INTERNATIONAL MONETARY FUND

Artificial Intelligence and Aggregate Labor Productivity: Evidence From Patent Data

Kodjovi M. Eklou

WP/26/204

2026
SEP

WORKING PAPER

 WP/26/204

IMF Working Paper
African Department

Artificial Intelligence And Aggregate Labor Productivity: Evidence From Patent Data
Prepared by Kodjovi M. Eklou*

Authorized for distribution by Pablo Lopez Murphy
Month 2026

ABSTRACT: This paper investigates the aggregate impact of Artificial Intelligence (AI) technology on labor productivity, exploiting patent data in OECD countries during 2000-2017. We first document that after accelerating in 2000, the issuance of AI technology related patents has more than tripled by 2017 and OECD countries held about 89 percent of all these patents across the world during the same period. Second, using a production function approach, we find that considering the pace of AI patent applications over the 2000-2017, labor productivity, measured as output per worker, has consequently increased by between 0.8 percent to 1.2 percent. The estimates also imply that innovation in AI technology could raise aggregate labor productivity by up to 3.8 percent in the long-run. These suggest that productivity gains could be larger in the future as the pace of innovation in AI gains new speed and spread to more sectors of the economy. These results are robust to accounting for a proxy of AI technology spillovers from other countries. Further we find that countries with a high share of employees in professional and managerial roles benefit from larger labor productivity gains from AI technology. Furthermore, these gains from task complementarity may take time to materialize as workers learn to fully appropriate the technology. Finally, labor market flexibility could also play a role in shaping labor productivity gains by enabling workers mobility.

RECOMMENDED CITATION: Kodjovi M. Eklou "Artificial Intelligence And Aggregate Labor Productivity: Evidence From Patent Data." IMF Working Paper 26/204.

JEL Classification Numbers:	O31, O34, J24.
Keywords:	Artificial Intelligence; Labor Productivity; Patents.
Author's E-Mail Address:	keklou@imf.org

* The author would like to thank Martin Schindler, Constant Lonkeng, Felix Vardy, Farayi Gwenhamo, Mohamed Norat, Marius Adom and other colleagues and participants in AFR seminars for helpful comments and suggestions.

WORKING PAPERS

Artificial Intelligence And Aggregate Labor Productivity: Evidence From Patent Data

Prepared by Kodjovi M. Eklou[1]

[1] The author would like to thank Martin Schindler, Constant Lonkeng, Felix Vardy, Farayi Gwenhamo, Mohamed Norat, Marius Adom and other colleagues and participants in AFR seminars for helpful comments and suggestions.

Contents

Introduction

Artificial Intelligence (AI) technology, a general-purpose technology (GPT) holds the promise of spurring productivity growth mainly by either automating tasks or by complementing tasks that are not fully automated. For instance, by automating routine tasks and catalyzing the development of new business models, AI could optimize workflows and generate labor productivity gains. AI could also serve as cognitive complements that dramatically compress the time required to complete high-skill technical tasks, enhance coordination but also learning and thereby improve labor productivity. The magnitude of these productivity gains at the macroeconomic or aggregate level are however uncertain and recent estimates reveal a lack of consensus. For instance, while microeconomic studies such as Brynjofsson et al. (2023) estimate a 14 percent increase in productivity the first month reaching 25 percent after three months for employees who had access to AI assistant in a U.S. customer service firm, Acemoglu (2024) estimates more modest aggregate impacts of about 0.7 percent increase in total factor productivity over 10 years using a task-based framework.

In this paper, we investigate the aggregate impact of AI technology on labor productivity exploiting patent data. Indeed, patents are known as a standardized output measure of inventive activities (Griliches 1990). We ask the following research question: How large are the aggregate labor productivity gains from innovations in artificial intelligence technology? To answer this question, we use a sample of 38 OECD countries over the period 2000-2017, as they held about 89 percent of AI-related patents. The paper relies on an empirical approach derived from a production function augmented with a knowledge stock (Lokshin et al., 2008; Hall et al., 2010 and Belderbos et al., 2015). The results show that even after controlling for patent activity in non-AI technology and potential spillovers from other countries, innovation in artificial intelligence technology has a positive impact on aggregate labor productivity. The estimates imply that the accumulation of AI technology related patents over the period 2000-2017, has been associated with aggregate labor productivity gains between 0.8 percent and 1.2 percent.

The paper also uncovers heterogeneity in the productivity gains from AI technology both across time and countries. First, we split the sample around the global financial crisis (GFC), which was followed by both a global productivity decline (see Dieppe, 2021) and more innovation in AI technology as measured by the number of patents (as documented in this paper).[2] The results show that the productivity gains are statistically significant mainly over the period after the GFC (2009-2017), suggesting that as AI technology expands more rapidly and spread across more sectors of the economy, productivity gains could become larger. Second, we also investigate the role of labor market characteristics such as the composition of the labor force and the degree of flexibility in labor market institutions. Based on findings in recent studies on labor market exposure to AI by occupations category (see Felten et al. 2021 and Pizzinelli et al., 2023), we investigate the role of professional and managers identified as a group highly exposed to, but also with high complementarity with AI technology.[3] We find that countries with a high share of employees in professional and managerial roles benefit from larger labor productivity gains from AI technology. In addition, advancement of AI technology could also lead to productivity gains by displacing workers and generating new labor-intensive tasks (see Acemoglu

[2] This approach is also followed by Damioli et al. (2021) who estimate the impact of AI patents on firm level productivity using Orbis data.

[3] We investigated also whether the occupation group of clerical and service sales (known to have high exposure but low complementarity with AI technology) in total employment plays a role but found no conclusive evidence. In addition, we also investigated the role of skilled labor share and found no conclusive evidence which could be driven by low variation across countries in the sample.

and Restrepo, 2019; Acemoglu, 2024), which could be more likely when labor market institutions are flexible to support workers mobility. Local projection estimates show that both task complementarity and workers displacement channels matter and that labor productivity gains from large AI innovation shocks could persist over a few years. Further, productivity gains from task complementarity may take time to materialize as workers learn to fully appropriate the technology.[4] Finally, labor market flexibility could also play a role in shaping labor productivity gains by enabling workers' mobility (labor displacement channel) but estimates are not statistically different from average effect in the sample.

To the best of our knowledge, this paper is among the first to provide aggregate productivity estimates of AI technology using patent data across a relatively large sample of countries, and to examine the resulting macroeconomic implications. It is closely related to the literature using patent and firm level data to investigate the impact of AI technology on productivity (see for instance Alderucci et al., 2019 and Damiola et al., 2021). In addition, it also relates to the microeconomic literature on AI use and productivity (Calvino and Fontanelli, 2023a, Calvino and Fontanelli, 2023b, Czarnitzki, et al., 2023 and, da Silva Marioni et al, 2024), AI-based assistant and productivity (Brynjolfsson et al., 2023). The paper adds to this literature by providing aggregate productivity estimates and insight on the potential role of the labor market structure (the composition of employment) in shaping these productivity gains from AI. Our results on the role of the share of professional and managers lend support to the task complementarity channel identified in Acemoglu and Restrepo (2019). Indeed, this category is composed of high-skill occupations with a high concentration of cognitive-based tasks (Felten et al. 2021, Pizzinelli et al., 2023 and Briggs, J. and D. Kodnani, 2023). This literature using firm level data usually finds quite large productivity gains which are not necessarily plausible at the aggregate level.[5]

The findings in this paper also provide an understanding of how macro-critical productivity implications of AI could be in the future. For instance, a recent work has contributed to this discussion by exploiting the parallel between AI revolution and past technology revolutions (Aghion and Bunel, 2024) and a task-based framework (Acemoglu, 2024) for the US. While Aghion and Bunel, (2024) and Acemoglu (2024) used different approaches and focused on total factor productivity, we provide estimate using patents data. Acemoglu (2024) finds a small impact of about 0.66 percent over 10 years. Aghion and Bunel (2024) estimate that AI revolution could increase aggregate productivity by between 0.8 and 1.3 percentage point per year over the next decade.[6] In addition, using a task-based approach, Aghion and Bunel (2024) find a median estimate of 0.68 percentage point additional annual growth in TFP over the next decade.[7] Our estimates, are somewhat in between those found by Acemoglu (2024) and Aghion and Brunel (2024) as we find an implied long-term impact of innovations in AI technology as captured by patents to raise labor productivity by up to 3.8 percent. Finally, we also provide some evidence on the potential persistence of productivity gains. The rest of the paper is organized as follows. Section I discusses stylized facts and data including trend in AI patents developments across the world.

[4] Bäck et al. (2022) find that productivity gains are delayed by at least 3 years following AI adoption in a sample of Finnish firms owing to technological immaturity and investment delays. Their finding provides an explanation for the so-called AI-related Solow-paradox which suggests that AI is everywhere except in the productivity statistics.

[5] For instance, Damioli et al. (2021), which is very comparable to this paper finds productivity gains of about 3 percent from doubling AI-related patent stock (about two times larger impact than found here) but focused on firms actively engaged in AI patenting. da Silva Marioni et al (2024) find that European firms see productivity gains between 6 to 17 percent, following AI patent application. Peng et al (2023) found one of the largest productivity gain estimates of 55.8 percent.

[6] They assume that AI wave in the next decade will either be comparable to electricity wave of 1920s in Europe or similar to the digital technology wave of the 1990s and 2000s in the United States.

[7] Li and Noureldin (2024) estimate that while the potential of AI to boost labor productivity is uncertain, the technology could add up to 0.8 percentage points to global growth.

Section II is dedicated to the empirical analysis including, the identification strategy and the results. Finally, section III concludes.

I. Data and Stylized Facts

A. Data

To investigate the potential aggregate impact of Artificial Intelligence (AI) technology on labor productivity we exploit patent data, covering 38 OECD countries during 2000-2017.[8] The focus on OECD countries is motivated as discussed in the section below by the concentration of the patents in these countries and over a period where there is significant development in AI technology. Table A1 in Appendix presents a summary of all variables used in the paper and Table A2 describes their sources.

Labor Productivity.

Following a long tradition in cross-country studies, we measure labor productivity as the ratio of output per employee. More specifically, we calculate labor productivity as the ratio between real GDP output side (chained PPP in 2017 USD) and the number of people engaged using data from Penn World Tables (PWT) 10.01. A large portion of the related (microeconomic) literature on the impact of AI technology on labor productivity employs similar measures of labor productivity such as turnover per employee (Damioli et al., 2021, Calvino and Fontanelli, 2023a) and value added per employee (Calvino and Fontanelli, 2023b). We used also output per hour worked as an alternative measure.

Patent Data.

The patent data are taken from OECDSTAT. Artificial intelligence (AI) is often defined as General Purpose Technology (GPT), and thus can spill over many technological areas, making the identification of AI-related patents challenging. Patents in technologies related to artificial intelligence are identified using a combination of patent classification codes and keywords, as described in Baruffaldi et al. (2020). Patents are considered as AI-related if they belong to the Human interface and Cognition and meaning understanding categories listed in the OECD 2017 taxonomy of ICT technologies (and detailed in Inaba and Squicciarini, 2017), in addition to those in International Patent Classification (IPC) class G06N. The OECD taxonomy relies on IP5 “patent families” denoting inventions protected in at least two jurisdictions, at least one of which needs being one of the five intellectual property offices including the European Patent Office (EPO), Japan Patent Office (JPO), Korean Intellectual Property Office (KIPO), the US Patent and Trademark Office (USPTO) and the China National Intellectual Property Administration (CNIPA). Baruffaldi et al. (2020) have proposed a taxonomy that reflects more accurately AI-related patents and a list of 193 keyworks for their text features. AI-related patents (see Table A3 for details) include Natural Language Processing ranging from automating repetitive tasks to analyzing large documents (with applications such as virtual assistants including Alexa and Siri and chatbots used in legal and customer services for instance).

The number of non-AI related, or other patents is obtained as a difference between total patents (also from OECDSTAT) and AI-related patents. Controlling for non-AI patents, allows us to account for the overall innovation capacity in the country outside the field of AI. The reference date used for patents is the priority date

[8] The data availability from OECDSTAT at the time of the study (see Table A2 for details) limits the sample period. This study does not therefore capture recent developments including in Generative AI.

which refers to the earliest filing date in a family of patent applications and the country of residence of the inventor is considered.

Controls in the Production Function.

Based on a production function specification (discussed later), we include among controls the changes in the logarithm of physical capital stock and employment. The data on real physical capital stock, the number of people employed, and hours worked are taken from PWT 10.01.

Other variables.

To investigate potential heterogeneity effects originating from labor market characteristics, we use data on the share of professional and managers in total employment from OECDSTAT (World Indicators of Skills database) as well as data on labor market flexibility from the Fraser Institute's Economic Freedom of the World database. The labor market regulation index covers multiple areas including for instance i) hiring and dismissal regulations, ii) minimum wage and iii) centralized collective bargaining. The index is rescaled from 0 to 1 where a higher value reflects higher flexibility in the labor market institutions (higher freedom).

B. Stylized Facts

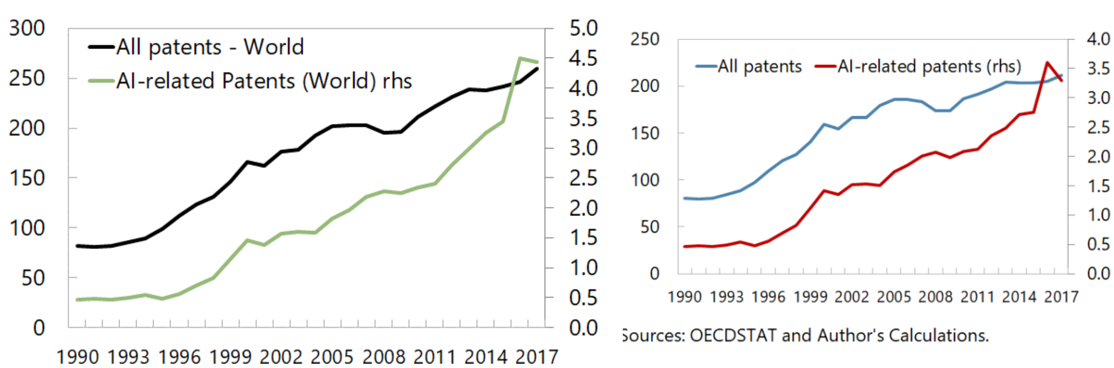
In this section, we turn to the description of the data focusing on the trend in artificial intelligence patents across the world and some cross-country correlation between AI technology and labor productivity.

Figure 1 shows that AI technology related patents have increased steadily over the last three decades, growing by almost 10 times between 1990-2017. The data show also that AI technology related patents picked up in early 2000s but remained low as share of total patents worldwide in 2017 (about 1.7 percent). Further, AI technology patents are concentrated in OECD countries with about 89 percent of worldwide patents over 2000-2017, however with high heterogeneity within OECD (see Figure 2). It is worth noting that the data show a peak in 2016, followed by a leveling off in 2017. While the data at hand does not allow for an in-depth analysis, 2016 was widely seen as a pivotal year for AI, marked by major breakthroughs including advances in neural networks which underpin advancement in intelligent automation, with expected productivity gains across industries.

Figure 1: Trend in AI Technology Related Patents Across the World and OECD Countries

Number of Patents - World
(In thousands)

Number of Patents - OECD Countries
(In thousands)

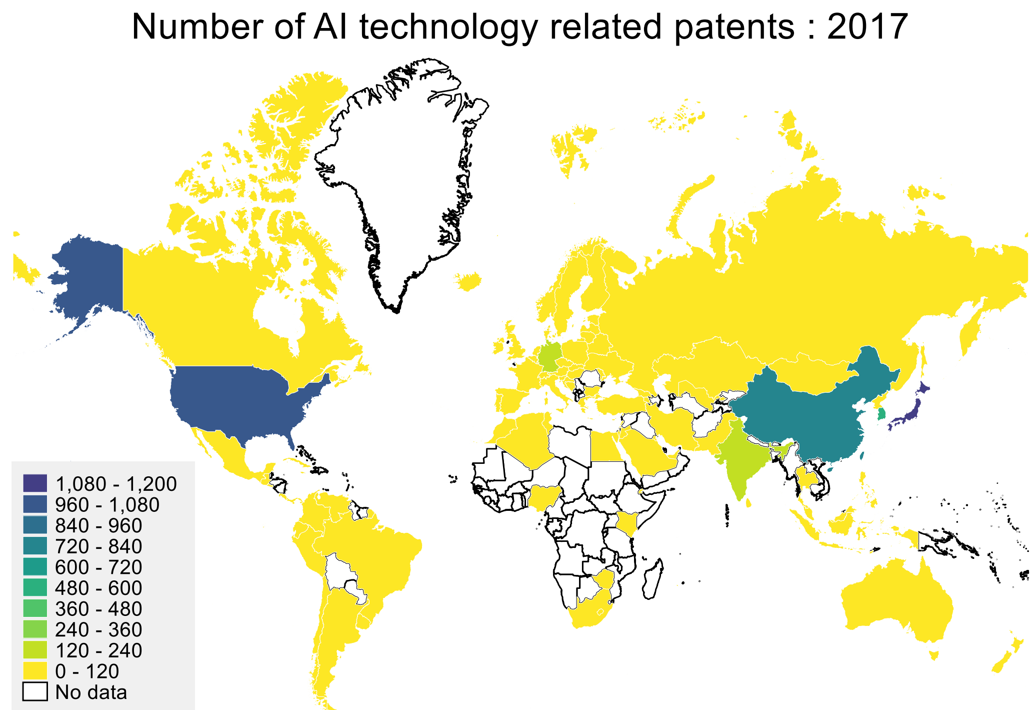


Sources: OECDSTAT and Author's Calculations.

Sources: OECDSTAT and Author's Calculations.

Note: Patents data relate to patents that have been filed in at least two Intellectual Property (IP) offices worldwide, one of which among the five IP offices (European Patent Office, Japan Patent Office, Korean Intellectual Property Office, the US Patent and Trademark Office and the China National Intellectual Property Administration (CNIPA).

Figure 2: Number of AI Patents across Countries, 2017[9]



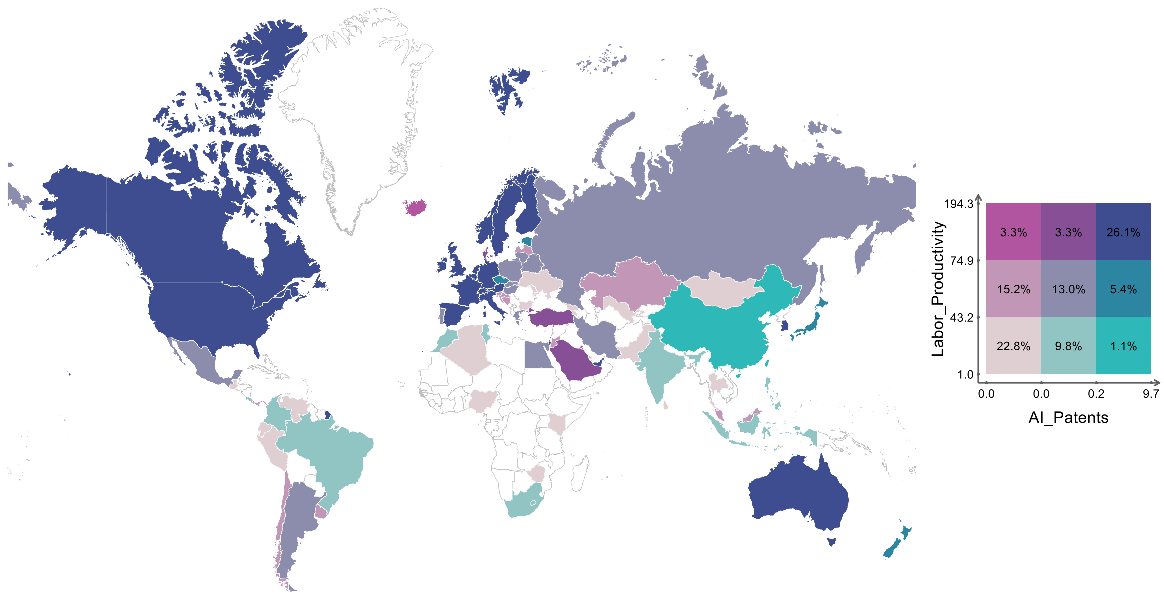
Source: OECDSTAT and World Bank data files

Figures 3 and 4 show respectively the cross-country correlation between the number of AI related patents and labor productivity across countries in the world with available data and in OECD countries respectively. Figure 3 displaying a bivariate map shows a positive correlation for a large number of observations or countries as shown by the percentage of countries on the first diagonal totaling about 62 percent. This suggests that for most countries, the level of labor productivity was positively correlated with the number of AI-related patents in 2017. Focusing on OECD countries over the period 2000-2017, Figure 4 depicts a positive correlation as well. In the next section, we will further investigate this relationship by accounting for potential confounding factors.

[9] Disclaimer on the maps used in this paper (Figure 2 and 3): The author nor the IMF accepts no liability for omissions or errors in the data or content. The boundaries, colors, denominations, and any other information shown on the maps do not imply any judgment on the legal status of any territory or any endorsement or acceptance of such boundaries

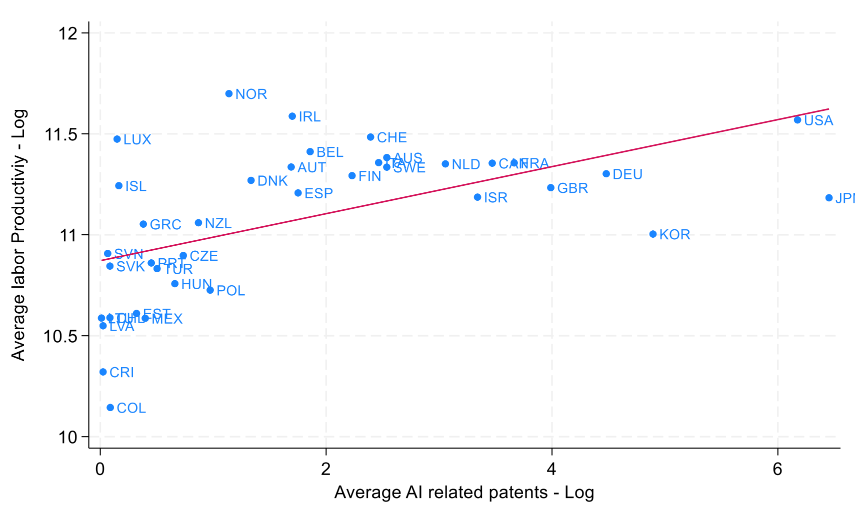
Figure 3: Cross-Country Correlation Between AI Technology Patent and Labor Productivity, 2017

Labor Productivity Level vs Number of AI Technology related Patents per Million Inhabitants : 2017



Source: OECDSTAT, Penn World Table and World Bank data files

Figure 4: AI Patents and Labor Productivity in OECD Countries



Source: OECDSTAT, Penn World Tables and Author's calculations.

II. Artificial Intelligence and Aggregate Labor Productivity: Empirical Analysis

A. Empirical Strategy

Our empirical approach to estimate the potential impact of AI technology on labor productivity is based on an aggregated Cobb Douglas production function augmented with a knowledge stock following Lokshin et al (2008), Hall et al. (2010) and Belderbos et al (2015). In this framework, the output level (Y) depends on the stock of capital (K), labor (L) and the available knowledge stock (Ω) at a given time *t* as follows:

$$Y_{ct} = \rho_c K_{ct}^{\alpha} L_{ct}^{\eta} \Omega_{ct}^{\gamma} e^{\phi_{ct}} \text{ (1)}$$

Where α, η and γ are respectively the elasticity of output with respect to physical capital, labor and knowledge stock. The constant term ρ_c captures country-specific and time-invariant determinants of productivity and ϕ_{ct} is a time-variant country-specific efficiency parameter capturing how far a country is from the productivity frontier at a given time. From equation (1), we can obtain a dynamic specification for labor productivity by dividing both sides by labor, taking the logarithm, and differentiating in two consecutive periods as follows[10]:

$$y_{ct} = (1+\delta)y_{ct-1} + \alpha\Delta k_{ct} + (\eta - 1)\Delta l_{ct} + \gamma\Delta\omega_{ct} + \theta_c + \xi_{ct} \text{ (2)}$$

With lower case variables expressed in logarithm, y_{ct} is the logarithm of labor productivity, Δk_{ct} , Δl_{ct} and $\Delta\omega_{ct}$ are respectively the first difference of the logarithm of physical capital, labor input and the knowledge stock. θ_c represent country-specific fixed effects and ξ_{ct} an error term. From Equation (2), we obtain the following specification to estimate the impact of AI technology on labor productivity, including year fixed effects (τ):

$$y_{ct} = \beta_1 y_{ct-1} + \beta_2\Delta k_{ct} + \beta_3\Delta l_{ct} + \beta_4 AIpatents_{ct} + \beta_5(Other - patents)_{ct} + \theta_c + \tau + \xi_{ct} \text{ (3)}$$

This specification assumes that the change in the knowledge stock in country *c* in year *t* , can be proxied by the flow of new patent applications each year both in AI related technology ($AIpatents_{ct}$) and in other areas non-related to AI technology ($(Other - patents)_{ct}$). This approach implies that the patent portfolio of a country is a good proxy of current knowledge -– that is local inventive activity – usable for production, in particular for a general-purpose technology such as AI (Damioli et al,2021). In addition, previous study (Alderucci et al, 2020) also argue that “firms that succeed in using artificial intelligence to create new goods and services have strong incentives to patent at least some of their innovation”. While the use of patents as a measure of innovation

[10] This equation is obtained following the assumption that the change in country-specific efficiency level is function of past productivity to allow for a gradual convergence in efficiency levels among countries as follows (see Lokshin et al, 2008): $\Delta\phi_{ct} = \delta y_{ct-1} + \xi_{ct}$, where $\delta < 0$, reflecting the fact that countries with high productivity levels (those at the frontier) tend to have slower productivity growth; compared to those with lower levels of productivity.

presents some limitations (see for instance Hall et al., 2014), they offer the practical advantage of allowing to analyze the use of AI technology across countries and over time.[11]

Estimating dynamic production functions present several well-known challenges including simultaneity, endogeneity and the so-called Nickell bias. The standard fixed effect estimator is known to be biased in the presence of the lagged dependent variable (Nickell, 1981). To tackle these issues, following the related literature, we employ the system GMM estimator (Blundell and Bond, 1998, 2000). In addition, the GMM estimator also helps address potential endogeneity issues related to omitted variables or reverse causality. Further, given the relatively poor performance of GMM estimators in small samples and the known instability over alternative set of instruments, we also use the recently developed bootstrap-based bias corrected fixed effect estimator (Everaert and Pozzi, 2007) to address the Nickell bias.

Finally, we explore whether productivity gains could be delayed and persistent following an AI technology innovation shock, using an extension of Equation (3) in a local projection framework as follows:

$$y_{ct+h} = \varphi_1 y_{ct-1} + \beta^h AI\_shock_{ct} + \gamma^h (AI\_shock_{ct} \times G_c) + \sum_{j=0}^{5} \theta_j^h Z_{ct-j} + \alpha_c + \tau + \xi_{ct+h} \qquad (4)$$

Where AI_shock_{ct} is a dummy taking the value 1 when an AI innovation shock defined as a growth in AI patents at least equal to the 75th percentile of AI patents growth over the period and zero otherwise.[12] G_c captures whether a country belongs to high or low share of professional and managers, and labor market flexibility based on sample median. Z_{ct} is a set of control variables including lags of AI innovation shock, lags of other control variables included in equation (3) and the remaining variables retain the same meaning. Our specification in equation (4) is similar to the semi-parametric approach of Cloyne et al. (2023), providing a flexible way to estimate the impact of AI innovation shocks without any assumption about the functional form. The horizon, *h,* is up to five years. The local projection approach offers several advantages, including robustness to misspecifications. Local projection inference is both simpler and more robust than standard autoregressive inference, whose validity is known to depend sensitively on the persistence of the data and on the length of the horizon (Montiel Olea and Plagborg-Møller, 2021).

Equation (4) explores the role of labor market characteristics in shaping labor productivity gains from significant AI innovations. We consider the share of professional and managers in total employees and the degree of flexibility of labor market institutions. Recent studies on labor market exposure to AI by occupation categories (see Felten et al. 2021 and Pizzinelli et al., 2023) have identified professional and managers as a group highly exposed to, but also with high complementarity with AI technology. Indeed, this category is composed of high-skill occupations with a high concentration of cognitive-based tasks (Felten et al. 2021, Pizzinelli et al., 2023 and Briggs, J. and D. Kodnani, 2023). We test therefore whether countries with a high share of employees in professional and managerial roles benefit from larger labor productivity gains from AI technology. In addition, advancement in AI technology could also lead to productivity gains by displacing workers and generating new

[11] For instance, patent data could provide an incomplete picture of AI's potential effect on productivity since not all AI technologies would be patented as some firms could decide to not patent their AI-related innovations. However, this would plausibly imply that patents data offer lower bound estimates of potential impact of AI technology on productivity. Indeed, as the theoretical `true coefficient' is expected to be positive, this measurement error would entail a typical attenuation bias where coefficients are biased toward zero.

[12] We have identified 120 of such large shocks in the sample given the five-years horizon for the local projections.

labor-intensive tasks (see Acemoglu and Restrepo, 2019; Acemoglu, 2024), which could be more likely when labor market institutions are flexible to support workers' mobility.

B. Results

Table 1 below shows our baseline estimates of the impact of AI innovation captured by AI-related patents, on labor productivity. We find relatively moderate but significant impact of AI technology on labor productivity growth over the period in the sample of OECD countries. Doubling the number of AI patent applications over the period has been associated with an increase in labor productivity by between 0.6 and 0.9 percent over the period 2000-2017.[13] Considering that AI patent applications have grown by 132.6 percent in OECD countries over the period 2000-2017, our estimates suggest that labor productivity has consequently increased by between 0.8 percent and 1.2 percent. Compared to microeconomic studies employing AI patents to estimate the impact of AI technology on productivity (Damioli et al., 2021), our aggregate estimates are much lower. Indeed, Damioli et al (2021) find using firm level data that doubling the number of AI patent applications is associated with a 3 percent increase in labor productivity.[14] In addition, comparing AI-technology to other technologies, estimates in Table 1 shows larger impact of the latter with aggregate productivity gains between 1.5 percent to 3.8 percent from doubling patent applications.

The relatively modest estimates are comprised between findings by Acemoglu (2024) and, Aghion and Bunel (2024). Acemoglu (2024) and, Aghion and Bunel (2024) estimate however the impact of AI technology on TFP. Based on the task-based model, they estimate respectively about 0.66 percent over ten years and 0.68 percentage point additional growth per year over the next decade in productivity growth. In addition, Aghion and Bunel (2024) estimate that AI revolution could increase aggregate productivity by between 0.8 and 1.3 percentage point per year over the next decade. We exploit the GMM estimates to derive long-term aggregate productivity gains.[15] Using estimates from Table 1, column (4) and (6) imply a long-term aggregate productivity gain from AI technology of about 3.8 percent and 3.3 percent respectively.[16]

Next, we split the sample into two subsamples before and after the global financial crisis (GFC). This is motivated by both the global productivity decline following the GFC (see Dieppe, 2021) and the increase in AI-related patents seen in the recent period (as shown in Figure 1). The related results also shown in table 1 depict an interesting finding that the positive impact of AI-technology innovations on productivity is mostly present over the period 2009-2017. Indeed, we find a positive and statistically significant effect over the period 2009-2017, ranging between 0.8 percent to 1.4 percent associated with doubling the number of AI patent applications. This finding, which is consistent with Damioli et al (2021) using firm level data, could imply that in the long-term, as innovation in AI-technology increases more rapidly, spreads across various sectors of the economy and users increase, productivity gains could become larger. This result could also reflect the maturity of AI technology over time (see for instance Bäck et al., 2022).

[13] Our results using Output per hour worked are similar to these baseline findings (see Table A4 in Annex).

[14] The large impact found in Damioli et al (2021) could be driven by their focus on firms that are active in AI patenting and thus more technology intensive. Their estimates could therefore represent an upper-bound estimate.

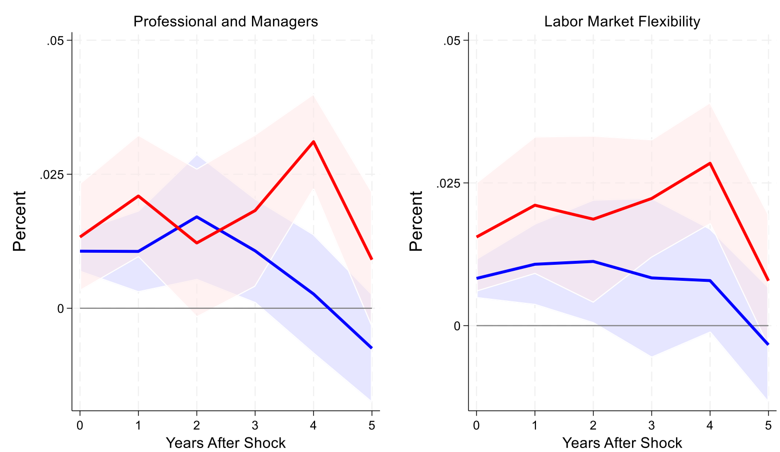
[15] The long-term impact is obtained as $\frac{\beta_4}{1-\beta_1}$.

[16] These long-term effects are still lower compared to Damioli et al (2021) with implied long-term productivity gains of about 7 percent at the firm level.

Further, we augment the baseline model in equation (3) by exploring the potential role of labor market characteristics in shaping the magnitude of the labor productivity gains from innovation in AI-technology in Table 2. Results show that countries with a large share of professional and managers in their total number of employees have larger labor productivity gains from AI technology innovations. More specifically, our estimates show that labor productivity gains could range between 0.8 percent to 2 percent from doubling the number of AI patent applications.[17] However, we do not find any conclusive evidence on the role of labor market flexibility from Table 2.

Finally, we explore the role of significant AI innovations in the local projection framework as specified in equation (4). Figure 5 shows that significant AI innovations could generate persistent productivity gains over a few years.[18] Further, the role of the share of professionals and managers in the total number of employees in shaping labor productivity gains is more discernable in the medium-term, as the results show statistically different productivity gains (from the average impact) only after 4 years (about 2.5 percent higher). This could suggest that the task complementarity channel may require a learning process to reap the full benefit from the new technology. The results show a higher productivity gain for countries with high labor market flexibility compared to the average country (proxy for labor displacement channel), but the difference is not statistically significant.[19]

Figure 5: Large AI innovation shocks and Labor Productivity – The Role of Labor Market Characteristics



Notes: This figure shows the response of labor productivity to a large AI innovation shock (growth in AI patent at least at 75th percentile in the sample). The blue line shows average impact (β^h), while the red line shows the impact of the shock, conditional on whether the labor market characteristic is above the sample median in the sample (θ^h+γ^h). 90 percent confidence interval from Kraay and Driscoll standard errors in shaded areas

[17] We did not find any conclusive evidence on the share of clerical and service sales (often found to have high exposure but low complementarity with AI technology) in total employment. Further, we also investigated the role of skilled labor share and found no conclusive evidence which could be driven by low variation in our sample.

[18] See Figure A1 in Annex showing similar results for labor productivity measured by output per hour.

[19] We have also investigated the impact of AI patent on employment growth and found no statistically significant effect (results available upon request). Investigating this channel may require more granular data. Note also that the main effect of AI patents is imprecisely estimated especially for regression investigating the role of the share of professional and managers in the labor force.

Overall, our results show moderate but sizeable impact of AI-technology on labor productivity driven by the importance of occupations featuring a high complementarity with AI technology. Our findings point to the potential role of structural characteristics of the labor market in shaping productivity gains.

Table 1: AI Technology and Labor Productivity - Baseline

	Fixed Effects			GMM System			Bootstrap Estimator		
					Periods				
	2000-2017	2000-2008	2009-2017	2000-2017	2000-2008	2009-2017	2000-2017	2000-2008	2009-2017
Log Output per employee (t-1)	0.830***	0.770***	0.708***	0.761***	0.795***	0.592***	0.888***	0.904***	0.912***
	(0.028)	(0.046)	(0.049)	(0.069)	(0.045)	(0.101)	(0.027)	(0.043)	(0.084)
AI Patents (Log)	**0.006***	**0.007**	**0.008****	**0.009***	**0.008**	**0.014****	**0.006***	**0.006**	**0.010***
	(0.003)	**(0.006)**	**(0.004)**	**(0.005)**	**(0.007)**	**(0.007)**	**(0.003)**	**(0.007)**	**(0.005)**
Other Patents (Log)	0.017**	0.015*	0.010	0.033*	0.038***	0.042	0.012*	0.011	0.007
	(0.008)	(0.008)	(0.014)	(0.018)	(0.013)	(0.037)	(0.007)	(0.009)	(0.015)
Δ Employment (Log)	-0.005***	-0.006***	-0.002	-0.003*	-0.006***	-0.000	-0.004***	-0.005*	-0.000
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)
Δ Capital Stock (Log)	0.009***	0.013***	0.014***	0.006	0.001	0.018***	0.009***	0.011**	0.011**
	(0.002)	(0.004)	(0.003)	(0.005)	(0.005)	(0.007)	(0.002)	(0.006)	(0.005)
Countries	38	38	38	38	38	38	38	38	38
R-squared	0.83	0.72	0.65						
P-value AR(1)				0.00	0.00	0.01			
P-value AR(2)				0.17	0.06	0.27			
P-value Hansen				0.20	0.70	0.21			
Observations	684	342	342	684	342	342	646	304	304

Notes: The Bootstrap estimator is the bootstrap-based bias-corrected fixed effect (Everaert and Pozzi, 2007) with 500 replications. The related estimates are robust to misspecifications. Clustered standard errors (fixed effects), robust standard errors (GMM system) and bootstrapped standard errors are in parentheses. * p<0.1, **p<0.05, *** p<0.01.

Table 2: AI Technology and Labor Productivity - The role of labor market Characteristics

	Share of Professional and Managers			Labor Market Flexibility		
	Fixed Effects (1)	GMM System (2)	Bootstrap Estimator (3)	Fixed Effects (4)	GMM System (5)	Bootstrap Estimator (6)
Log Output per employee (t-1)	0.823*** (0.029)	0.850*** (0.065)	0.884*** (0.026)	0.829*** (0.027)	0.762*** (0.080)	0.888*** (0.023)
AI Patents (Log) x Prof & Managers	**0.008*** **(0.004)**	**0.039***** **(0.013)**	**0.010**** **(0.005)**			
AI Patents (Log) x Labor Market Flexibility				**-0.011** **(0.009)**	**-0.059** **(0.046)**	**-0.011** **(0.011)**
AI Patents (Log)	**0.000** **(0.003)**	**-0.019**** **(0.010)**	**-0.000** **(0.003)**	**0.012**** **(0.005)**	**0.046*** **(0.028)**	**0.013*** **(0.007)**
Labor Market Flexibility				0.064** (0.031)	0.119 (0.144)	0.056* (0.034)
Countries	36	36	36	38	38	38
Production Function Controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.82			0.83		
P-value AR(1)		0.00			0.00	
P-value AR(2)		0.25			0.62	
P-value Hansen		0.91			0.97	
Observations	648	648	612	684	684	646

Notes: The Bootstrap estimator is the bootstrap-based bias-corrected fixed effect (Everaert and Pozzi, 2007) with 500 replications. The related estimates are robust to misspecifications. Note that we do not include the share of professional and Managers among controls because it only has cross-country-variation, which are already captured by country-fixed effects. Given data availability constraint, we take the average of the share of professional and managers in the labor force and interact AI patents with a dummy taking the value 1 for countries above the sample median and zero otherwise. Clustered standard errors (fixed effects), robust standard errors (GMM system), and bootstrapped standard errors (bootstrapped estimator) are in parentheses. * p<0.1, **p<0.05, *** p<0.01.

C. Robustness check

We now submit the baseline results to an additional robustness check by augmenting equation (3) with other control variables beyond the production function. More specifically, while the GMM system estimator allows us to mitigate endogeneity issues related to the identification of the effect of AI innovation on productivity, we include more controls that are likely to be correlated both with labor productivity and domestic AI innovation. To this end, we control for human capital, trade openness and foreign AI innovation. Human capital index from Penn World Table is an index based on the average years of schooling from Barro and Lee (2013) and an assumed rate of return to education based on Mincer equation estimates around the world (Psacharopoulos, 1994). Trade openness is measured as total trade in percentage of GDP and taken from the World Development Indicators (WDI). Finally foreign AI innovation or Foreign AI patents for country *c* and year *t* is calculated as $Foreign\ AI\ patents_{ct} = \sum_{j \neq c} w_{cj} \times AI\ Patent_{jt}$, that is a weighted average of foreign AI patents, where the weight $(\mathrm{w_{cj}})$ is the share of bilateral trade between country *c* and *j* in total country *c*'s trade in 1999 (as pre-sample trade weight). The bilateral trade weights are calculated based on data from the CEPII gravity database (Conte et al, 2022). We use (pre-sample) fixed weight following the international macroeconomic literature to mitigate endogeneity issues related to potential simultaneous feedback or reverse causality.

Trade openness can raise labor productivity (Alcalá and Ciccone, 2004) while also stimulating innovation. It boost domestic innovation through both the import channel or learning-by-importing where imports of goods and technologies introduces new knowledge and stimulate learning through adaptation (see for instance Chen et al., 2024) and through export channel or learning-by-exporting where firms are incentivized to innovate in order to compete in foreign markets (see Grossman and Helpman, 1991). These considerations also motivate using bilateral trade weights to compute a proxy for AI innovation spillovers. While the existence of AI technology spillovers to local productivity is beyond the scope of this paper, the aim here is mainly to control for potential confounding effect of AI innovation taking place elsewhere.

Table 3 below shows the results controlling for these variables. Overall, the baseline results are not qualitatively altered in the fact that the new estimates support a positive effect of AI innovation on labor productivity, with larger effects.[20] For instance, GMM estimates for the full period show an estimated impact of 1.7 percent increase in labor productivity compared to 1.2 percent estimate in the baseline following the average growth rate in AI patent application in the sample. Fixed effects estimates, on the other hand, remain broadly similar to baseline estimates. Finally, the evidence shown in Table 3 also points to some broadly positive spillovers from AI innovation in other OECD countries to domestic labor productivity.

[20] While there could be other potential omitted variables from the empirical analysis, the inclusion of these key controls outside the basic production function should help mitigate endogeneity concerns at least partly.

Table 3: AI Technology and Labor Productivity – Robustness Checks

	Fixed Effects			GMM System			Bootstrap Estimator		
	Periods								
	2000-2017	2000-2008	2009-2017	2000-2017	2000-2008	2009-2017	2000-2017	2000-2008	2009-2017
Log Output per employee (t-1)	0.814***	0.770***	0.674***	0.796***	0.809***	0.528***	0.872***	0.898***	0.861***
	(0.026)	(0.043)	(0.046)	(0.045)	(0.024)	(0.040)	(0.026)	(0.049)	(0.108)
AI Patents (Log)	**0.006***	**0.008**	**0.007***	**0.013*****	**0.007****	**0.012*****	**0.006**	**0.007**	**0.009***
	(0.003)	**(0.005)**	**(0.004)**	**(0.005)**	**(0.003)**	**(0.004)**	**(0.004)**	**(0.007)**	**(0.005)**
Other Patents (Log)	0.018**	0.013	0.003	0.017	0.018**	0.034**	0.013*	0.009	0.003
	(0.007)	(0.008)	(0.014)	(0.013)	(0.007)	(0.014)	(0.008)	(0.010)	(0.018)
Δ Employment (Log)	-0.006***	-0.007***	-0.003*	-0.006***	-0.007***	-0.002*	-0.005***	-0.006*	-0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.003)
Δ Capital Stock (Log)	0.010***	0.014***	0.014***	0.005**	0.005***	0.013***	0.010***	0.012*	0.011**
	(0.002)	(0.004)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.006)	(0.005)
Human capital	-0.029	-0.047	0.113	0.045	0.015	0.087	-0.005	-0.009	0.090
	(0.032)	(0.092)	(0.087)	(0.050)	(0.029)	(0.061)	(0.042)	(0.084)	(0.087)
Foreign AI patents (Log)	0.029	0.026	0.008	0.196**	0.035	0.121*	0.024	0.009	-0.005
	(0.023)	(0.023)	(0.035)	(0.098)	(0.031)	(0.063)	(0.028)	(0.031)	(0.042)
Trade openness	0.001**	0.001***	0.001**	0.002***	0.001***	0.002***	0.001*	0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Countries	38	38	38	38	38	38	38	38	38
R-squared	0.83	0.73	0.67						
P-value AR(1)				0.00	0.00	0.00			
P-value AR(2)				0.58	0.24	0.61			
P-value Hansen				0.71	0.76	0.92			
Observations	684	342	342	684	342	342	646	304	304

Notes: The Bootstrap estimator is the bootstrap-based bias-corrected fixed effect (Everaert and Pozzi, 2007) with 500 replications. The related estimates are robust to misspecifications. Clustered standard errors, robust standard errors and bootstrapped standard errors for fixed effects, system GMM and the bootstrapped estimators are respectively in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

III. Conclusion

This paper exploits patents data covering 38 OECD countries over the period 2000- 2017 and relies on an empirical approach derived from a production function augmented with a knowledge stock to investigate the impact of innovations in AI technology on aggregate labor productivity. We find that AI technology has a moderate positive impact on aggregate labor productivity. Further, the paper shows heterogeneity both across time and the structure of the labor market. More specifically, labor productivity gains were more significant post-GFC as AI technology boomed, and in countries with a larger share of professional and managers in their labor force. These suggest that productivity gains could be larger in the future as the pace of innovation in AI gains new speed and spreads to further sectors of the economy (as AI technology matures). Further, the finding on the impact of the share of professional and managers, an occupation group highly exposed to, but also with high complementarity with AI technology, lends some support to the channel of task complementarity. Furthermore, gains from task complementarity may take time to materialize as workers learn to fully appropriate the technology. Finally, labor market flexibility could also shape productivity gains by supporting workers' mobility.

The paper provides novel estimates of aggregate productivity gains of AI technology and thus an assessment of macro-criticality but still represents a first pass on a broader research agenda. Important questions remain to be answered in future research as more data becomes available. For instance, how could other dimensions of the labor market structure, including skill composition shape aggregate productivity gains from AI technology? A longer sample period including recent developments in Generative AI could also be an important next step. An important area also relates to how to reconcile large estimates at microeconomic level with more moderate aggregate productivity estimates at the macroeconomic level. Granular data on AI patents across sectors of the economy could also provide more insight into the impact of the technology on productivity. Further, understanding potential implications for developing countries is also an important area for future work including the importance of digital infrastructure (see for instance Gmyrek et al, 2024 stressing that the digital divide is a major barrier to realizing the positive impact of AI technology) and potential negative spillovers through the loss of their labor-cost advantage (see Korinek and Stiglitz, 2021).

Annex

Table A1: Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Output per employee (Log)	684	11.172	0.393	9.965	12.177
Output per hour worked (Log)	684	5.438	1,565	1.876	9.313
AI patents (Log)	684	1.882	1.874	0.000	7.182
Other patents (Log)	684	6.173	2.388	0.861	11.107
Δ Employment (Log)	684	0.801	1.438	-7.437	6.145
Δ Capital Stock (Log)	684	2.621	1.654	-1.160	9.299
Labor market flexibility	684	0.635	0.160	0.276	1.000
Professionals and Managers (% employees)	648	10.840	3.076	4.100	16.062
Foreign AI patents (Log)	684	4.857	0.672	3.746	7.060
Human capital	684	3.180	0.399	1.997	3.807
Trade openness	684	91.360	52.299	19.560	353.794

Table A2: Data source

Variable	Definition	Data Source
Output per employee (Log)	Logarithm of Output-side real GDP at chained PPPs (in mil. 2017US$) per employee	Penn World Table (PWT) 10.01 and calculation
Output per hour worked (Log)	Logarithm of Output-side real GDP at chained PPPs (in mil. 2017US$) per hour worked	PWT 10.01 and calculation
AI patents (Log)	Logarithm of the number of AI-related patents	OECDSTAT and calculation
Other patents (Log)	Logarithm of the difference between total patents and the number of AI-related patents	OECDSTAT and calculation
Δ Employment (Log)	Fist difference of the logarithm of the number of persons employed	PWT 10.01
Δ Capital Stock (Log)	First difference of the logarithm of real capital stock	PWT 10.01
Labor market flexibility	Labor market regulation index	Fraiser Institute
Professionals and Managers (% employees)	Professional and managers in total employment from OECDSTAT (World Indicators of Skills database)	OECDSTAT and calculation
Foreign AI patents (Log)	Logarithm of the average patents in the trade partners countries (weighted by bilateral trade share)	OECDSTAT, CEPII Gravity data and calculation
Human capital index	Human capital index	PWT 10.01
Trade Openness	Total trade as share of GDP	World Development Indicators

Note: Patent data from OECDSTAT was extracted on May 09, 2024 while data on Professionals and Managers were extracted on June 07, 2024.

Table A3: Taxonomy of AI-related Patents

IPC code	Description
G06F15/18	Learning machines
G06F17/20	Handling natural language data
G06F17/27	*Automatic analysis, e.g. parsing, orthograph correction, handling natural language data*
G06F17/28	*Processing or translating of natural language*
G06F17/30	Database structures for information retrieval
G06K9/00	Methods or arrangements for reading or recognizing printed or written characters or for recognizing patterns
G06K9/46	Extraction of features or characteristics of the image
G06K9/48	*by coding the contour of the pattern*
G06K9/50	*by analyzing segments intersecting the pattern*
G06K9/52	*by deriving mathematical or geometrical properties from the whole image*
G06K9/62	Methods or arrangements for recognition using electronic means
G06K9/64	*using simultaneous comparisons or correlations of the image signals with a plurality of references*
G06K9/66	*with references adjustable by an adaptive method, e.g. learning*
G06K 9/68	*using sequential comparisons of the image signals with a plurality of reference, e.g. addressable memory*
G06K 9/70	*the selection of the next reference depending on the result of the preceding comparison*
G06K 9/72	*using context analysis based on the provisionally recognized identity of a number of successive patterns*
G06K 9/74	Arrangements for recognition using optical reference masks
G06K 9/76	*using holographic masks*
G06K 9/78	Combination of image acquisition and recognition functions
G06K 9/80	Combination of image preprocessing and recognition functions
G06K 9/82	*using optical means in one or both functions*
G06N	Computer systems based on specific computational models
G06T1/40	General purpose image data processing using neural networks
G06T7/00	Image analysis
G06T7/20	Analysis of motion
G06T 7/207	*for motion estimation over a hierarchy of resolutions*
G10L15	Speech recognition

Source: Baruffaldi et al. (2020)

Table A4: AI Technology and Output per hour worked

	Fixed Effects		GMM System		Bootstrap Estimator	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Output per hour (t-1)	0.872***	0.911***	0.907***	0.942***	0.908***	0.900***
	(0.021)	(0.021)	(0.047)	(0.032)	(0.017)	(0.017)
AI Patents (Log)	**0.006***	**0.010*****	**0.012***	**0.013****	**0.007****	**0.010*****
	(0.003)	**(0.003)**	**(0.006)**	**(0.006)**	**(0.003)**	**(0.003)**
Other Patents (Log)	0.011	0.018*	0.009	0.011	0.006	0.004
	(0.007)	(0.009)	(0.015)	(0.022)	(0.007)	(0.008)
Δ Number of hours worked (Log)	-0.615***	-0.121	-0.536	-0.026	-0.535***	-0.524***
	(0.117)	(0.156)	(0.757)	(0.310)	(0.140)	(0.148)
Δ Capital Stock (Log)	0.016***	0.017***	0.015***	0.026***	0.015***	0.016***
	(0.002)	(0.002)	(0.005)	(0.004)	(0.002)	(0.002)
Post-GFC x AI Patents (Log)		-0.001		-0.000		-0.002
		(0.002)		(0.002)		(0.002)
Post-GFC		0.013		0.014		0.058***
		(0.009)		(0.012)		(0.014)
Countries	38	38	38	38	38	38
R-squared	0.88	0.96				
P-value AR(1)			0.00	0.00		
P-value AR(2)			0.12	0.09		
P-value Hansen			0.94	0.88		
Observations	684	684	684	684	646	646

Notes: The Bootstrap estimator is the bootstrap-based bias-corrected fixed effect (Everaert and Pozzi, 2007) with 500 replications. The related estimates are robust to misspecifications. Clustered standard errors (Fixed effects), robust standard errors (GMM system) and bootstrapped standard errors are in parentheses. * p<0.1, **p<0.05, *** p<0.01.

Countries in the sample:

Australia, Austria, Belgium, Canada, Switzerland, Chile, Colombia, Costa Rica, Czechia, Germany, Denmark, Spain, Estonia, Finland, France, United Kingdom, Greece, Hungary, Ireland, Iceland, Israel, Italy, Japan, Korea, Lithuania, Luxembourg, Latvia, Mexico, Netherlands, Norway, New Zealand, Poland, Portugal, Slovak Republic, Slovenia, Sweden, Türkiye, United States.

Figure A1: Large AI innovation shocks and Output Per Hour – The Role of Labor Market Characteristics

Notes: This figure shows the response of labor productivity to a large AI innovation shock (growth in AI patent at least at 75th percentile in the sample). The blue line shows the average impact (β^h), while the red line the impact of the shock, conditional on whether the labor market characteristic is the above sample median in the sample ($\theta^h + \gamma^h$). 90 percent confidence interval from Kraay and Driscoll standard errors in shaded areas.

References

Acemoglu, D. (2024). *The Simple Macroeconomics of AI* (No. w32487). National Bureau of Economic Research.

Acemoglu, D., and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of economic perspectives*, *33*(2), 3-30.

Aghion, P., and Bunel, S. (2024). *AI and Growth: where do we stand*. Mimeo LSE.

Alcalá, F., & Ciccone, A. (2004). Trade and productivity. *The Quarterly journal of economics*, *119*(2), 613-646.

Alderucci, D., Branstetter, L., Hovy, E., Runge, A., and Zolas, N. (2020, January). Quantifying the impact of AI on productivity and labor demand: Evidence from US census microdata. In *Allied social science associations—ASSA 2020 annual meeting*.

Bäck, A., Hajikhani, A., Jäger, A., Schubert, T., and Suominen, A. (2022). *Return of the Solow-paradox in AI?: AI-adoption and Firm Productivity*. Centre for Innovation Research (CIRCLE), Lund University.

Barro, R. J., and Lee, J. W. (2013). A new data set of educational attainment in the world, 1950–2010. *Journal of development economics*, *104*, 184-198.

Baruffaldi, S., van Beuzekom, B., Dernis, H., Harhoff, D., Rao, N., Rosenfeld, D., and Squicciarini, M. (2020). Identifying and measuring developments in artificial intelligence: Making the impossible possible.

Belderbos, R., Lokshin, B., and Sadowski, B. (2015). The returns to foreign R&D. *Journal of International Business Studies*, *46*, 491-504.

Blundell, R., and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115-143.

Blundell, R., and Bond, S. (2000). GMM estimation with persistent panel data: an application to production functions. *Econometric reviews*, *19*(3), 321-340.

Briggs, J. and D. Kodnani (2023). The potentially large effects of artificial intelligence on economic growth. Global Economics Analyst.

Brynjolfsson, E., Li, D., and Raymond, L. R. (2023). *Generative AI at work* (No. w31161). National Bureau of Economic Research.

Calvino, F. and Fontanelli, L. (2023a), "A portrait of AI adopters across countries: Firm characteristics, assets' complementarities and productivity", OECD Science, Technology and Industry Working Papers, No. 2023/02, OECD Publishing, Paris,

Calvino, F., and Fontanelli, L. (2023b). *Artificial intelligence, complementary assets and productivity: evidence from French firms* (No. 2023/35). LEM Working Paper Series.

Chen, Z., Yi, J., and Huang, J. (2024). Detecting learning from importing: The effect of importing behaviour on R&D expenditures of Chinese firms. *The World Economy*, *47*(7), 3244-3278.

Cloyne, J., C. Ferreira, M. Froemel, and P. Surico. (2023). “Monetary Policy, Corporate Finance and Investment.” *Journal of the European Economic Association*

Conte, M., P. Cotterlaz and T. Mayer (2022), "The CEPII Gravity database". CEPII Working Paper N°2022-05, July 2022.

Czarnitzki, D., Fernández, G. P., and Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization*, *211*, 188-205.

da Silva Marioni, L., Rincon-Aznar, A., and Venturini, F. (2024). Productivity performance, distance to frontier and AI innovation: Firm-level evidence from Europe. *Journal of Economic Behavior & Organization*, *228*, 106762.

Damioli, G., Van Roy, V., and Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, *11*, 1-25.

Dieppe, A. (Ed.). (2021). *Global productivity: Trends, drivers, and policies*. World Bank Publications.

Everaert, G., and Pozzi, L. (2007). Bootstrap-based bias correction for dynamic panels. *Journal of Economic Dynamics and Control*, *31*(4), 1160-1184.

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, *42*(12), 2195-2217.

Gmyrek, P., Winkler-Seales, H. J.,and Garganta, S. (2024*).* Buffer or Bottleneck? Employment Exposure to Generative AI and the Digital Divide in Latin America (No. 10863). The World Bank.

Grossman, G., and Helpman, E. (1991). Innovation and Growth in the World Economy. MIT Press.

Hall, B. H., Mairesse, J., and Mohnen, P. (2010). Measuring the Returns to R&D. In *Handbook of the Economics of Innovation* (Vol. 2, pp. 1033-1082). North-Holland.

Hall, B., Helmers, C., Rogers, M., and Sena, V. (2014). The choice between formal and informal intellectual property: a review. *Journal of Economic Literature*, *52*(2), 375-423.

Inaba, T., and   Squicciarini, M. (2017). ICT: A new taxonomy based on the international patent classification. OECD Science, Technology and Industry Working Papers, No. 2017/01.

Korinek, A., and Stiglitz, J. E. (2021). Artificial intelligence, globalization, and strategies for economic development (No. w28453). National Bureau of Economic Research.

Li, N and Noureldin, D. (2024) World Must Prioritize Productivity Reforms to Revive Medium-Term Growth. IMF Blog, April 2024

Lokshin, B., Belderbos, R., and Carree, M. (2008). The productivity effects of internal and external R&D: Evidence from a dynamic panel data model. *Oxford bulletin of Economics and Statistics*, *70*(3), 399-413.

Montiel Olea, J. L., and Plagborg-Møller, M. (2021). Local projection inference is simpler and more robust than you think. Econometrica, 89(4), 1789-1823.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, 1417-1426.

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of ai on developer productivity: Evidence from github copilot. *arXiv preprint arXiv:2302.06590*.

Pizzinelli, C., Panton, A. J., Tavares, M. M. M., Cazzaniga, M., and Li, L. (2023). *Labor market exposure to AI: Cross-country differences and distributional implications*. International Monetary Fund.

Psacharopoulos, George (1994), “Returns to investment in education: A global update” World Development 22(9): 1325–1343

PUBLICATIONS

Artificial Intelligence and Aggregate Labor Productivity: Evidence from Patent Data

Working Paper No. WP/2026/204