal of Competitiveness*, *15*(3), 19-42. https://doi.org/10.7441/joc.2023.03.02

Webb, M. (2019). The Impact of Artificial Intelligence on the Labour Market. *Economics of Innovation eJournal*. http://dx.doi.org/10.2139/ssrn.3482150

Zhang, J., Budhdeo, S., William, W. et al. Moving towards vertically integrated artificial intelligence development. *npj Digit. Med. 5*, 143 (2022). https://doi.org/10.1038/s41746-022-00690-x