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Artificial intelligence and productivity: global evidence from AI patent and bibliometric data

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ABSTRACT

In this paper we analyse the relationship between technological innovation in the artificial intelligence (AI) domain and macroeconomic productivity. We embed recently released data on patents and publications related to AI in an augmented model of productivity growth, which we estimate for the OECD countries and compare to an extended sample including non-OECD countries. Our estimates provide evidence in favour of the modern productivity paradox. We show that the development of AI technologies remains a niche innovation phenomenon with a negligible role in the officially recorded productivity growth process. This general result, i.e. a lack of a strong relationship between AI and registered macroeconomic productivity growth, is robust to changes in the country sample, in the way we quantify labour productivity and technology (including AI stock), in the specification of the empirical model (control variables) and in estimation methods.

1. Introduction

This paper evaluates the role played by technological innovations in the artificial intelligence (AI)[1] domain in the productivity growth process. The starting point for our analysis is the observation of a significant slowdown in the rate of productivity growth worldwide. This is visible in advanced economies such as the OECD countries (OECD, 2021a), the USA (Byrne et al., 2016) and the UK (Crafts and Mills, 2020) but also in emerging markets.[2] Obviously, the very recent economic slowdown (i.e. since 2019) can largely be attributed to the Covid-19 pandemic, when real GDP declined by 3.4% worldwide in 2020 (OECD, 2022) and the recovery, which generated large imbalances between and within countries (World Bank, 2021a), was delayed by a new set of adverse shocks due to the war in Ukraine (OECD, 2022). However, looking from a longer perspective, the tendency of weak productivity growth is surprising, especially if one takes into account the breakthrough innovations and impressive pace of technological progress in recent decades. In particular, how is it possible that there is no *acceleration* in productivity growth given that at the same time a striking advance can be observed in digital technologies[3] using advanced software, robots, AI, machine learning and cloud computing? Since the 1980s, the world's technological capacity to store, communicate and compute information has exploded (Hilbert and López, 2011). The volume of data, processing power and bandwidth double every 2–3 years, while global production only doubles every 20–30 years (Growiec, 2022a: 1732). Acceleration in AI technologies has been widely documented (Tseng and Ting, 2013;

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[1] We follow the OECD Council on Artificial Intelligence's definition of AI as a "(…) *machine based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy*" (Baruffaldi et al., 2020: 11). AI solutions are capable of learning and improving while ICT software is typically pre-programmed.

[2] According to data reported by The Conference Board (2022), in mature economies (including the US, the EU and Japan) GDP per hour worked only grew by 1.1 per cent a year in 2011–2019 (compared to 2.1 per cent a year in the pre-2008 crisis period, i.e. 2000-2007). Productivity growth in major emerging economies (including China) also slowed down, from 5.2 per cent a year in 2000–2007 to 4.8 per cent a year in 2011–2019. In 2022 output per hour worked is forecast to decline by 0.2 cent in mature economies and grow by 1 per cent in emerging economies (The Conference Board, 2022).

[3] We use the term 'digital technologies' to refer to broadly understood ADP (Advanced Digital Production) technologies defined as "*technologies that combine hardware (advanced robots and 3D printers), software (big data analytics, cloud computing and artificial intelligence) and connectivity (the Internet of Things)*" (UNIDO, 2019, Industrial Development 2020 main report: xvi). Artificial intelligence technologies (AI) are therefore part of the ADP or technologies related to the so-called fourth industrial revolution (4IR), which is characterised by a fusion of technologies blurring the lines between the physical, digital and biological spheres (Schwab, 2017).

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WIPO, 2019; IPO, 2019; Fujii and Managi, 2018; Van Roy et al., 2020; OECD. AI, 2022; USPTO, 2020). In 2016, OECD countries reported 34 times as many AI patent applications than in 1985 (for comparison, the total number of patents and publications had tripled (OECD, 2021c; see Section 3 for more detailed evidence). In the US between 2002 and 2018 the annual number of AI patent applications increased by more than 100% while the share of AI patent applications grew from 9% to 16% (USPTO, 2020). Nevertheless, pro-growth effects of "the second machine age" (Brynjolfsson and McAfee, 2014; Bughin et al., 2018; Aghion et al., 2019) are not reflected in productivity records.

The slowdown in the productivity growth rate registered in official statistics despite impressive developments in the digital sphere has become an intriguing theme in economic research (Brynjolfsson et al., 2019, 2021; Byrne et al., 2016; Crafts, 2018; Gal et al., 2019; Syverson, 2017; van Ark, 2016; Venturini, 2022). The phenomenon has been named the 'modern productivity paradox' (i.e. negligible productivity growth with simultaneous dramatic technological progress – Brynjolfsson, 1993), echoing Solow's popular claim "*You can see the computer age everywhere but in the productivity statistics*" (Solow, 1987, p. 36). Given the size of the AI market[4] (Righi et al., 2022; OECD. AI, 2022; Dalla Benetta et al., 2021), its expansion in terms of AI-related patents and publications (Zhang et al., 2022) and expectations related to the growth potential of AI technologies (Purdy and Daugherty, 2016; Bughin et al., 2018), weak productivity records are a source of disappointment.

The key motivation for our study comes from this still unresolved productivity puzzle but our contribution is based on an explicit focus on AI technology production assessed from a broad cross-country perspective. Using data on AI patent applications and AI publications we focus strictly on the AI production effect, i.e. the effect associated with the development of AI technologies and related technological knowledge.[5] We focus on AI because an overwhelming part of the existing evidence on the impact of modern technologies on productivity relies on ICT data (Jorgenson et al., 2008; van Ark et al., 2008; Inklaar et al., 2005; Timmer and Van Ark, 2005; Oliner et al., 2007; Acemoglu et al., 2014; Pieri et al., 2018) or, more recently, on automation statistics concerning the use of robots (Ballestar et al., 2020; Kromann et al., 2020; Acemoglu et al., 2020; Graetz and Michaels, 2018; Koch et al., 2021; Van Roy et al., 2020). Although it is developing, AI-focused research on the productivity-technology nexus is still scant, mainly due to methodological challenges related to the conceptualisation and measurement of highly intangible technological solutions such as AI. However, noticeable progress in this sphere (Baruffaldi et al., 2020; EPO, 2020; OECD. AI, 2022; USPTO, 2020; Zhang et al., 2022) has opened new ground for AI-productivity research. Another research gap which we fill is related to the incomplete international picture: the modern productivity paradox has been documented for well-developed economies such as the US, Germany and the UK (Byrne et al., 2016; van Ark, 2016; Elstner et al., 2018) and a sample of industrialised countries (Venturini, 2022). To the best of our knowledge, no studies have assessed the macroeconomic productivity-AI nexus in a setting which (i) uses both AI patent and AI bibliometric data and (ii) compares trends in the industrialised (here, the OECD) and non-industrialised worlds. This paper addresses these research gaps.

Following other studies using patent data in a macroeconomic context (Frietsch, 2014; Venturini, 2022), our analysis builds on a key assumption that AI technology production is reflected in the number of AI patent applications and additionally AI scientific publications (EPO, 2020; Tseng and Ting, 2013; USPTO, 2020). We use the latest methodological advances in the measurement of AI progress and employ information on AI-related patents (from OECD, 2021c) and AI-related scientific publications (from Elsevier/Scopus – Zhang et al., 2021) in an augmented model of productivity growth, which we estimate for OECD and non-OECD countries from the mid-1980s onwards.

The remainder of the paper is structured as follows. Section 2 provides a review of the literature on the role of digital technologies, including AI, in productivity growth. Section 3 presents the empirical setting – the data and key international evidence on AI technology production (patents and publications) and productivity developments. Estimates of the productivity growth model are described and discussed in Section 4 and the last section concludes.

Table 1
Shares of AI patents/AI scientific publications in all patents/all scientific publications (%), 1985–2017.

	A. Share of AI patents in all patents – by applicants		B. Share of AI patents in all patents – by inventors		C. Share of AI publications[a] in all publications	
	OECD	non-OECD	OECD	non-OECD	OECD	non-OECD
1985	0.18	0.00	0.17	0.00	–	–
1990	0.57	0.10	0.57	0.09	–	–
1995	0.49	0.10	0.49	0.13	0.68[b]	1.07[b]
2000	0.89	0.40	0.89	0.51	0.71	1.16
2005	0.94	0.45	0.93	0.53	0.94	1.80
2010	1.14	0.88	1.12	0.99	0.87	1.98
2017	1.80[c]	2.17[c]	1.78[c]	2.28[c]	1.38	2.16

Note: The list of countries can be found in Appendix A(Table A1).
Source: Authors' elaboration using data from OECD (2021c) and Scopus/Elsevier data from Zhang et al. (2021).
[a] Data available from 1998 onwards.
[b] Data for 1998.
[c] Last available data for 2016 – see footnote 7.

2. Digital technologies and productivity – a literature review

For a long time technological progress has been viewed as a key element in economic growth (Solow, 1956; Romer, 1990; Jones, 1995; Aghion and Howitt, 1992) either by improving the physical capacity and productivity of labour or with growth-enhancing innovations generated by R&D (Romer, 1990; Jones, 2005). Historically, big technological breakthroughs like the steam power revolution and electrification accompanied productivity growth (Crafts, 2004; Schurr et al., 1960) so similar hopes have arisen in the digital era. The widely documented rise in automation and digital technology, including AI (Hilbert and López, 2011; Tseng and Ting, 2013; WIPO, 2019; IPO, 2019; Fujii and Managi, 2018; Van Roy et al., 2020; OECD. AI, 2022; USPTO, 2020; Zhang et al., 2022) has led to both concerns about potential negative effects on labour (mainly via the human replacement effect, Acemoglu and Restrepo, 2018) and enthusiasm about its ability to boost growth (Brynjolfsson and McAfee, 2014; Bughin et al., 2018; Aghion et al., 2019). In the extreme case, "*rapid growth in computation and artificial intelligence will cross some boundary or singularity after which economic growth will accelerate sharply as an ever-accelerating pace of improvements cascade through the economy*" (Nordhaus, 2021: 299).

[4] As the OECD.AI Policy Observatory reported, worldwide venture capital (VC) investment in AI rose from 3220 million USD in 2012 to 194,414 million USD in 2021. The number of annual VC AI investments in 2021 was 10 times higher than a decade before, while the median AI investment size increased fivefold. The EU invested between €7.9 billion and €9 billion in AI in 2019 (Dalla Benetta et al., 2021) and is likely to exceed its annual AI investment target of €22 billion by 2030 (Righi et al., 2022).

[5] The production effect of more broadly defined 4IR technologies has been analysed at the macro level by Venturini (2022) and at the micro level by Benassi et al. (2022). An alternative mechanism, not investigated in our study, deals with the adoption effect quantified by the number of installations of robots (Ballestar et al., 2020; Kromann et al., 2020; Acemoglu et al., 2020; Graetz and Michaels, 2018) or by trade in capital goods embodying 4IR technologies (robots, 3D printers or numerically controlled machines) capturing technology diffusion and so adoption across countries (Foster-McGregor et al., 2019; Castellani et al., 2022).

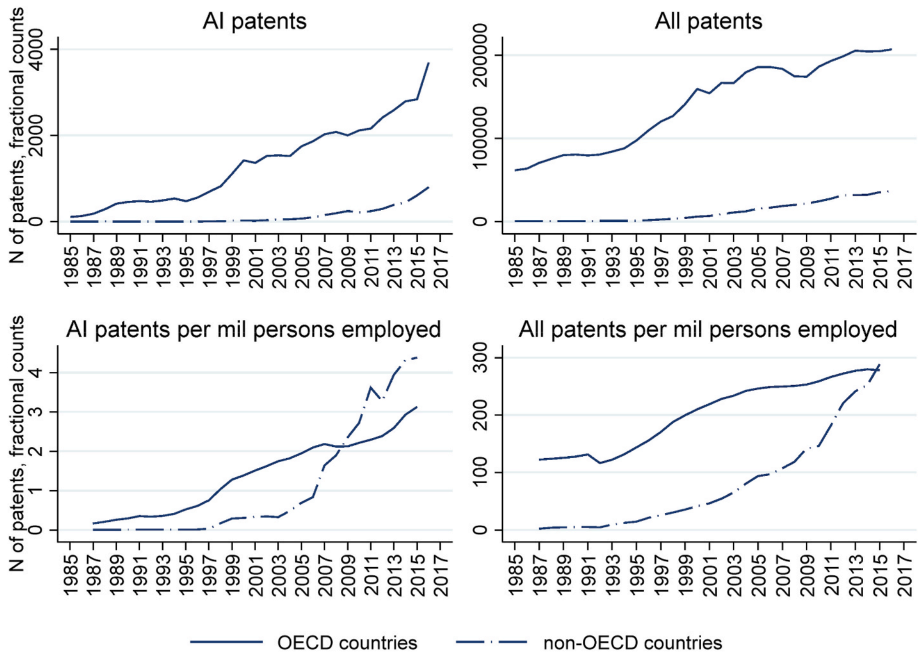

Fig. 1. Numbers of patents (AI and all) by applicants, OECD and non-OECD countries, 1985-2016
Note: The scales in the four graphs differ. 5-period moving average for patents expressed in millions of persons employed. The list of countries can be found in Appendix A (Table A1).
Source: Authors' elaboration using data from OECD (2021c).

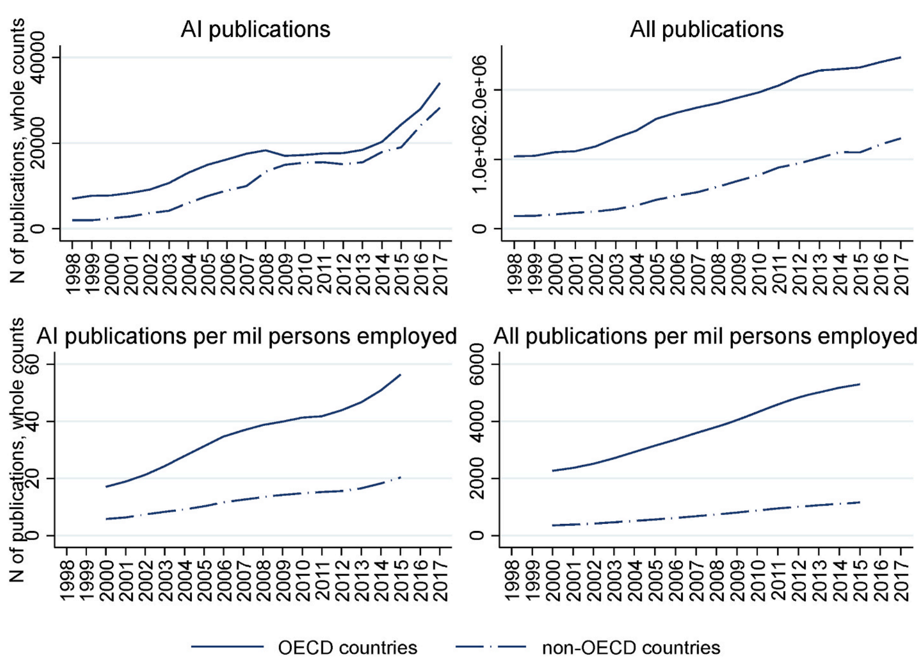

Fig. 2. Numbers of scientific publications (AI and all), OECD and non-OECD countries, 1998-2017
Note: The scales in the four graphs differ. 5-period moving average for patents expressed in millions of persons employed. The list of countries can be found in Appendix A (Table A1).
Source: Authors' elaboration using Scopus/Elsevier data from Zhang et al. (2021).

Table 2
Correlations between AI patents/AI scientific publications and labour productivity.

	AI patents		AI publications[a]		AI patents per person employed		AI publications per person employed[a]	
	OECD	OECD & non-OECD	OECD	OECD & non-OECD	OECD	OECD & non-OECD	OECD	OECD & non-OECD
A. Labour productivity - *level* [PPPs in 2017 US$ per hour worked]	0.147*	0.199*	0.224*	0.120*	0.334*	0.428*	0.397*	0.601*
B. Labour productivity *growth* [annual rate of growth, in %]	−0.075*	−0.069*	−0.071*	0.016	−0.055	−0.102*	−0.093*	−0.119*

Note: * denotes significance at the 10% level. For the list of countries, see Appendix A (Table A1).
Source: Authors' elaboration using data from OECD (2021c), Elsevier/Scopus (Zhang et al., 2021) and PWT 10.0.
[a] Data available from 1998 onwards.

Models of automation[6] with endogenous technological progress conceptualise the contribution of intangible technologies, such as AI, to growth. They assume that some (or even all) tasks, including R&D, can be automated (Zeira, 1998; Acemoglu and Restrepo, 2018; Aghion et al., 2019; Growiec, 2020, 2022a). The importance of AI for growth can be modelled through reinterpretation of the knowledge production function (Jones, 1995) with breakthroughs in AI enhancing discovery rates and boosting economic growth (Agrawal et al., 2019). However, the related empirical literature focuses on the puzzling mismatch between expectations related to the development and use of digital technologies and their poor reflection in productivity records (Crafts, 2018). The modern productivity paradox (see, among many others, Brynjolfsson et al., 2019, 2021; Polák, 2017; Acemoglu et al., 2014) is a redux of the information technology productivity paradox of the late 1980s (Brynjolfsson, 1993). A significant drop in the productivity growth rate observed in parallel with increasing spending on new digital technologies and decreasing prices of them has been identified in such mature economies as the US, the UK and Germany (Byrne et al., 2016; van Ark, 2016; Elstner et al., 2018) and may be part of a "secular stagnation" (Haskel and Westlake, 2017).

Among the alternative explanations of the modern productivity paradox, we find a "mismeasurement hypothesis" (Syverson, 2017; Byrne et al., 2016; Elstner et al., 2018) of underestimation of real GDP, productivity and income growth in the technologically advanced age (Watanabe et al., 2018). Intangible assets are difficult to capture in national accounts and their omission may have led to serious underestimation of changes in output per worker (Corrado et al., 2009, 2021). A similar problem relates to the magnitude of AI investment, which is also likely to be mismeasured (Gordon, 2018). Indeed, collection and discussion of AI statistics, especially in the international context, are difficult as AI is a cross-cutting technology likely to be improperly captured by existing classifications of products and economic activities (Righi et al., 2022: 9). Nevertheless, while differences in AI levels are present in different studies, the growth in AI investment activity has been documented worldwide (e.g. Righi et al., 2022; EU AI investments report – Dalla Benetta et al., 2021; OECD. AI, 2022).

An alternative explanation of the paradox conceptualised through the J-curve hypothesis (Brynjolfsson et al., 2019, 2021) relates to the time lag between technological progress and the commercialisation of new innovative ideas, often relying on complementary investments typical of general-purpose technologies (GPTs, Bresnahan and Trajtenberg, 1995). The productivity J-curve illustrates the productivity slowdown accompanying the advent of GPTs: "*total factor productivity growth will initially be underestimated because capital and labor are used to accumulate unmeasured intangible capital stocks. Later, measured productivity growth overestimates true productivity growth because the capital service flows from those hidden intangible stocks generate measurable output*" (Brynjolfsson et al., 2021: 334). Empirical evidence on the time pattern of productivity spillovers associated with digital technologies is mixed. It either supports the J-curve view (US: Brynjolfsson et al., 2021; Japan: Miyagawa et al., 2021; industrialised countries: Venturini, 2022) or finds arguments against it (Corrado et al., 2021 on 11 European countries and the US). Technological pessimists argue that growth at the technological frontier has slowed down because it is harder and more expensive to find new good ideas (Bloom et al., 2020).

Many studies have attempted to estimate the productivity effects of the digital revolution but most of them refer to digital technologies before AI (namely, ICT: see, among many others, Jorgenson et al., 2008; van Ark et al., 2008; Inklaar et al., 2005; Timmer and Van Ark, 2005; Oliner et al., 2007; Acemoglu et al., 2014; Ceccobelli et al., 2012). In general, the contribution of ICT capital to growth has been lower in the EU than in the US (Inklaar et al., 2005), where information technology played a critical role in the post-1995 productivity resurgence (Jorgenson et al., 2008) and contributed to the Atlantic divide (Van Ark et al., 2008, 2019; Timmer and Van Ark, 2005). In most OECD countries (the focus of our study) the contribution of ICT to growth was rather disappointing (Pilat et al., 2003) and, as Ceccobelli et al. (2012) argued, acted as GPT requiring complementary investments and temporal lags to lead to productivity benefits. The picture is more optimistic once the effect of ICT in OECD countries is analysed jointly with the effects of R&D activity accelerating technical change and generating spillovers within sectors (Pieri et al., 2018).

Some (fewer) studies explicitly focus on the productivity effects of robotisation. Graetz and Michaels (2018) analyse a panel of industries in seventeen countries (1993–2007) and find that increased use of robots contributes approximately 0.36 percentage points to annual labour productivity growth, while Kromann et al. (2020) document that an increase of one standard deviation in robot intensity is associated with even 6% higher total factor productivity (in a sample of nine advanced countries and 10 manufacturing industries, 2004–2007). In addition, firm-level studies (such as Koch et al., 2021 and Ballestar et al., 2020 on firms in Spain and Acemoglu et al., 2020 on French companies) find a significant impact of robot adoption on productivity.

The literature focusing explicitly on the AI-productivity nexus is still in its infancy, mainly due to methodological challenges related to the measurement of highly intangible AI solutions and their overlap with ICT. Recent attempts to quantify AI-based technological progress draw on bibliometric or patent records (Baruffaldi et al., 2020), replicating the well-established use of patent data as a general indicator of innovation (among others, see Griliches, 1990; Archibugi and Pianta, 1992; Frietsch et al., 2014; Jaffe and Trajtenber, 2005). Paradoxically, the development of AI and advanced machine learning techniques have enabled more accurate quantification of patent activity in specific technological domains, such as AI (USPTO, 2020). Qualitative factors have been incorporated in time-consuming search techniques detecting AI-related patents via classification codes (such as Cooperative Patent Classification (CPC) and analogous UPC/IPC – Tseng and Ting, 2013)

[6] Growiec (2022a) points out that the distinction between mechanisation (the replacement of human physical work by machines), automation (the replacement of human cognitive work by pre-programmed software) and AI (i.e. software capable of learning and improving) is crucial.

Table 3
The relationship between AI technology production (AI patents by applicants) and labour productivity growth, OECD countries.

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Number of patent applications[a]		Patent stock					
	OLS				IV-GMM[b]		IV-GMM[c]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.055***	−0.061***	−0.088***	−0.109***	−0.099***	−0.119***	−0.138***	−0.265***
	(0.014)	(0.017)	(0.025)	(0.030)	(0.021)	(0.024)	(0.028)	(0.046)
$\Delta\ln\left(\frac{K}{L}\right)$	0.375***	0.391***	0.395***	0.418***	0.363***	0.386***	0.149	0.193*
	(0.079)	(0.081)	(0.100)	(0.094)	(0.088)	(0.087)	(0.112)	(0.113)
$\ln\left(\frac{AI\ Pat}{L}\right)$	0.003	0.002						
	(0.002)	(0.002)						
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$			0.001	0.001	−0.001	−0.001	−0.005	0.000
			(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
$\ln(GI)$		0.006		0.016**		0.016***		0.030***
		(0.006)		(0.008)		(0.006)		(0.008)
N	736	736	746	746	720	720	260	260
N of countries	34	34	33	33	33	33	16	16
R-squared	0.406	0.410	0.304	0.312	0.310	0.318	0.420	0.453
K-P rk LM (p-val)					0.000	0.000	0.000	0.000
K-P rk Wald F					550.6	270.7	121.5	86.89
Hansen J (p-val)							0.304	0.244

Notes: *, ** and *** denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors are provided in parentheses. All specifications contain country and time fixed effects. K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per hour worked.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.
[a] Estimations are based on a 5-period moving average.
[b] Patents are instrumented with their first lag.
[c] Patents are instrumented with the instrument described in Section 4.1 and supported by the first lag of the explanatory variable.

and/or by screening patent descriptions for AI-related keywords (EPO, 2020). This approach has been used at the micro level by Benassi et al. (2022), who show a positive and significant relationship between firm productivity and the accumulated stock of the fourth industrial revolution (4IR) technological knowledge. A similar conclusion is reached by Damioli et al. (2021), who confirm a positive and significant impact of AI patent applications on labour productivity in a worldwide sample of AI patenting firms. Additionally, Bassetti et al. (2020) find that firms that are successful at obtaining a greater number of AI patents tend to increase not only total factor productivity but also wages. In addition, the adoption of digital technologies in an industry can be associated with productivity gains at the firm level (Gal et al., 2019).

Macro-level studies relying on patent data describe the global landscape of AI technology document its impressive rise since the 1990s, which was accompanied by extreme geographical concentration (WIPO, 2019; IPO, 2019; USPTO, 2020) with just a handful of players involved in intensive AI development (Dernis et al., 2019; Van Roy et al., 2020). Venturini (2022) documents that knowledge (patent stock) related to broadly defined "intelligent technologies" (corresponding to 4IR technology areas) accounts for 3%–8% of the observed productivity change in a sample of 32 industrialised countries (1990–2014). In the empirical analysis presented in the next sections we focus exclusively on the productivity effects of AI technology and compare patent and bibliometric data in a wider sample (OECD and non-OECD) and a longer time perspective.

3. The data and descriptive evidence

3.1. Dataset(s)

This paper compares the effect associated with the production of AI technologies (and the development of related technological knowledge – Venturini, 2022; Benassi et al., 2022) as recorded in patent applications (dataset 1: 35 OECD and 23 non-OECD economies, 1985–2016[7]) and in scientific publication records (dataset 2: 35 OECD countries and 28 non-OECD countries, 1998–2017) with growth in countries' productivity. In line with Righi et al. (2022:11), patent applications are used to address innovation capacity while AI publications serve as an additional proxy for involvement in frontier AI research. Information about the countries in particular samples is included in Appendix A, Table A1.

In the patent analysis, the number of AI patent applications comes from the OECD Science, Technology and Patents database (OECD, 2021c). The OECD provides separate data for such technology domains as ICT, artificial intelligence, nanotechnology, biotechnology and environment-related and health-related technologies. AI patents were identified using patent classification codes and keywords as is described in detail in Baruffaldi et al. (2020: 66–68).[8] We selected patents filed with at least two intellectual property offices (which belong to IP5 patent families[9]). These are presented according to the priority date.[10] In the benchmark analysis we use patent data identified by the *applicant's* country of residence (data by the *inventor's* country of residence are used in the robustness checks).[11] All the patent figures are based on fractional counts reflecting the contributions of applicants/inventors (by country)

[7] Patent data (OECD, 2021c) are available until 2017 but we follow the OECD practice (Baruffaldi et al., 2020: 53) and truncate the series in 2016 because the 2017 data are incomplete due to legal delays in publishing patent information.

[8] Given that AI can be related to the development of robotics, some of the AI-related keywords refer to robots (e.g. humanoid robot, human-robot interaction) but for the AI-patent search these words are only included in combination with IPC or CPC classes (Baruffaldi et al., 2020: 67) so overlaps should be limited. ICT is a separate category in the OECD (2021c) data.

[9] IP5 refers to the five intellectual property offices, i.e. the European Patent Office, the Japan Patent Office, the Korean Intellectual Property Office, the US Patent and Trademark Office and the State Intellectual Property Office of the People's Republic of China.

[10] The patent priority date reflects the first worldwide filing of an invention and is close to the invention date. IP5 patent families are only available according to priority date.

[11] The data by applicant allow us to take a closer look at the innovativeness of firms (legal patent application owners) in a given country regardless of the location of their research centres. Applicants have a legal right to exploit and commercialise an invention covered by a patent. Patents considered from the applicants' perspective should translate into country productivity growth more easily. The data by inventor, in turn, capture the innovativeness of a country's researchers and laboratories (OECD, 2021c).

Table 4
The relationship between AI technology production (AI patents by applicants) and labour productivity growth, full sample (OECD and non-OECD countries).

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Number of patent applications[1]		Patent stock					
	OLS				IV-GMM[2]		IV-GMM[3]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.034***	−0.051***	−0.062***	−0.089***	−0.065***	−0.091***	−0.075***	−0.124***
	(0.011)	(0.013)	(0.013)	(0.022)	(0.017)	(0.018)	(0.029)	(0.037)
$\Delta\ln\left(\frac{K}{L}\right)$	0.497***	0.506***	0.420***	0.442***	0.402***	0.429***	0.289***	0.266**
	(0.102)	(0.099)	(0.094)	(0.077)	(0.075)	(0.072)	(0.106)	(0.104)
$\ln\left(\frac{AI\,Pat}{L}\right)$	0.003*	0.000						
	(0.002)	(0.002)						
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$			0.001	−0.002	0.001	−0.003	0.004	0.001
			(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
$\ln(GI)$		0.013**		0.016*		0.017***		0.021**
		(0.007)		(0.010)		(0.005)		(0.008)
N	1046	1046	1000	1000	956	956	361	361
N of countries	57	57	52	52	51	51	22	22
R-squared	0.260	0.290	0.272	0.286	0.275	0.289	0.336	0.362
K-P rk LM (p-val)					0.000	0.000	0.000	0.000
K-P rk Wald F					711.4	294.5	315.2	176.7
Hansen J (p-val)							0.051	0.725

Notes: as under Table 3.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.

in cases of multiple authorship. To complete the research conclusions based on AI patent data, we also analyse the number of peer-reviewed AI scientific publications recorded in the Elsevier/Scopus database (Zhang et al., 2021).[12]

Apart from considering countries' annual AI technology production activity, we compute AI patent stock (and AI publication stock), AI^{ST}, which quantifies the knowledge (ideas) accumulated in the area of AI technologies (similarly to Venturini, 2022 and Benassi et al., 2022, who focus on 4IR technology patent stock). We employ the perpetual inventory method (Belderbos et al., 2022; Venturini, 2022) and use the formula $AI^{ST}_{i,t} = AI_{i,t} + (1-\delta)\times AI^{ST}_{i,t-1}$ with the initial value of AI^{ST} defined as $AI^{ST}_{i,t_0} = \frac{AI_{i,t_0}}{g_i+\delta}$, where g_i is the average rate of growth in a period analysed. Following Schankerman and Pakes (1986), we assume a depreciation rate δ of 15% (both for patents and publications), which is often used in patent research (Belderbos et al., 2022; Venturini, 2022).[13]

AI technology production data are matched with labour productivity measured in terms of output (GDP at chained PPPs in millions of 2017 US dollars) per hour worked, and alternatively per person employed in the robustness checks. The data come from Penn World Table 10.0 (PWT 10.0, Feenstra et al., 2015), which is also a source of capital stock (at constant 2017 prices in millions of 2017 US dollars) and labour force data.

Following the literature, we consider other country-specific factors that may affect productivity growth apart from AI. First, we follow Venturini (2022) and Damioli et al. (2021) and add a proxy for countries' general innovation incorporating overall patenting (OECD, 2021c) and scientific publication activity (Zhang et al., 2021). Next, given that regardless of country income the quality of human resources positively influences productivity (Miller and Upadhyay, 2000; Botev et al., 2019 on OECD), we consider human capital measured with average years of schooling (Barro and Lee, 2013) and assumed rate of return to education, based on Mincer equation estimates around the world (PWT 10.0, Feenstra et al., 2015). We then incorporate trade openness in the model (the sum of exports and imports of goods and services as a share of GDP from World Bank, 2021b) because productivity tends to benefit from countries' outward orientation (Buccirossi et al., 2013; Miller and Upadhyay, 2000). Finally, we also take into account the regulatory quality index in World Bank (2021c), which reflects the quality of governance and institutions, also important in the growth process (Acemoglu et al., 2005; Buccirossi et al., 2013).

3.2. Evidence of AI technology production

The acceleration in AI technology production is reflected in the increasing shares of AI patents and AI publications in all patents and publications (Table 1). Regardless of the way patents are attributed to countries (by applicants/inventors – the former is used in the benchmark analysis), in the OECD countries there is a clear increase in the share of AI patents – from as little as 0.18% (0.17% by inventors) in 1985 to 1.80% (1.78%) in 2016. In non-OECD countries, this increase is even higher as they started from scratch, but at the end of the period 2.17% (2.28%) of their patents concerned AI. Analysis of AI scientific publications (Table 1, column C) reveals that their importance among all publications also increased and, similarly to patent data, this is more visible in non-OECD countries (1.09 p. p. growth) than in OECD (0.70% p. p. growth).

Fig. 1 illustrates the boom in AI patenting activity in OECD countries since 1985.[14] Non-OECD countries started to be active in the field of AI patenting later, from 1999.[15] Compared to the growth rate of the total number of patents, the growth rate of AI patents in both OECD and non-OECD countries is much more intense. At the end of 2016, in OECD countries AI patenting activity was reflected in almost 3700 applications, which is 34 times more than in 1985. In the same period, the total number of patents only increased 3.3 times. The increase in AI patents in

[12] AI publication activity is identified in the Elsevier/Scopus database (Zhang et al., 2021) using papers' tags with keywords, publication dates, country affiliations and other bibliographic information. Elsevier's methodology of counting AI papers uses a bottom-up approach with about 800 keywords. The details of Elsevier's dataset defining AI, country affiliations and AI subcategories can be found in the 2018 AI Index Report Appendix (https://hai.stanford.edu/sites/default/files/2020-10/AI_Index_2018_Annual_Report.pdf).

[13] The 15% depreciation rate set by Schankerman and Pakes (1986) is representative of the rate of decay in returns from patent protection.

[14] The exact numbers of AI-related patents and publications may differ across studies due to methodological differences in AI-patent definitions and ways of AI activity identification. However, the general trend of increasing AI activity since 1980/the 1990s has been reported in numerous sources (Baruffaldi et al., 2020; Corrado et al., 2021; WIPO, 2019; Venturini, 2022; OECD.AI, 2022; USPTO, 2020).

[15] In 1999, the number of AI patents in non-OECD countries registered in the OECD (2021c) database exceeded 20 applications.

Table 5
The relationship between AI technology production (AI patents) and labour productivity growth, OECD countries and full sample (OECD and non-OECD countries) – estimations with control variables.

Dependent variable: Δln $\left(\frac{Y}{L}\right)$	OECD countries				OECD & non-OECD countries			
	Number of patent applications[1]	Patent stock			Number of patent applications[1]	Patent stock		
	OLS		IV-GMM[2]	IV-GMM[3]	OLS		IV-GMM[2]	IV-GMM[3]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.075***	−0.168***	−0.206***	−0.313***	−0.064***	−0.133***	−0.141***	−0.171***
	(0.014)	(0.026)	(0.041)	(0.064)	(0.014)	(0.031)	(0.029)	(0.043)
$\Delta\ln\left(\frac{K}{L}\right)$	0.326***	0.421***	0.388***	0.242*	0.310***	0.411***	0.365***	0.213**
	(0.108)	(0.091)	(0.119)	(0.124)	(0.103)	(0.086)	(0.097)	(0.095)
$\ln\left(\frac{AI\ Pat}{L}\right)$	0.002				0.001			
	(0.003)				(0.003)			
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$		0.005	0.008	0.002		0.002	0.005	0.006
		(0.005)	(0.007)	(0.007)		(0.004)	(0.005)	(0.006)
ln (GI)	0.012*	0.025**	0.028**	0.047***	0.021***	0.027***	0.022**	0.029**
	(0.007)	(0.010)	(0.012)	(0.013)	(0.006)	(0.009)	(0.010)	(0.011)
HC	−0.022	−0.032	−0.059	0.001	−0.019	−0.043*	−0.043	−0.080**
	(0.037)	(0.038)	(0.043)	(0.053)	(0.022)	(0.024)	(0.028)	(0.034)
Trade	0.000**	0.001**	0.001***	−0.000	−0.000	0.000	0.000	−0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RQ	−0.004	0.003	0.004	0.025**	−0.012	−0.009	−0.008	0.027**
	(0.010)	(0.015)	(0.012)	(0.012)	(0.009)	(0.015)	(0.013)	(0.013)
N	511	512	499	196	743	699	674	269
N of countries	34	33	33	16	55	50	49	21
R-squared	0.399	0.324	0.349	0.480	0.310	0.321	0.316	0.447
K-P rk LM (p-val)			0.000	0.000			0.000	0.000
K-P rk Wald F			75.41	37.95			81.15	59.56
Hansen J (p-val)				0.701				0.357

Notes: as under Table 3.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.

non-OECD countries is even more spectacular. In 1999, about 20 AI applications were filed. During the period analysed, that number increased 37 times and in 2016 it amounted to about 800 AI patents. The growing importance of these countries in AI patenting is also visible when we express patents as a share of employment. In non-OECD countries this share started growing intensively in 1999 and in 2009 it exceeded the analogous share recorded in OECD countries.

To complete this description of developments in AI technology production, the increase in the number of scientific publications related to AI is compared to the overall trend in scientific publication activity (Fig. 2). Due to limited data availability, the bibliometric analysis covers a shorter period (1998–2017) but it is sufficient to observe a rapid growth of the AI phenomenon. Both for OECD and non-OECD countries there are periods with more than 10% year-on-year increases in the number of AI publications (e.g. 2014 and 2017 in OECD countries and 2016–2017 in non-OECD countries). More importantly, the inclination of the lines clearly shows that while increases in the total number of publications are quite stable throughout the whole period, increases in AI scientific production became even faster after approximately 2013. Similarly to the absolute number of publications, the share per million persons employed also grew with comparative average growth rates of 8.3% in OCED countries and 8.8% in non-OECD countries (for all publications these average growth rates are 5.8% and 8.2% respectively).

Which economies are the leaders in the production of AI technology? Unsurprisingly, countries with higher levels of labour productivity tend to be more engaged in AI patenting and publication activity. This is confirmed by the positive and significant correlations between the levels of output per hour worked and AI patenting, both for OECD countries and the extended group of economies reported in Table 2 (row A). This is also visible when the number of AI patents is considered in relative terms, per person employed, and in this case the correlations are even stronger.

However, AI patenting correlates negatively with labour productivity growth (Table 2, row B), which contradicts the view that AI boosts macroeconomic productivity growth. This correlation is weak, however, and even close to null regardless of which group of countries is analysed. Similar observations are valid when the production of AI technologies is proxied by AI publications (overall and per person employed). The next step is a more complete analysis of the relationship between productivity growth and AI technology production.

4. AI and productivity growth – empirical analysis

4.1. The model and the estimation strategy

To derive the empirical equation linking AI activity with productivity growth, we use the basic country-level aggregate production function $Y = AF(K, L)$ as the point of departure. Output Y depends on total factor productivity A, and is a function F of capital K and labour L. Capital can be both physical (tangible, directly measurable) and intangible. Technological solutions derived from AI are difficult to measure (Corrado et al., 2009, 2021), so in line with Brynjolfsson et al. (2021), unmeasured intangible capital investments are considered, which once implemented provide inputs into the production function. In the setting presented, U mirrors the production of AI knowledge and is quantified in two ways – based on AI patent activity and AI scientific activity (see Section 3). The extended aggregate production function, $Y' = A'F'(K, U, L)$, which includes the intangible input U, serves to derive the empirical model. After dividing both sides of the formula by L, log-linearising it, and assuming that productivity growth tends to depend on past productivity levels (a beta convergence-type mechanism: Sala-i-Martin, 1996), we obtain the empirical model of labour productivity growth:

$$\Delta\ln\left(\frac{Y}{L}\right)_{it} = \beta_0 + \beta_1 \ln\left(\frac{Y}{L}\right)_{i,t-1} + \beta_2 \Delta\ln\left(\frac{K}{L}\right)_{it} + \beta_3 \ln\left(\frac{AI}{L}\right)_{it} + \beta_4 \ln Z_{it} + \mu_i + \upsilon_t + \varepsilon_{it} \quad (1)$$

The productivity growth $\Delta\ln\left(\frac{Y}{L}\right)$ for countries i and time periods t depends on lagged productivity levels $\ln\left(\frac{Y}{L}\right)$, growth of the capital to labour ratio $\Delta\ln\left(\frac{K}{L}\right)$, AI technology production $\ln\left(\frac{AI}{L}\right)$ resulting in the

Table 6
The relationship between AI technology production (AI scientific publications) and labour productivity growth, OECD countries.

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Number of scientific publications[a]		Publication stock					
	OLS				IV-GMM[b]		IV-GMM[c]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.055***	−0.059***	−0.119***	−0.125***	−0.143***	−0.149***	−0.145***	−0.144***
	(0.015)	(0.018)	(0.015)	(0.016)	(0.024)	(0.024)	(0.029)	(0.030)
$\Delta\ln\left(\frac{K}{L}\right)$	0.355**	0.351**	0.411***	0.414***	0.454***	0.456***	0.411***	0.411***
	(0.139)	(0.141)	(0.090)	(0.088)	(0.076)	(0.075)	(0.084)	(0.084)
$\ln\left(\frac{AI\,Pub}{L}\right)$	0.007***	0.003						
	(0.002)	(0.006)						
$\ln\left(\frac{AI^{ST}Pub}{L}\right)$			0.024***	0.014*	0.026***	0.013	0.024***	0.020**
			(0.005)	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)
$\ln(GI)$		0.010		0.027*		0.031***		0.014
		(0.015)		(0.015)		(0.011)		(0.013)
N	560	560	695	695	660	660	318	318
N of countries	35	35	35	35	35	35	18	18
R-squared	0.349	0.351	0.333	0.339	0.357	0.360	0.456	0.457
K-P rk LM (p-val)					0.000	0.000	0.000	0.000
K-P rk Wald F					400.7	180.8	531.9	214.3
Hansen J (p-val)							0.721	0.860

Notes: *, ** and *** denote significance at the 1%, 5% and 10% levels respectively. Robust standard errors are provided in parentheses. All specifications contain country and time fixed effects. K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per hour worked.
Source: Authors' elaboration using data from Elsevier/Scopus (Zhang et al., 2021) and PWT 10.0.
[a] Estimations are based on a 5-period moving average.
[b] Publications are instrumented with their first lag.
[c] Publications are instrumented with the instrument described in Section 4.1 and supported by the first lag of the explanatory variable.

creation of intangible input U and a set of other country-time specific characteristics (Z). Possible effects of new technology on productivity need time to materialise but we do not introduce a lagged AI variable due to significant delays in publication and patenting activity. The AI patents and publications observed in the data at time t actually correspond to earlier AI technology production.

In a benchmark estimation of equation (1), to measure $\left(\frac{Y}{L}\right)$ we consider labour productivity per hour worked (while productivity per person employed, is used in a robustness check). $\left(\frac{AI}{L}\right)$ is based on alternative indicators: the number of patents related to AI as a ratio with employment $\left(\frac{AI\,Pat}{L}\right)$, AI patent stock related to employment $\left(\frac{AI^{ST}\,Pat}{L}\right)$, the number of AI publications and AI publication stock both measured in relative terms, i.e. per million persons employed $\left(\frac{AI\,Pub}{L}\right.$ and $\left.\frac{AI^{ST}Pub}{L}\right)$. In the regressions containing the numbers of patents and the numbers of publications related to employment, the data series are smoothed with the aid of 5-period moving averages. The set of control variables Z consists of: the general innovativeness (GI) of countries (measured with the overall number of patents/publications related to employment),[16] human capital (HC), trade openness ($Trade$) and the institutional measure of regulatory quality (RQ) (described in Section 3.1); μ_i and ν_t control for all the remaining country- and time-specific fixed effects, and ε_{it} is a random term. A correlation matrix of all the explanatory variables is included in Table A2 in Appendix A while Table A3 contains summary statistics of the variables used in (1).

To confirm the benchmark results, we employ numerous robustness checks concerning five areas – the dependent variable, explanatory variables, the cross-sectional dimension (OECD countries and the extended sample including a set of non-OECD countries), the time dimension and estimation techniques. Concerning the estimation method, basic OLS is the starting point. Then we address the problem of endogeneity in AI technology production (potential reverse causality) and switch to instrumental variable (IV) estimation. It is difficult to find suitable instruments for AI and the related innovation literature instead offers by-passing solutions to this problem.[17] In a first step, we follow Damioli et al. (2021) and employ (i) first lags of patents and publications. In a second step we consider (ii) an external instrument based on the share of R&D expenditure in the engineering and technology fields, which are presumably the ones most related to AI (from OECD, 2021c), matched with total R&D expenses over GDP (from OECD, 2021d). R&D data by field is limited so this approach, unfortunately, significantly limits the sample size. In a third approach (iii) we use the average number of patent applications by countries belonging to the same income group, excluding the number of patent applications from a country of interest. Additionally (iv), we use an IV estimation with heteroskedasticity-based instruments proposed by Lewbel (2012). This method allows us to identify the structural parameters in a model with endogenous regressors if traditional identifying information, such as external instruments or repeated measurements, are absent. We test this kind of instrument, as well as (v) heteroskedasticity-based instruments supported by the first lags of patent applications/publications, and (vi) heteroskedasticity-based instruments supported by instrument built according to the third approach described above.

4.2. Results and discussion

According to the basic estimates of eq. (1) (reported in Table 3), in OECD countries the rate of labour productivity growth is negatively related to lagged levels of productivity (consistently with the beta convergence hypothesis) and positively related to capital deepening

[16] Alternatively, we have used the measure based on non-AI technologies instead of overall innovation. The estimation results are strongly robust and are available upon request.

[17] Firm-level studies often use lags. Benassi et al. (2022) exclude contemporaneous variables (using lags of patent-based explanatory variables) to reduce the problem of reverse causality. Bassetti et al. (2020) and Damioli et al. (2021) use lags of AI patent applications in a GMM model. Venturini (2022) relies on cointegration estimators and argues that reverse causality between digital technologies and macro level productivity is a minor concern as "intelligent" (4IR) technologies are produced by few global players/companies (see also the evidence in: EPO, 2020; WIPO, 2019; IPO, 2019; USPTO, 2020; Dernis et al., 2019; Van Roy et al., 2020), whose patenting activity is determined internally rather than by external (country-level) conditions.

Table 7
The relationship between AI technology production (AI scientific publications) and labour productivity growth, full sample – OECD and non-OECD countries.

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Number of scientific publications[1]		Publication stock					
	OLS				IV-GMM[2]		IV-GMM[3]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.052***	−0.053***	−0.105***	−0.109***	−0.110***	−0.111***	−0.108***	−0.112***
	(0.009)	(0.010)	(0.015)	(0.015)	(0.014)	(0.015)	(0.022)	(0.023)
$\Delta\ln\left(\frac{K}{L}\right)$	0.409***	0.410***	0.494***	0.491***	0.471***	0.470***	0.390***	0.392***
	(0.091)	(0.091)	(0.068)	(0.068)	(0.057)	(0.057)	(0.074)	(0.075)
$\ln\left(\frac{AI\,Pub}{L}\right)$	0.006	0.004						
	(0.003)	(0.005)						
$\ln\left(\frac{AI^{ST}Pub}{L}\right)$			0.020***	0.015*	0.019***	0.016***	0.022***	0.017**
			(0.005)	(0.008)	(0.005)	(0.006)	(0.008)	(0.008)
$\ln(GI)$		0.003		0.013		0.007		0.014
		(0.009)		(0.011)		(0.009)		(0.013)
N	969	969	1216	1216	1154	1154	445	445
N of countries	63	63	63	63	63	63	25	25
R-squared	0.313	0.314	0.319	0.321	0.322	0.322	0.393	0.394
K-P rk LM (p-val)					0.000	0.000	0.000	0.000
K-P rk Wald F					1266	406.1	623.6	243.1
Hansen J (p-val)					.	.	0.934	0.887

Notes: as under Table 6.
Source: Authors' elaboration using data from Elsevier/Scopus (Zhang et al., 2021) and PWT 10.0.

(growth in $\frac{K}{L}$). Obviously, our key interest is in the potential growth-enhancing effects of AI knowledge production. According to basic OLS estimates (reported here just for comparison), productivity growth in OECD countries is linked in a statistically significant way neither to AI patenting level nor to AI patent stock, both of which are related to employment (columns 1–4). In the IV setting (columns 5–8; the quality of instruments is confirmed by weak identification tests, under-identification tests and overidentification tests of all instruments),[18] a lack of a significant relationship between AI patent stock and productivity growth is confirmed regardless of how we consider AI patents, separately or controlling for them with the aid of a measure of countries' overall innovation. Similar conclusions are obtained for the wider sample of OECD and non-OECD countries (Table 4). The results are robust to particular changes in the method of IV estimation.

Table 5 reports estimates of model (1) with additional control variables corresponding to factors that are likely to influence the productivity growth process: human capital (*HC*), country trade openness (*Trade)* and regulatory quality (*RQ*). Including them does not affect the key coefficients: the relationship between AI patenting activity and productivity growth is negligible. Once the production of AI technologies is quantified using AI-related bibliometric records we observe a positive and significant relationship between AI publications and productivity growth in both OECD and non-OECD countries (Table 6 and Table 7), which indicates that bibliometric data can capture other wider types of AI innovation than patents can.

Table B1 and Table B2 (in Appendix B) show the results of further robustness checks. Country-level indicators of AI patenting activity by employment are obtained using the identification of inventors instead of applicants. For OECD countries the results confirm the conclusions presented in Table 3. For non-OECD countries the slightly positive coefficient associated with AI patents disappears once we control for countries' overall innovativeness. Next, in Table B3 we consider an alternative measure of labour productivity (per million persons employed). Finally, we check the results with the period of the analysis split in two sub-periods (1985–2000 and 2001–2016, Table B4), and with the same time frame for both types of data (sticking to 1996–2016, as in the AI publications models, Table B5). We also consider different instruments for scientific activity as described in section 4.1 (Table B6). None of these modifications alter the general conclusion: despite the undeniable growth in the production of AI knowledge reflected in patent and bibliometric records, we do not find strong support for the view that knowledge accumulated in AI patent stocks plays a role in the productivity growth process, either in OECD countries or in a wider sample.

However, other mechanisms can be at play at the micro and sectoral level. Patents associated with the 4IR, including AI patents, can have a positive effect on companies' labour productivity (Benassi et al., 2022; Damioli et al., 2021); AI innovation in firms produces strong learning effects (Igna and Venturini, 2023) while adoption of digital technologies in an industry can be associated with productivity gains at the firm level (Gal et al., 2019). Our results can also differ from estimates using broader patent stock data in which AI patents are combined with other technological fields attributed to the 4IR (Venturini, 2022; Benassi et al., 2022).

5. Conclusions

An increasing body of empirical literature documents the puzzling mismatch between expectations related to the production and diffusion of modern digital technologies on the one hand and the poor reflection of them in official productivity records of many countries on the other. Evidence on the modern productivity paradox referring explicitly to the effects of AI technologies is still scant. Our study has differed from other works on the productivity-digital technology nexus in that (i) it explicitly focuses on AI technologies (while the cross-country literature on the 'modern productivity paradox' refers mainly to an earlier wave of technological progress, namely ICT); (ii) it quantifies the importance of highly intangible AI solutions using both patent and publication data; and (iii) it provides a complete international picture of the AI innovation-productivity nexus comparing developments in the OECD countries with a wider non-OECD sample from the mid-1980s onwards (while the related literature is country-specific and/or only focuses on industrialised countries).

[18] For the external instrument ((iii) approach to build instruments) used in IV regression, for IV method with heteroskedasticity-based instruments in its basic form, and for IV method with heteroskedasticity-based instruments supported with the external instrument (iii), the post-estimation tests for under-identification and weak identification fail to reject the null hypothesis. The results are available upon request. The estimation results based on (vi) approach that uses heteroskedasticity-based instruments supported by external instrument built according to (iii) are presented in the Appendix, Table B6 and are treated as a robustness check.

By comparing AI data with productivity records we have shown that an increase in patenting and scientific activity can indeed be observed in the AI domain. However, this activity is at odds with evidence on productivity growth. Our results point towards negligible macro-level effects of AI technology production, especially of that reflected in patent records. This result characterises OECD countries but they do not differ from the rest of the world, as is shown by our wider estimates also taking into account non-OECD countries.

Our results, confirming the niche character of AI, enrich the findings assessing the long-run productivity effects of broader 4IR technologies encompassing AI among other domains (Benassi et al., 2022; Venturini, 2022). We need to be aware, though, that the way we can measure the impact of AI technologies is still imperfect and potentially underestimating the fully global digital economy (Growiec, 2022b: 118). Moreover, our study needs to be read in the context of related micro-level evidence. Even if the engagement of countries in the production of knowledge leading to AI technological innovation is not (yet?) reflected in their aggregate productivity growth records, as this study has shown, productivity gains and learning effects from AI can be manifested within firms (Benassi et al., 2022; Damioli et al., 2021; Gal et al., 2019; Igna and Venturini, 2023). At the microeconomic level digital technologies can even accelerate the recovery of production to pre-COVID-19 levels (Cugno et al., 2022).

Data availability

The data along with the codes will be available through the institutional data repository (https://doi.org/10.34808/rjk6-ry03).

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Appendix A

Table A.1
List of countries

Group of countries (number of countries)	Countries
OECD (35)[1)]	Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States
non-OECD (28)[2)]	Argentina, Brazil, Bulgaria, China (People's Republic of), China Hong Kong SAR[3)], Colombia, Costa Rica, Croatia, Cyprus, Ecuador, India, Indonesia, Jamaica, Lithuania, Malaysia, Malta, Pakistan, Peru, Philippines, Romania, Russian Federation, Singapore, South Africa, Sri Lanka, Taiwan[3)], Thailand, Uruguay, Venezuela

Note: [1)] The OECD group includes countries that were OECD members at the end of the research period, i.e. at the end of 2017, thus it does not classify Colombia, Costa Rica, and Lithuania as OECD economies; [2)] the analysis based on AI scientific publications uses all listed non-OECD countries. Due to data limitations, the analysis using AI patent data includes only countries that are underlined [3)] original data sources (OECD, Penn World Table) report separate statistics for these territories despite their complex political status and/or relationship with China. The patent data in the OECD (2021c) is reported separately for China (People's Republic of), Hong Kong - Special Administrative Region of China, and Chinese Taipei (TWN). Penn World Table (PWT 10.0, Feenstra et al., 2015) reports separate productivity statistics for China; China Hong Kong SAR, and Taiwan (TWN).

Table A.2
Pairwise correlations between explanatory variables

	$\ln\left(\frac{K}{L}\right)$	$\ln\left(\frac{AI\ Pat}{L}\right)$ APP	$\ln\left(\frac{AI\ Pat}{L}\right)$ INV	$\ln\left(\frac{AI\ Pub}{L}\right)$	$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ APP	$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ INV
$\ln\left(\frac{K}{L}\right)$	1					
$\ln\left(\frac{AI\ Pat}{L}\right)$ APP	0.2359*	1				
$\ln\left(\frac{AI\ Pat}{L}\right)$ INV	0.2928*	0.9610*	1			
$\ln\left(\frac{AI\ Pub}{L}\right)$	0.6012*	0.2575*	0.3764*	1		
$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ APP	0.2896*	0.9217*	0.9080*	0.3381*	1	
$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ INV	0.3720*	0.8968*	0.9354*	0.4302*	0.9125*	1
$\ln\left(\frac{AI^{ST}\ Pub}{L}\right)$	0.5896*	0.2797*	0.4132*	0.9730*	0.3398*	0.4693*
$\ln(GI\ Pat)$	0.6768*	0.7673*	0.7875*	0.5983*	0.7995*	0.7900*
$\ln(GI\ Pub)$	0.6449*	0.4628*	0.6031*	0.8448*	0.5231*	0.6486*
HC	0.2781*	0.5310*	0.5652*	0.3933*	0.4798*	0.6191*
Trade	0.3042*	0.1918*	0.0980*	0.2283*	0.1499*	0.0798*
RQ	0.3925*	0.4765*	0.5381*	0.3692*	0.5545*	0.6033*

	$\ln\left(\frac{AI^{ST}\ Pub}{L}\right)$	$\ln(GI\ Pat)$	$\ln(GI\ Pub)$	HC	Trade	RQ
$\ln\left(\frac{AI^{ST}\ Pub}{L}\right)$	1					
$\ln(GI\ Pat)$	0.6120*	1				
$\ln(GI\ Pub)$	0.8665*	0.7655*	1			

(continued on next page)

Table A.2 (*continued*)

	$\ln\left(\frac{AI^{ST}\ Pub}{L}\right)$	$\ln(GI\ Pat)$	$\ln(GI\ Pub)$	HC	Trade	RQ
HC	0.4178*	0.6404*	0.5868*	1		
Trade	0.1528*	0.1669*	0.0663*	0.1547*	1	
RQ	0.3342*	0.6113*	0.5672*	0.5064*	0.1799*	1

Note: * correlations significant at the 10% level. Correlations were calculated using a sample of OECD countries. APP refers to patents by applicants, INV refers to patents by inventors.

Table A.3
Summary statistics for the variables employed in the empirical model (eq. (1))

	Sample: OECD countries				
Variable	Obs	Mean	Std. Dev.	Min	Max
$\Delta\ln\left(\frac{Y}{L}\right)$ per mil hours worked	1067	0.0252	0.0396	−0.1788	0.2341
$\Delta\ln\left(\frac{Y}{L}\right)$ per mil persons employed	1095	0.0223	0.0420	−0.2776	0.2371
$\ln\left(\frac{K}{L}\right)$	1102	5.3641	0.5425	3.3437	6.1937
$\ln\left(\frac{AI\ Pat}{L}\right)$ APP	661	−7.4707	1.5255	−13.4920	−4.3902
$\ln\left(\frac{AI\ Pat}{L}\right)$ INV	713	−7.5629	1.5035	−13.3582	−4.6190
$\ln\left(\frac{AI\ Pub}{L}\right)$	693	−4.1367	0.8907	−7.5803	−2.4903
$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ APP	753	−6.1734	1.6691	−12.2431	−2.9458
$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ INV	825	−6.3283	1.6382	−12.8581	−2.9814
$\ln\left(\frac{AI^{ST}\ Pub}{L}\right)$	695	−2.6775	0.9851	−6.3222	−1.0777
$\ln(GI\ Pat)$	1066	−1.5892	2.1103	−9.3829	1.2106
$\ln(GI\ Pub)$	700	2.0932	0.9251	−1.1019	3.6010
HC	1130	3.0913	0.4173	1.7016	3.8071
Trade	1089	81.826	50.742	15.810	408.36
RQ	665	1.2786	0.4477	0.0351	2.0980
	Sample: OECD & non-OECD countries				
Variable	Obs	Mean	Std. Dev.	Min	Max
$\Delta\ln\left(\frac{Y}{L}\right)$ per mil hours worked	1844	0.0270	0.0489	−0.2660	0.2699
$\Delta\ln\left(\frac{Y}{L}\right)$ per mil persons employed	2909	0.0198	0.1195	−2.6832	1.9689
$\ln\left(\frac{K}{L}\right)$	1910	4.7776	1.0025	1.8120	6.1937
$\ln\left(\frac{AI\ Pat}{L}\right)$ APP	861	−7.9732	1.9569	−14.5201	−4.3902
$\ln\left(\frac{AI\ Pat}{L}\right)$ INV	953	−8.1393	1.9404	−15.2881	−4.6190
$\ln\left(\frac{AI\ Pub}{L}\right)$	1198	−4.9412	1.7210	−11.3604	−2.2619
$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ APP	1010	−6.8452	2.2017	−14.3949	−2.9458
$\ln\left(\frac{AI^{ST}\ Pat}{L}\right)$ INV	1169	−7.1415	2.1583	−13.6259	−2.9814
$\ln\left(\frac{AI^{ST}\ Pub}{L}\right)$	1219	−3.5962	1.9023	−10.6454	−0.8520
$\ln(GI\ Pat)$	1829	−3.2134	2.9628	−11.0590	1.2106
$\ln(GI\ Pub)$	1234	1.1076	1.7140	−4.7007	3.6010
HC	2712	2.6855	0.5819	1.2079	3.9742
Trade	2773	85.273	60.845	9.1358	442.62
RQ	1767	0.4888	0.9264	−2.2362	2.2605

Note: For the list of countries, see Appendix A(Table A1). APP refers to patents by applicants, INV refers to patents by inventors.

Appendix B. Robustness checks

Table B.1
The relationship between AI technology production stock (measured by AI patents by inventors) and labour productivity growth, OECD countries

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Patent stock					
	OLS		IV-GMM[1)]		IV-GMM[2)]	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.079***	−0.098***	−0.080***	−0.097***	−0.110***	−0.193***
	(0.022)	(0.026)	(0.019)	(0.022)	(0.029)	(0.038)
$\Delta\ln\left(\frac{K}{L}\right)$	0.467***	0.483***	0.440***	0.456***	0.350***	0.361***
	(0.103)	(0.099)	(0.079)	(0.079)	(0.108)	(0.105)
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$	0.001	−0.001	−0.001	−0.002	0.004	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
ln (*GI Pat*)		0.014*		0.013**		0.026***
		(0.008)		(0.006)		(0.008)
N	818	818	791	791	309	309
N of countries	34	34	34	34	17	17
R-squared	0.317	0.325	0.301	0.309	0.384	0.422
K-P rk LM (p-val)			0.000	0.000	0.000	0.000
K-P rk Wald F			823.3	365.3	102.2	87.30
Hansen J (p-val)			.	.	0.093	0.997

Notes: *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors are provided in parentheses; all specifications contain country and time fixed effects; K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per hour worked. [1)] Patents are instrumented with the aid of their first lag, [2)] Patents are instrumented with the aid of instrument described in Section 4.1 and supported by first lag of explanatory variable.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.

Table B.2
The relationship between AI technology production stock (measured by AI patents by inventors) and labour productivity growth, full sample OECD and non-OECD countries

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Patent stock					
	OLS		IV-GMM[1)]		IV-GMM[2)]	
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.064***	−0.090***	−0.064***	−0.091***	−0.080***	−0.114***
	(0.014)	(0.017)	(0.013)	(0.016)	(0.023)	(0.027)
$\Delta\ln\left(\frac{K}{L}\right)$	0.508***	0.508***	0.487***	0.493***	0.384***	0.368***
	(0.079)	(0.075)	(0.062)	(0.061)	(0.087)	(0.085)
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$	0.003	−0.000	0.004*	0.000	0.010**	0.006
	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)
ln (*GI Pat*)		0.016**		0.017***		0.017**
		(0.006)		(0.004)		(0.007)
N	1159	1159	1111	1111	427	427
N of countries	56	56	55	55	23	23
R-squared	0.282	0.295	0.274	0.288	0.332	0.347
K-P rk LM (p-val)			0.000	0.000	0.000	0.000
K-P rk Wald F			1127	445.8	290.8	124.8
Hansen J (p-val)					0.118	0.949

Notes: *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors are provided in parentheses; all specifications contain country and time fixed effects; K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per hour worked. [1)] Patents are instrumented with the aid of their first lag, [2)] Patents are instrumented with the aid of instrument described in Section 4.1 and supported by first lag of explanatory variable.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.

Table B.3
The impact of AI technology production (measured by AI patents stock by applicants and by AI scientific publications stock) on labour productivity (output per number of persons employed) for OECD countries and full sample OECD and non-OECD countries

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Patent stock				Publication stock			
	OECD countries		OECD & non-OECD countries		OECD countries		OECD & non-OECD countries	
	IV-GMM[1)]	IV-GMM[2)]	IV-GMM[1)]	IV-GMM[2)]	IV-GMM[1)]	IV-GMM[2)]	IV-GMM[1)]	IV-GMM[2)]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.113***	−0.211***	−0.008	−0.062**	−0.150***	−0.150***	−0.023	−0.105***
	(0.023)	(0.033)	(0.054)	(0.027)	(0.024)	(0.029)	(0.066)	(0.021)
$\Delta\ln\left(\frac{K}{L}\right)$	0.358***	0.150	0.426***	0.340***	0.379***	0.311***	0.491***	0.372***
	(0.112)	(0.136)	(0.101)	(0.122)	(0.098)	(0.101)	(0.069)	(0.090)
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$	−0.002	−0.008*	0.007	0.003				
	(0.004)	(0.004)	(0.005)	(0.005)				

(continued on next page)

Table B.3 (*continued*)

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Patent stock				Publication stock			
	OECD countries		OECD & non-OECD countries		OECD countries		OECD & non-OECD countries	
	IV-GMM[1)]	IV-GMM[2)]	IV-GMM[1)]	IV-GMM[2)]	IV-GMM[1)]	IV-GMM[2)]	IV-GMM[1)]	IV-GMM[2)]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{AI^{ST}Pub}{L}\right)$					0.025***	0.023***	0.009	0.021***
					(0.008)	(0.007)	(0.007)	(0.008)
N	720	260	1035	363	660	318	1641	448
N of countries	33	16	57	22	35	18	90	25
R-squared	0.334	0.446	0.203	0.348	0.371	0.462	0.152	0.420
K-P rk LM (p-val)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K-P rk Wald F	567.3	122.9	1092	318.1	398.9	514.9	2941	618.2
Hansen J (p-val)	.	0.208	.	0.043	.	0.766	.	0.828

Notes: *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors are provided in parentheses; all specifications contain country and time fixed effects; K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per number of persons employed. 1) Publications are instrumented with the aid of their first lag, 2) Publications are instrumented with the aid of instrument described in Section 4.1 and supported by first lag of explanatory variable.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.

Table B.4
The relationship between AI technology production (measured by AI patents) and labour productivity growth, two sub-periods: 1985–2000 and 2001–2016.

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Patent stock							
	Time period: 1985–2000				Time period: 2001–2016			
	OECD countries		OECD & non-OECD countries		OECD countries		OECD & non-OECD countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.162***	−0.266***	−0.184***	−0.280***	−0.196***	−0.220***	−0.126***	−0.143***
	(0.025)	(0.056)	(0.028)	(0.086)	(0.037)	(0.053)	(0.024)	(0.037)
$\Delta\ln\left(\frac{K}{L}\right)$	0.104	0.034	0.205	0.122	0.440***	0.367***	0.352***	0.274**
	(0.144)	(0.199)	(0.140)	(0.211)	(0.101)	(0.114)	(0.089)	(0.118)
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$	−0.001	0.008	−0.007	0.005	0.001	−0.002	0.002	0.006
	(0.004)	(0.008)	(0.005)	(0.010)	(0.007)	(0.007)	(0.005)	(0.007)
N	260	76	299	99	460	184	656	262
N of countries	23	7	27	10	33	16	51	22
R-squared	0.282	0.435	0.259	0.339	0.339	0.465	0.319	0.421
K-P rk LM (p-val)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
K-P rk Wald F	717.0	147.1	702.9	103.9	102.4	47.47	166.6	117.6
Hansen J (p-val)		0.135		0.195		0.322		0.818

Notes: *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors are provided in parentheses; all specifications contain country and time fixed effects; K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per hour worked. Columns (1,3,5,7) – patents are instrumented with the aid of their first lag, Columns (2,4,6,8) – patents are instrumented with the aid of instrument described in Section 4.1 and supported by first lag of explanatory variable.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.

Table B.5
The relationship between AI technology production (measured by AI patents) and labour productivity growth, sub-period: 1998–2016.

Dependent variable: $\Delta\ln\left(\frac{Y}{L}\right)$	Patent stock Time period: 1998–2016			
	OECD countries		OECD & non-OECD countries	
	(1)	(2)	(3)	(4)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.133***	−0.139***	−0.093***	−0.106***
	(0.032)	(0.045)	(0.022)	(0.034)
$\Delta\ln\left(\frac{K}{L}\right)$	0.353***	0.133	0.379***	0.271**
	(0.115)	(0.135)	(0.090)	(0.120)
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$	0.001	−0.007	0.005	0.009
	(0.006)	(0.006)	(0.004)	(0.005)
N	566	215	783	308
N of countries	33	16	51	22
R-squared	0.303	0.400	0.285	0.366
K-P rk LM (p-val)	0.000	0.000	0.000	0.000
K-P rk Wald F	223.5	79.11	378.4	242.3
Hansen J (p-val)		0.096		0.221

Notes: *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors are provided in parentheses; all specifications contain country and time fixed effects; K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per hour worked. Columns (1,3) – patents are instrumented with the aid of their first lag. Columns (2,4) – patents are instrumented with the aid of instrument described in Section 4.1 and supported by first lag of explanatory variable.
Source: Authors' elaboration using data from OECD (2021c) and PWT 10.0.

Table B6
The relationship between AI technology production (AI patents) and labour productivity growth, OECD countries and full sample (OECD and non-OECD countries) – estimation with an alternative instrument

	OECD countries			OECD & non-OECD countries		
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln\left(\frac{Y}{L}\right)_{t-1}$	−0.113***	−0.118***	−0.359***	−0.050***	−0.068***	−0.294***
	(0.016)	(0.014)	(0.047)	(0.013)	(0.013)	(0.043)
$\Delta\ln\left(\frac{K}{L}\right)$	0.379***	0.444***	0.470***	0.392***	0.408***	0.306***
	(0.078)	(0.070)	(0.094)	(0.071)	(0.061)	(0.087)
$\ln\left(\frac{AI^{ST}Pat}{L}\right)$	−0.002	−0.001	0.005	−0.001	−0.003	0.003
	(0.003)	(0.002)	(0.006)	(0.002)	(0.002)	(0.004)
$\ln(GI\ Pat)$		0.009**	0.033**		0.009**	0.043***
		(0.004)	(0.014)		(0.003)	(0.012)
HC			0.008			0.001
			(0.007)			(0.007)
Trade			0.001**			0.000
			(0.000)			(0.000)
RQ			−0.004			0.001
			(0.012)			(0.014)
N	720	720	283	956	956	370
N of countries	33	33	30	51	51	40
R-squared	0.303	0.307	0.474	0.270	0.280	0.458
K-P rk LM (p-val)	0.000	0.000	0.005	0.000	0.000	0.001
K-P rk Wald F	62.23	45.04	22.53	74.96	51.95	17.37
Hansen J (p-val)	0.730	0.236	0.910	0.948	0.539	0.551

Notes: *,**,*** denote significance at the 1%, 5%, 10% levels respectively; robust standard errors are provided in parentheses; all specifications contain country and time fixed effects; K-P refers to Kleibergen-Paap test statistics. All estimations are based on productivity per hour worked. Patents are instrumented with heteroskedasticity-based instruments supported by first lag of patent applications.
Source: Authors' elaboration using data from OECD (2021c), World Bank (2023), and PWT 10.0.

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