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REGULAR ARTICLE

The impact of artificial intelligence on labor productivity

Giacomo Damioli[1] · **Vincent Van Roy**[2] · **Daniel Vertesy**[3,4]

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Abstract

Recent evidence indicates an upsurge in artificial intelligence and robotics (AI) patenting activities in the latest years, suggesting that solutions based on AI technologies might have started to exert an effect on the economy. We test this hypothesis using a worldwide sample of 5257 companies having filed at least a patent related to the field of AI between 2000 and 2016. Our analysis shows that, once controlling for other patenting activities, AI patent applications generate an extra-positive effect on companies' labor productivity. The effect concentrates on SMEs and services industries, suggesting that the ability to quickly readjust and introduce AI-based applications in the production process is an important determinant of the impact of AI observed to date.

Keywords Artificial intelligence · Patents · Labor productivity · GMM-SYS

JEL Classification O31 · O33 · J24

1 Introduction and motivation

The past decades have witnessed major developments in artificial intelligence (AI) technology. The profound social and economic changes brought about by the deployment and advancement of AI applications in the production of goods and

✉ Giacomo Damioli
giacomo.damioli@ec.europa.eu

Vincent Van Roy
vincent.van-roy@ec.europa.eu

Daniel Vertesy
daniel.vertesy@itu.int

1 European Commission, Joint Research Centre (JRC), Ispra, Italy

2 European Commission, Joint Research Centre (JRC), Seville, Spain

3 International Telecommunication Union, Geneva, Switzerland

4 UNU-MERIT, Maastricht, The Netherlands

services, transportation and logistics, or service provision have triggered an intense debate on the present and future impact of AI on society (Makridakis 2017). As in the case of past general-purpose technologies, AI has the potential to disrupt almost all industries and businesses on a worldwide scale.

Recent studies have investigated the upsurge in AI technological developments in recent decades by analyzing the evolution of AI patent applications and AI-related scientific publications (De Prato et al. 2018; European Commission 2018; Fujii and Managi 2018; Cockburn et al. 2019; Van Roy et al. 2020; WIPO 2019). The innovative landscapes of AI, emerging from these studies, reveal similar patterns; the largest increase in AI took place in the last five years and are dominated by China, Japan, South Korea and the United States. Although AI developments are mainly concentrated in the telecommunications and software services and electronics manufacturing sectors, there are clear signs that almost all other industries are increasingly exploiting the opportunities of a new degree of automation brought about by AI technologies.

While there is a consensus among researchers about the rising trends and transformative nature of AI, the speculative interpretations about its economic impact and value for productivity are less conclusive, echoing the concerns synthetized in the popular Solow's paradox "You can see the computer age everywhere but in the productivity statistics" (Solow 1987, p. 36). A more positive stream of literature claims that the disruptive content of the AI technology, leveraged through the automation of tasks, reduction of uncertainty, the recombination of existing and generation of new innovations (Agrawal et al. 2019a, b; Cockburn et al. 2019) will have a productivity-enhancing impact (Brynjolfsson et al. 2019). In sharp contrast, other theoretical models predict that the ongoing productivity slowdown is likely to continue due to increased inequalities (Gries and Naudié, 2018), learning costs (Jones 2009) and a lower rate of disruptiveness of AI compared to other general-purpose technologies (Gordon 2016, 2018).

Along with these contrasting predictions, there is a growing need for quantitative analyses to measure the impacts of AI on economic outcomes such as growth, productivity and employment, yet the requirement for high quality, firm-level data acts as an important barrier (Raj and Seamans 2019; Furman and Seamans 2019). Empirical studies have only recently emerged to help better understand the impact of AI on firm labor productivity and are restricted to a handful of papers (e.g. Graetz and Michaels 2018; Alderucci et al. 2020). To our knowledge, none of the empirical papers quantified the impact of AI technologies on firm productivity while accounting for a cause–effect relationship.

This study aims to fill the gap observed in prior research with further and novel empirical evidence. Using a comprehensive definition of AI that refers to the combination of software and hardware components including robotics and taking stock from the literature of innovative AI landscapes (Van Roy et al. 2020), we employ a unique database of 5257 AI patenting firms to evaluate the effect of AI technologies on firm labor productivity. We test for this potential impact using a worldwide sample of companies from four continents that have filed at least one patent related to the field of AI between 2000 and 2016, combining patent applications from the Worldwide Patent Statistical database (PATSTAT) of the European Patent Office with firms' financial information from Bureau Van Dijk's ORBIS database. The empirical analysis makes use of a dynamic panel data model estimated with System General Method of Moments (GMM-SYS) and derived from a knowledge-stock augmented production function, which allows us to control for endogeneity and for persistent firm-level differences in productivity levels.

While controlling for patenting activities in non-AI related fields, our findings reveal a positive and significant impact of AI patent applications on labor productivity. This effect concentrates on small and medium enterprises (SMEs) and services industries, suggesting that in the largest companies and most innovative manufacturing sectors the effect of AI patenting is (perhaps yet) not-distinguishable from the larger effect of non-AI patenting. We attribute the heterogeneity of the effects to the diverse pace of different types of firms to fully exploit AI applications in their production process.

The remainder of this paper is organized as follows. In the next section, we provide an overview of the theoretical and empirical literature exploring the recent upsurge of artificial intelligence and we highlight in particular the literature analyzing the relationship between artificial intelligence and productivity. In Sect. 3, we present the empirical model based on an augmented productivity model, in which AI patent applications are used to capture a firm's change in knowledge stock in AI. The data construction, variables used in the empirical estimations and summary statistics are highlighted in Sect. 4. After presenting the empirical results in Sect. 5, we discuss our findings and their implications. We conclude with a discussion of the limitations of our study and possible avenues for future research.

2 Literature on artificial intelligence and productivity

The recent upsurge of innovations in technologies related to AI and robotics spurred an intense debate on their consequences on interlinked social outcomes such as growth, productivity, employment, earnings and inequality. Classical economic theories predict that, ultimately, economic growth depends on technological change and innovation (Solow 1957; Romer 1990; Aghion and Howitt 1992). More recent theories, such as the one of skill-biased technological change, posit that technological innovation may lead to wage polarization through relative increases in the demand of skilled workers with respect to unskilled ones (Autor et al. 2003; Barbieri et al. 2020), and to possible job losses through the automation of tasks (Autor and Dorn 2013; Vivarelli 1995, 2013; Piva and Vivarelli 2018; Josten and Lordan 2020). Yet, displacement effects may be potentially outweighed by a productivity effect if automation expands labor demand through the efficiencies brought to production (Acemoglu and Restrepo 2018, 2019a, b, 2020).

As for productivity, economic theories predict a positive impact of technological change on productivity. Yet, sluggish productivity characterizes advanced economies since the 1970s, even within industries intensively investing in digital innovation (the so-called "Productivity Paradox", Brynjolfsson 1993), with almost half of the slowdown attributed to labor productivity (Gordon 2018). Recent progresses in the AI technology and its vast applicability raised hopes to revert the persistently gloomy productivity trend and revitalize the economy as a whole. AI has the potential to generate productivity gains through a number of channels including the reduction of uncertainties in reason of increased precision of forecasts (Agrawal et al. 2019a), the automated recombination of existing technologies (Agrawal et al. 2019b) and, more generally, the generation of new innovations (Bartelsman et al. 2019; Cockburn et al. 2019). The fact that low productivity growth is continuing even in recent years of sharp technological improvements in AI may depend on the time lag the AI revolution requires to allow complementary inventions to develop, businesses to reorganize and workers to upskill in order to diffuse across the economy (Brynjolfsson et al. 2019).

Not all authors agree on such an enthusiastic view. Gordon (2016, 2018) argues that the productivity slowdown is permanent and that current innovations, including the digital and even the AI revolutions, raised too optimistic expectations as being less disruptive that those that generated the spectacular productivity growth observed in the United Sates between the 1920s and 1970s, such as the electric power and the internal combustion engine. Using a large dataset of inventors, Jones (2009) shows that both the age at first invention, and the specialization and teamwork increase over time. He argues that more and more learning is required for researchers to get capable of pushing the frontier forward. Bloom et al. (2020) document a sharp decline in research productivity across various industries, products, and firms and argue that ideas are getting harder to find. On a different angle, Gries and Naudé (2018) stress the potential role of aggregate demand. In particular, automation and AI lead to declining earnings and labor share as well as increasing inequality with few agents getting the surplus of innovations, which may hinder the full potential capacity for growth and hence productivity.

Given the multiple contrasting theoretical views at stake, rigorous empirical investigation is required to shed light on the issue. The key contribution of this study is to be among the first to assess to what extent AI and robotics innovation affect the productivity of the firms that develop such technologies. Empirical evidence to date is scant, mainly focused on the use of robots at the aggregate level, and not conclusive. As stressed by Raj and Seamans (2019), augmenting empirical evidence on AI invention, AI adoption, and its effects at the firm level is highly valuable. Graetz and Michaels (2018) use country-level data on worldwide delivery of industrial robots and find that robots may have increased average aggregate productivity growth by more than 15 percent for 17 countries between 1993 and 2007. Among the few studies at the firm level, the European Commission (2016), based on a sample of 3000 manufacturing firms in seven European countries, reports that the use of industrial robots is associated with higher levels of labor productivity.

Closer to this study, Alderucci et al. (2020) combine patents related to AI with firm-level microdata from the US Census Bureau for the period 1997–2016, and assess the impact of AI on various outcomes. By comparing AI-inventing firms with a comparable set of similar control firms (i.e. that never patented in AI), they find that the invention of the first AI patent in their sample is related to subsequent increases in sales, employment and within-firm earnings inequality compared to the control group. The study does not claim to report causal effects as both the choice to make the first invention in AI and the outcomes could be due to some common unobserved reason and being therefore endogenous. As for sales per worker, which is similar to the outcome measure under investigation in this study, the authors report an average 4.15% increase after the first AI-related invention, and a negative effect on manufacturing and positive one in services. These are arguably the only existing benchmarks for our analysis and findings, and we will come back to them in the discussion of results.

3 Empirical model

We derive our empirical specification from a knowledge stock augmented Cobb Douglas model (e.g., Lokshin et al. 2008; Hall et al. 2012; Belderbos et al. 2013, 2015), in which a firm's productivity is a function of capital stock, labor, and the available knowledge stocks for firm i at time t:

$$Y_{it} = \alpha_i L_{it}^{\beta} C_{it}^{\gamma} K_{it}^{\delta} e^{\sigma_{it}} \tag{1}$$

where Y is output, L is labor input, C is the physical capital stock and K is the knowledge stock. The parameters β, γ and δ are elasticities with respect to labor, physical capital and the knowledge stock. The constant term α_i represents firm-specific and time-invariant characteristics that enable to reach higher productivity levels (such as organizational or managerial abilities). The parameter σ_{it} is a time-variant firm-specific efficiency parameter.

Dividing both sides by labor, taking natural logarithms, and differentiating the resulting equation in two consecutive periods (through which the firm fixed effects α_i drop out), we obtain the equation in its growth form:

$$p_{it} = (1 + \theta)p_{it-1} + (\beta - 1)\Delta l_{it} + \delta \Delta c_{it} + \gamma \Delta k_{it} + \mu_i + \varepsilon_{it} \tag{2}$$

where lower case letters denote variables in natural logarithms, p_{it} denotes labor productivity, Δl_{it} is the growth in labor input, Δc_{it} is growth in fixed capital and Δk_{it} is the change in knowledge stock. Lastly, μ_i is the idiosyncratic individual and time-invariant firm's fixed effect and ε_{it} the usual error term.

Moving from the static expression (1) to a dynamic specification as in (2) allows to account for persistency in productivity differences (Klette 1996). This specification allows for gradual convergence in efficiency levels between firms, which has been observed to be important in the empirical productivity literature, with lagging firms able to improve their productivity faster (Klette 1996; Klette and Johansen 1998; Blundell and Bond 2000; Lokshin et al. 2008; Hall et al. 2012). The convergence parameter is denoted by θ and highlights the share of productivity lead that disappears through convergence in a year.

We take the change in knowledge capital stock as a function of the inflow of AI and non-AI patent applications (respectively denoted by Pat_{it}^{AI} and Pat_{it}^{Non-AI}):

$$\gamma \Delta k_{it} = \varphi Pat_{it}^{AI} + \eta Pat_{it}^{Non-AI} \tag{3}$$

The rationale for approaching the knowledge stock as a function of the innovation efforts in AI and non-AI related fields is discussed in Sect. 4.

The estimation of dynamic production functions is not a straightforward process as methodological problems due to simultaneity and endogeneity can result in biased estimations of factor elasticities. To tackle these issues, we use a system GMM approach as developed by Blundell and Bond (1998, 2000). The system GMM model provides a flexible estimation method to deal with endogenous, predetermined or strictly exogenous regressors. As such, system GMM allows for consistent and efficient estimates when dealing with dynamic panel data, as is the case for our data. This is achieved by means of a system of equations, including a level equation and an equation in first differences that are running simultaneously. In these equations, lagged and differenced lagged variables are used to solve for persistency in time series and endogeneity problems.

By construction, the dynamic production function suffers from endogeneity given the presence of the lagged labor productivity. However, as pointed out in the majority of studies using knowledge-stock augmented Cobb–Douglas models (Piva and Vivarelli 2005; Lokshin et al. 2008; Bogliacino et al. 2012; Van Roy et al. 2018), production input variables of labor, physical capital and knowledge stock may be equally affected. In line with the literature, all the explanatory variables have been considered as potentially endogenous to labor productivity and instrumented in all models.

In the level equation, we use differenced values of the right-hand side variables as instruments, i.e. twice-lagged differences in labor productivity, AI and non-AI patent applications, employment growth, fixed capital growth, and firm size. The level equations also include a set of sector, country and year dummies. In the equations in differences we employ twice-lagged values of the above-mentioned explanatory variables as instruments. The lag limits of the instruments were chosen as to satisfy the outcomes of the autocorrelation tests, to identify a valid set of instruments and to limit instrument proliferation, as highlighted in Roodman (2009a, b).

4 Data and variables

4.1 Dataset construction

The choice of using firms' patent portfolios as a measure of the stock of prior knowledge for new knowledge production relies on several considerations. Many previous studies resume to R&D expenditures as a measure of firms' effort to innovate that presumably translates into new knowledge (e.g. Hall and Mairesse 1995; Hall et al. 2012; Belderbos et al. 2015; Ortega-Argilés et al. 2015; Castellani et al. 2019). Yet, R&D expenditures are typically aggregated measures retrieved through firms' balance sheets, having thus no purpose in studies aiming to focus on specific types of knowledge inputs, as this study does for AI. While traditionally considered as a measure of innovation output (Griliches 1990; Ernst 1995), the present study argues that the patent portfolio of a firm at a given point in time makes a good job at measuring its current knowledge usable for production, by capturing to a good degree of approximation its previous innovative efforts.

This is particularly true for general-purpose technologies such as AI, and even more for machine learning, which has been described as a "method of invention" (Cockburn et al. 2019). This approach is shared by the only other paper to our knowledge that studies the effects of AI at the firm level (Alderucci et al. 2020). In particular, Alderucci et al. (2020, p. 2) claim that "Firms that succeed in using artificial intelligence to create new goods and services have a strong incentive to patent at least some of their inventions. If they fail to do so, other firms can copy their innovations without penalty or use patents to block the original innovator from applying their inventions in the marketplace." We are aware of the limitations that patents have in capturing innovation, as extensively discussed in previous studies (e.g. Hussinger 2006; Hall et al. 2014), for instance the fact that company may prefer not to patent their inventions to keep them secret. Yet, patents have the appealing advantage to allow tracking and analyzing the use and diffusion of AI technologies in the economy across time and space. Second, patents provide a practical solution for the problem of identifying on a global scale firms that innovate in AI.

Identifying patents related to AI technologies is far from a trivial task. First, there is no established definition to set out the composition and boundaries of AI. The rapid evolution of the field of AI makes its definitions challenging for many of its observers (OECD 2017; European Commission 2018; WIPO 2019). AI typically refers to a diversity of software technologies including, inter alia, machine learning, neural networks, logic programing, and speech recognition. The most important aspects of any definition are the ability of systems to think and act humanly (reasoning and behavioral perspective) aiming to obtain rational outcomes (Ertel 2018; Russell and Norvig 2016). Since automation is a key feature of AI technologies, many studies consider robotics as an integral part of it (European Commission 2018; Fujii and Managi 2018; WIPO 2019). This is especially true as the diffusion of AI brings about the digital interconnection of robots and sensors and the use of "big data" for better optimizing the production process in what is often referred to as Industry 4.0. We believe that to best capture this ongoing, expanding process, it is more appropriate to follow the approach of the European Commission (2018) and apply for this study a comprehensive definition of AI and refer to the combination of software and hardware components (including robotics).

A second main difficulty in identifying patents in the field of AI relates to the nature of AI technologies. As any other general-purpose technology, AI is transversal in nature, i.e. cutting through many scientific disciplines and used in an increasing number of sectors. To overcome these difficulties, previous studies used a keyword approach (De Prato et al. 2018; European Commission 2018) or a pre-selection of AI-related technological classes (Fujii and Managi 2018) or a combination of the two approaches (Cockburn et al. 2019; WIPO 2019). Alderucci et al. (2020) is the first study to make use of advanced AI machine learning techniques to parse the patent corpus in order to identify AI-related patents.

Van Roy et al. (2020), on which this study relies upon for the selection of patents, used a keyword-based approach consisting in the development of a dictionary of AI-related keywords to be retrieved in either the patent's title or abstract. Text-mining searches have been conducted on patent families[1] in the Spring 2018 edition of the PATSTAT database from the European Patent Office (see Van Roy et al. 2020 for additional details).[2] Next, the application number of all identified AI patent families served as a link with the patent and company balance sheet data in Bureau van Dijk Electronic Publishing (BvD) ORBIS databases. A first link was established with the ORBIS Patent database in order to obtain the firm's identifier for those patents having among the applicants a firm collected in the ORBIS Companies database. For the linked firms, key location and financial information could be obtained from the ORBIS Companies database. For the purpose of this study, the sample of firms was augmented with their portfolio of all non-AI patent families (Appendix 1 shows a scheme summarizing the data collection process). While the issues of coverage and data availability are known limitations of ORBIS, these are by far outweighed by its advantage of offering a comprehensive cross-country micro-level dataset for scientific research purposes (e.g. Gal 2013; Hallak and Harasztosi 2019).

4.2 Variables and sample

The final dataset covers 5257 firms active in AI patenting for the years 2000–2016. It has a worldwide coverage and includes firms belonging to manufacturing and service sectors. It provides information on firms' patenting activities in AI and non-AI related fields, accounting information (including turnover, employment, and capital formation), country location, and industrial activity (NACE sector at 2-digit level). By including only firms active in AI patenting, the sample may be affected by a "cherry-picking" effect as it is, by construction, more technology-driven and, in the case of SMEs, there might be selection of the champions, not necessarily representing the majority of small companies.

Our dependent variable is defined as the natural logarithm of firm labor productivity. This choice of dependent variable derives from a knowledge-augmented production function framework, which we adopt to model the effects of innovative AI technologies on firm performance (see Sect. 3).

The key explanatory variable of interest is AI patent applications, which measures the change in a firm's knowledge stock in the field of AI. Since patents can differ both in economic and technological value, simple patent count may give a distorted impression of a firm's technological basis. Therefore, other indicators have been proposed to correct for quality or value of patents, such as forward citation-weighted patents and family size (Harhoff et al. 2003; Hall et al. 2005; Gambardella, et al. 2008; Neuhäusler et al. 2011; Squicciarini et al. 2013; Van Roy et al. 2018). Using any of these quality-corrected indicators is particularly difficult in the case of AI, as the real take-off of AI patenting activities took place relatively late (since

[1] The key advantage of using patent families is that it avoids double counting of the same or similar inventions filed in different patent offices.

[2] Bianchini et al. (2020a) compare different keyword-based criteria on a sample of world leading corporate R&D investors (the COR&DIP© database) and find that the Van Roy et al. (2020)'s approach is more selective compared to other classifications (i.e. it reduces false positives).

Table 1 Summary statistics of the dependent and explanatory variables for the full sample and across periods

Variable name	Full sample		Period 2000–2008		Period 2009–2016	
	N=40,717		N=17,247		N=23,470	
	Mean	SD	Mean	SD	Mean	SD
Labor productivity	280,319	312,349	261,061	293,628	294,471	324,699
AI patent applications	0.48	2.60	0.37	2.00	0.56	2.97
Non-AI patent applications	61.18	160.81	65.11	171.52	58.29	152.40
Labor productivity growth	10.03	44.16	9.91	44.73	10.12	43.74
Employment growth	5.76	27.11	6.82	28.91	4.98	25.68
Fixed capital growth	17.68	62.94	16.81	64.43	18.31	61.81
Firm size	5995	16,561	5670	15,466	6233	17,318

the late 2000s), and boomed only from 2015 onwards (Cockburn et al. 2019; WIPO 2019; Van Roy et al. 2020).

In addition to the number of AI patent applications as proxy for a firms' knowledge stock, we also take into account innovative efforts in non-AI related fields. This is done by incorporating the number non-AI patent applications into the knowledge stock function. We use the actual number of patents in a given year rather than the cumulative number as to proxy for the change in knowledge stock as highlighted in Sect. 3. Other variables included in the dynamic productivity model are the growth in employment, measured as the number of employees expressed in full-time equivalents, and the growth in the capital stock, approximated by the growth in fixed capital. The models control for firm size (employment), industry, year and country-specific differences in labor productivity dynamics. Definitions of the variables entering the empirical models are provided in Appendix 2.

Table 1 reports the summary statistics of the dependent and explanatory variables used in the estimations. It presents scores for the full sample as well as for two subperiods. The two sub-periods are defined based on the following considerations. The financial and economic crises of 2008–2009 serves as a natural divide, as it was followed by a marked, prolonged global slowdown in productivity growth (Dieppe 2020). The crisis also entailed opportunities for firms to follow strategies of creative destruction rather than creative accumulation (Archibugi et al. 2013). Furthermore, it allows reflecting the difference in growth rate in AI patenting activities, which increased substantially over time, especially in the last decade (as also documented in, e.g. Van Roy et al. 2020). To remove observations with possible erroneous values in the data and to prevent outliers from heavily affecting estimation results, we omitted the top 1% values of the distribution of all accounting variables in both the summary statistics and empirical analyses.

Firms in the sample report an average labor productivity growth of 10%, and employment and fixed capital growth rates of, respectively, 5% and 17%. These high growth rates are not surprising as the sample includes highly innovative firms having applied for at least one AI-related patent in the full period. AI patent applications are relatively low, about 1 AI-related patent per year every two firms in the sample, due to a highly skewed distribution, and increases from about 0.4 per firm-year on average between 2000 and 2008 to almost 0.6 between 2009 and 2016. Non-AI patent activity is, by contrast, substantial and slightly declines in the second subperiod (form about 65 to about 58 non-AI-related patent applications per company per year).

Table 2 presents the distribution of firms across sectors, high- and low-tech manufacturing and firm size. With respect to the distribution of firms across sectors, we note that 60% are active in manufacturing and 40% in services. Within manufacturing sectors, high-technology firms are largely over-represented, constituting about 80% of the sample. The machinery and electronics sector are the most represented manufacturing sectors with respective percentages of 25% and 14%. Not surprisingly, the telecommunications sector and the sector of professional, scientific and technical services constitute the largest service sectors with respective percentages around 16% and 8%. We refer to Appendix 3 for a more detailed distribution of firms across sectors.

In terms of geographical distribution, two-thirds of the firms are located in Asia. This large percentage is driven by the dominating AI patenting activity of Japanese, South-Korean and Chinese firms as highlighted in prior studies (WIPO 2019; Van Roy et al. 2020). A quarter of the firms are located in Europe, with highest percentages in Germany, United Kingdom and France. Lastly, firms in the United States constitute around 10% of the sample. The low share of firms based in the United States depend on the well-known low coverage of ORBIS in the United States. Yet, we opted to include them to enhance the geographic coverage of the sample. We refer to Appendix 3 for a more detailed distribution of firms across regions and countries.

5 Empirical results

The results from the one-step System GMM estimation defined in Eq. (2) using the full sample—40,717 observations originating from 5257 firms active in AI patenting activities—are presented in Table 3.[3] Overall, the full model performs well and reveals highly significant coefficients with the expected signs. Both the Wald test on the overall significance of the regressions and the LM tests on AR (1) and AR (2) autocorrelation dynamics provide fully reassuring diagnostic results on the model. At the same time, the null hypothesis of adequate instruments is rejected by the Hansen test. However, Blundell and Bond (2000) and Roodman (2009a) showed that the Hansen test over-rejects the null in case of very large samples. In order to address this issue, the same model was run and the Hansen test was performed on different random sub-samples comprising 10% of the original data. The null was

[3] Since a high instrument count may imply a downward bias in the two-step GMM-SYS standard errors (see Roodman 2009b, pp. 140–141), to be on the safer side we opted for a one-step methodology; however, a robustness check using a two-step methodology is reported in Appendix 4 (Table 9).

Table 2 Distribution of firms across sectors, high- and low-tech manufacturing and firm size

	Full sample				Period 2000–2008				Period 2009–2016			
	Observations		Firms		Observations		Firms		Observations		Firms	
	Numbers	%	Numbers	%	Numbers	%	Numbers	%	Numbers	%	Numbers	%
Sector												
Manufacturing	26,928	66.13	3205	60.97	11,709	67.89	2385	65.58	15,219	64.84	2918	61.68
Services	13,789	33.87	2052	39.03	5538	32.11	1252	34.42	8251	35.16	1813	38.32
Manufacturing												
High-tech	21,263	78.96	2578	80.44	9194	78.52	1920	80.50	12,069	79.30	2345	80.36
Low-tech	5665	21.04	627	19.56	2515	21.48	465	19.50	3150	20.70	573	19.64
Firm size												
SME	18,624	45.74	2833	53.89	7654	44.38	1813	49.85	10,970	46.74	2492	52.67
Large firm	22,093	54.26	2424	46.11	9593	55.62	1824	50.15	12,500	53.26	2239	47.33
Total	40,717	100.00	5257	100.00	17,247	100.00	3637	100.00	23,470	100.00	4731	100.00

We split manufacturing into high and low-tech sectors, according to the Eurostat classification (European Commission 2016; Hatzichronoglou 1997). For the definition of SMEs we follow the EC recommendation in which SMEs are denoted as firms with a number of employees below 250 and a turnover equal to or below € 50 million (European Commission 2003)

Table 3 Results for the GMM-SYS analysis—full model and subsamples across periods

	Labor productivity		
	Full model	Period	
		2000–2008	2009–2016
Labor productivity t-1	0.544***	0.621***	0.517***
	(0.054)	(0.060)	(0.092)
AI patent applications	0.032***	0.011	0.030**
	(0.011)	(0.014)	(0.015)
Non-AI patent applications	0.019***	0.024*	0.029***
	(0.007)	(0.013)	(0.010)
Employment growth	− 0.470***	− 0.480***	− 0.497***
	(0.032)	(0.036)	(0.052)
Fixed capital growth	0.088***	0.123***	0.080***
	(0.022)	(0.024)	(0.029)
Firm size	0.013	− 0.082	0.083
	(0.047)	(0.057)	(0.071)
Industry and country dummies	Included	Included	Included
Year dummies	Included	Included	Included
Observations	40,717	17,247	23,470
Number of firms	5257	3637	4731
Wald test	4648.64***	28,906.45***	5375.37***
AR(1)	− 8.78***	− 6.69***	− 6.50***
AR(2)	− 1.22	− 0.68	− 0.34
Nr. of instruments	107	94	97
Hansen test	11.59**	15.81***	851.67***

Standard errors in parentheses. Significance levels are represented as: ***p < 0.01, ** p < 0.05, * p < 0.1. All variables are expressed in natural logarithms

The models presented in the table are based on system GMM estimations with collapse option to reduce the number of instruments

never rejected in this bootstrapping exercise, providing reassurance on the validity of the selected instruments.[4]

The estimated coefficient of the lagged labor productivity equals 0.54.[5] This indicates a comparatively mild persistence in productivity: approximately half of the

[4] Results are available from the authors upon request.

[5] Table 9 in Appendix 4 reports the Pooled Ordinary Least Squared (POLS) and Fixed Effects (FE) estimations of the baseline specification, as robustness checks. However, POLS estimates provide very preliminary and approximate results, since they do not control for unobserved individual effects and for the endogeneity of (at least) the lagged dependent variable, the corresponding coefficient being over-estimated. On the other hand, FE estimates control for individual unobservables but are still affected by the endogeneity of (at least) the lagged dependent variable, the corresponding coefficient turning out to be under-estimated. Indeed, it can be noticed that the one-step GMM coefficients of the lagged dependent variable reported in Table 4 are correctly situated within the corresponding FE (lower bound) and OLS coefficients (upper bound).

Table 4 Results for the GMM-SYS analysis—subsamples for the period 2009-2016

	Labor productivity						
	Full model	Sector		Manufacturing		Firm type	
		Manufacturing	Services	High-tech	Low-tech	SMEs	Large firms
Labor productivity t–1	0.517***	0.567***	0.491***	0.551***	0.603***	0.447***	0.581***
	(0.092)	(0.086)	(0.175)	(0.090)	(0.129)	(0.105)	(0.180)
AI patent applications	0.030**	0.006	0.077**	0.003	− 0.005	0.069*	0.007
	(0.015)	(0.014)	(0.034)	(0.016)	(0.029)	(0.040)	(0.011)
Non-AI patent applications	0.029***	0.035***	0.022	0.033***	0.039	0.014	0.033***
	(0.010)	(0.011)	(0.021)	(0.012)	(0.027)	(0.017)	(0.010)
Employment growth	− 0.497***	− 0.491***	− 0.548***	− 0.456***	− 0.622***	− 0.436***	− 0.540***
	(0.052)	(0.056)	(0.097)	(0.056)	(0.106)	(0.074)	(0.086)
Fixed capital growth	0.080***	0.088***	0.072	0.099***	0.064	0.039	0.129**
	(0.029)	(0.030)	(0.055)	(0.026)	(0.068)	(0.043)	(0.050)
Firm size	0.083	0.069	0.163	0.022	0.248	0.086	− 0.049
	(0.071)	(0.088)	(0.126)	0.087)	(0.154)	(0.146)	(0.098)
Industry and country dummies	Included	Included	Included	Included	Included	Included	Included
Year dummies	Included	Included	Included	Included	Included	Included	Included
Observations	23,470	15,219	8251	12,069	3150	9780	13,690
Number of firms	4731	2918	1813	2345	573	2359	2566
Wald test	5375.37***	3853.71***	48,300.52***	4033.07***	1796.96***	41,176.39***	5531.24***
AR(1)	− 6.50***	− 6.29***	− 3.53***	− 5.79***	− 3.27***	− 5.71***	− 3.45***
AR(2)	− 0.34	− 0.56	0.08	− 0.76	0.38	0.25	− 2
Nr. of instruments	97	76	78	67	60	86	90
Hansen test	851.67***	16.65***	373.42***	16.71***	8.59	2.99***	2304.37***

Standard errors in parentheses. Significance levels are represented as: ***p<0.01, **p<0.05, *p<0.1. All variables are expressed in natural logarithms. We split manufacturing into high and low-tech sectors, according to the Eurostat classification (European Commission 2016; Hatzichronoglou 1997). For the definition of SMEs we follow the EC recommendation in which SMEs are denoted as firms with a number of employees below 250 and a turnover equal to or below € 50 million (European Commission 2003).

productivity lead disappears through convergence. The models indicate an elasticity of output with respect to employment of about 0.53 (1–0.47) and an elasticity of fixed capital around 0.09, while the coefficient estimated for firm size is not statistically significant. These estimates are in line with other studies using a similar production function framework (Fors 1997; Belderbos et al. 2013, 2015).

Turning our attention to the main variable of interest, the estimate shows a positive and significant effect of AI patent applications on labor productivity as measured by turnover per worker. This effect is far from negligible: if a firm increases its innovative effort in the field of AI and doubles its number of AI patent applications, the predicted increase in labor productivity amounts to 3%. For the full model, companies' stock of patent applications in technologies other than AI also turns out to be significant (with a lower effect of about 2%), confirming the potential of the AI technology to enhance productivity. This result is compatible with those by Alderucci et al. (2020), which report in the United States between 1997 and 2016 an average increase by 4.15% in the sales per worker of firms making their first AI-related invention as compared to a control group of similar firms that did not file any AI patent.

The results from the separate estimations on the 2000–2008 and 2009–2016 sub-periods indicate an increasing importance of AI over time. AI patent applications have no significant effect on labor productivity in the first sub-period, while having a positive, significant effect only in the sub-period following 2009. The AI technology in the first period was still less mature, characterized by less frequent patenting, and firms probably having less experience in fully exploiting it.

Further investigations were carried out on the subsample covering the more recent time period (2009–2016) in order to better understand structural differences in the impact of AI across industries and companies of varying size. Splitting the sample by industry reveals that AI patent applications are only significant in services (see Table 4). The effect of AI patent applications on labor productivity turns out to be relative strong, elevating at 7.7%. At the same time, the effects of non-AI patent applications as well as fixed capital growth are not significant in the service sector. By contrast, non-AI patent applications have a particularly stronger effect in manufacturing industries, mainly captured in the high-technology manufacturing. Interestingly, the study by Alderucci et al. (2020) on US companies also finds a positive significant effect of AI on sales per worker only in the service industries, while a negative one in manufacturing.

While firm size shows no significant effect on labor productivity, there is a marked difference between SMEs and large firms in the effect of AI patent applications on labor productivity. The effect is significant in the subsample comprising SMEs, with relatively high coefficients (0.07) similar to what was observed for the service sector, while insignificant for large firms. In contrast, large firms report a particularly strong effect of non-AI related patent applications.[6]

[6] We recall that SMEs show lower average levels and higher variance in labor productivity with respect to large firms. Large firms in the sample have a very diverse patent portfolio in which also the ratio of AI patents to their stock is lower than for SMEs. It is also important to recognize that the share of SMEs

6 Discussion and conclusion

As the ongoing debate on the impact of the technological development in AI and robotics on productivity offers contrasting predictions (Gordon 2016, 2018; Gries and Naudé 2018; Agrawal et al. 2019a, b; Brynjolfsson et al. 2019; Cockburn et al. 2019), empirical studies can offer important insights. Yet, only a handful of papers have investigated the effects of AI and robotics on productivity (Graetz and Micheals 2018; Alderucci et al. 2020). To our knowledge, none of the empirical papers quantified the impact of AI technologies on firm productivity while accounting for a causal-effect relationship.

In this study, we aim to contribute to closing this gap in the literature by employing a unique database of 5257 AI patenting firms to evaluate the short-term effect of AI technologies on firm labor productivity. We test for this potential impact using a sample of worldwide companies having filed at least a patent related to the field of AI between 2000 and 2016. While controlling for firms' patenting activities in non-AI related fields, our findings reveal a positive and significant impact of AI patent applications on labor productivity. This effect concentrates on SMEs and services industries, suggesting that in the largest and most innovative manufacturing sectors the effect of AI patenting is (perhaps yet) not-distinguishable from the larger effect of non-AI patenting.

Our findings indicate the presence of technological opportunities for economic activities and types of businesses typically characterized by comparatively low capital intensity, organizational complexity and patenting activity. We attribute this evidence to the low economic maturity of the AI technology. Smaller, more agile AI-patenting firms may have been able to readjust faster and introduce AI-based applications in their production processes at a scale allowing the creation of a significant impact on productivity. The larger, more diverse patent portfolio of non-AI technologies, by contrast, still dominates the productivity generating process of the larger and more complex firms, which could take longer to fully exploit in its value chain and upskill the existing workforce to fully benefit from their AI inventions. The low economic maturity of the AI technology is also confirmed by the finding that a significant effect is only observed in the more recent years of the sample. More time is needed to assess whether AI technology development and adoption will generate productivity gains also to large and manufacturing firms, a task which is left for future research to address.

In all subsamples used in the analysis, i.e. manufacturing and high-tech manufacturing, services, SMEs and large firms, the majority of firms patent more in non-AI than in AI technologies. Yet, there are clear signals of technological specialization among SMEs and firms operating in services. More than a quarter of the SMEs and more than 22% firms operating in services only record AI patenting activities and have no patents in other fields. The non-trivial share of firms patenting exclusively in AI contributes to explaining the positive effect on the firm's labor productivity growth as well as the lack of significance of non-AI patents on productivity for these groups of firms.

Footnote 6 (continued)

among manufacturing firms is much lower than among services (43 and 62%, respectively), which may explain the sectoral differences observed above.

Our study has a number of limitations, which qualify the results and suggest avenues for future research. First, only firms filing at least one patent in AI during the period 2000–2016 entered our sample at study. As patenting in AI is a signal of technological excellence, our sample may be affected by a "cherry-picking" effect, especially in the case of SMEs, and the results may incur in a sample selection bias. A clear opportunity for future research would be to test our findings on a sample also including companies that do not patent at all as well as companies patenting in non-AI related fields only.

A second limitation, which is common to most scientific studies related to AI, is the lack of a precise and universally accepted definition of artificial intelligence. Due to the lack of clarity and consensus around the term, studies aimed at mapping the innovative landscape of AI typically use different dictionaries of AI-related keywords (De Prato et al. 2018; European Commission 2018; Van Roy et al. 2020), sometimes combined with pre-selected technological or scientific fields (Cockburn et al. 2019; WIPO 2019). Results of this study rely on the keywords developed by Van Roy et al. (2020). To test the robustness of the analysis, it may be interesting to evaluate to what extent results holds when using different keywords. This calls for studies to compare the robustness of different keyword-based approaches (Bianchini et al. 2020a). In addition, keyword-based dictionaries require regular updates to capture the rapidly evolving changes in AI technologies. A promising avenue rests on AI itself. Recent contributions propose machine learning techniques that train their algorithms on pre-selected bundle of AI patents (Alderucci et al. 2020) or scientific publications (Bianchini et al. 2020b) in order to identify the most appropriate keywords (or clusters of them) to be used in larger sets of corpus.

Third, while AI patents have the important advantage to be available at a large scale across countries and time, it does not allow to capture the full richness of innovative developments in AI. As we rely on AI patent applications, our model does not include inventions protected by other formal (e.g. software copyrights) and informal (e.g. secrecy) intellectual property rights.

We have seen in our study that the acceleration and diffusion of AI and robotics inventions are more recent developments. This also explains why so few studies have attempted to conduct larger scale econometric analyses so far. We expect that as more evidence becomes available at the firm level over time, it will also open up new possibilities for refined analyses on both the economic impact of AI as well as the underlying mechanisms.

Appendix 1: Data sources and matching procedure

For the collection of AI patents, we draw on a database of AI patents developed by Van Roy et al. (2020). Given the transversal nature of AI, it is particularly difficult to identify which patents are related to the field of AI. To overcome this difficulty, many researchers have used keyword-based approaches in which a collection of AI-related terms (identified by experts in the field) are searched in the text of the patent document (European Commission 2018; Cockburn et al. 2019; De Prato et al., 2018; Keisner et al. 2015; WIPO, 2019). Taking stock of the AI-related keywords employed in this prior literature, Van Roy et al. (2020) developed an AI-related dictionary, displayed in Table 5.

Table 5 List of keywords related to Artificial Intelligence

Keywords related to artificial intelligence		
Artificial intelligence	Face recognition	Random forest
Artificial intelligent	Facial recognition	Reinforcement learning
Artificial reality	Gesture recognition	Robotics
Augmented realities	Holographic display	Self drive
Augmented reality	Humanoid robot	Sentiment analysis
Automatic classification	Internet of things	Smart glasses
Autonomous car	Knowledge representation	Speech recognition
Autonomous vehicle	Machine intelligence	Statistical learning
Bayesian modeling	Machine learn	Supervized learning
Big data	Machine to machine	Transfer learning
Computational neuroscience	Mixed reality	Unmanned aerial vehicle
Computer vision	Natural language processing	Unmanned aircraft system
Data mining	Neural network	Unsupervised learning
Data science	Neuro-linguistic programing	Virtual reality
Decision tree	Object detection	Voice recognition
Deep learn	Predictive modeling	
Evolutionary computation	Probabilistic modeling	

Based on Van Roy et al. (2020)

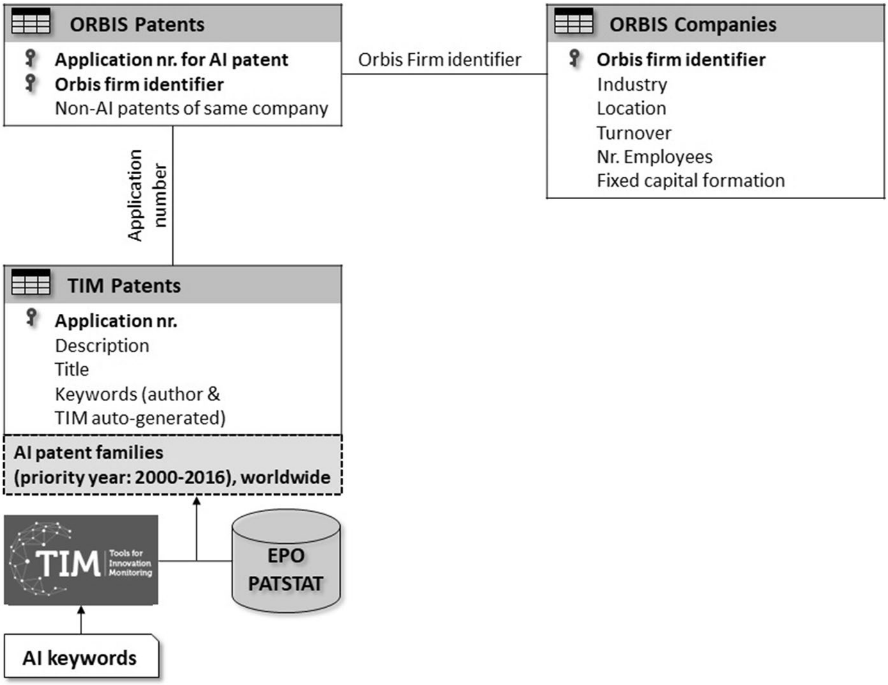

Fig. 1 Data matching procedure

Figure 1 presents a scheme summarizing the data collection process. To retrieve AI patents, the list of AI keywords has been processed by Tools for Innovation Monitoring (TIM), which is an analytics tool developed by the Joint Research Centre to support policy-making in the field of innovation and technological development. TIM provides access to patent documents of the PATSTAT database from the European Patent Office and allows for text-mining searches. TIM contains patents from more than 90 patent authorities including all the major patenting countries and regroups patent documents per patent family when at least one of the members of the family is in English.

Once the relevant patent families in AI have been retrieved with this text-mining technique, the patent family number has been linked with the ORBIS patent database. Subsequently, patent applicants have been linked to their BVD ID number to obtain account information on turnover, employment, fixed capital and sector.

Appendix 2: Variable names and definitions

See Table 6.

Table 6 Description of the variables

Variable name	Variable definition
Labor productivity	Natural logarithm of labor productivity (turnover/number of employees)
Labor productivity t−1	Natural logarithm of labor productivity in t−1
AI patent applications	Natural logarithm of the number of AI patent applications
Non-AI patent applications	Natural logarithm of the number of non-AI patent applications
Employment growth	Natural logarithm of employment in t—natural logarithm of employment in t−1
Fixed capital growth	Natural logarithm of fixed capital in t—natural logarithm of fixed capital in t−1
Firm size	Natural logarithm of number of employees

The number of AI and non-AI patent applications are defined as yearly patent applications

Appendix 3: Country and sector summary statistics

See Tables 7 and 8.

Table 7 Distribution of firms across regions and countries

	Observations		Firms	
	Numbers	%	Numbers	%
Asia	*26,626*	*65.39*	*3531*	*67.17*
Japan	11,432	28.08	888	16.89
South-Korea	9406	23.10	1468	27.92
China	4456	10.94	991	18.85
Taiwan	1065	2.62	149	2.83
Rest of Asia	267	0.66	35	0.67
Europe	*10,175*	*24.99*	*1252*	*23.82*
Germany	2381	5.85	337	6.41
United Kingdom	1494	3.67	150	2.85
France	1402	3.44	174	3.31
Italy	1075	2.64	117	2.23
Sweden	679	1.67	62	1.18
Spain	632	1.55	73	1.39
Belgium	348	0.85	30	0.57
Denmark	322	0.79	27	0.51
Finland	209	0.51	30	0.57
Netherlands	168	0.41	24	0.46
Romania	153	0.38	16	0.30
Austria	132	0.32	29	0.55
Poland	131	0.32	20	0.38
Czech Republic	126	0.31	18	0.34
Switzerland	107	0.26	7	0.13
Rest of Europe	816	2.00	138	2.63
United States	*3774*	*9.27*	*449*	*8.54*
Rest of World	*142*	*0.35*	*25*	*0.48*
Total	*40,717*	*100*	*5257*	*100*

Table 8 Distribution of firms across sectors

	Observations		Firms	
	Numbers	%	Numbers	%
Manufacturing	*26,928*	*66.13*	*3205*	*60.97*
Primary	279	0.69	29	0.55
Food	209	0.51	30	0.57
Textile	273	0.67	31	0.59
Paper	322	0.79	32	0.61
Chemistry	620	3.98	166	3.16
Pharmaceutical	708	1.74	71	1.35
Minerals	356	0.87	36	0.68
Metal	2038	5.01	213	4.05
Electronics	10,221	25.10	1353	25.74
Machinery	6602	16.21	750	14.27
Transport	2782	6.83	305	5.80
Other manufacturing	1518	3.73	189	3.60
Services	*13,789*	*33.87*	*2052*	*39.03*
Construction	1290	3.17	162	3.08
Electricity/water	465	1.14	58	1.10
Retail trade	2174	5.34	305	5.80
Transport services	167	0.41	19	0.36
Hotel and catering	59	0.14	6	0.11
Telecommunication	5554	13.64	856	16.28
Finance	163	0.40	28	0.53
Real estate and rental	881	2.16	123	2.34
Scientific	2709	6.65	426	8.10
Administration/education	115	0.28	26	0.49
Other services	212	0.52	43	0.82
Total	*40,717*	*100.00*	*5257*	*100.00*

Appendix 4: Model choice

See Table 9 .

Table 9 Results from OLS, fixed effects and GMM models

	Labor productivity					
	OLS	Fixed effects	Diff. GMM		Sys. GMM	
			One-step	Two-step	One-step	Two-step
Labor productivity t−1	0.793***	0.450***	0.336***	0.379***	0.544***	0.479***
	(0.014)	(0.028)	(0.046)	(0.044)	(0.054)	(0.057)
AI patent applications	0.008	0.009	0.011	0.012	0.032***	0.017*
	(0.006)	(0.007)	(0.009)	(0.009)	(0.011)	(0.010)
Non-AI patent applications	0.016***	0.036***	0.041***	0.030**	0.019***	0.026**
	(0.003)	(0.005)	(0.014)	(0.012)	(0.007)	(0.012)
Employment growth	− 0.558***	− 0.426***	− 0.349***	− 0.375***	− 0.470***	− 0.426***
	(0.026)	(0.026)	(0.033)	(0.031)	(0.032)	(0.038)
Fixed capital growth	0.163***	0.103***	0.020	0.025	0.088***	0.080***
	(0.021)	(0.025)	(0.031)	(0.029)	(0.022)	(0.023)
Firm size	− 0.003	− 0.125***	− 0.152	− 0.194	0.013	0.013
	(0.003)	(0.021)	(0.139)	(0.129)	(0.047)	(0.054)
Constant	2.628***	7.420***				
	(0.229)	(0.374)				
Industry and country dummies	Included				Included	Included
Year dummies	Included	Included	Included	Included	Included	Included
Observations	40,717	40,717	34,375	34,375	40,717	40,717
Number of firms	5257	5257	4651	4651	5257	5257
R-squared	0.794	0.566				
F test		(22,5256) 117.14***				
Wald test			1473.96***	1483.11***	4648.64***	310,084.15***
AR(1)			− 6.87***	− 7.49***	− 8.78***	− 8.86***
AR(2)			− 1.71	− 1.56	− 1.22	− 1.30
Nr. of instruments			28	28	107	107
Hansen test			7.61***	7.61***	11.59**	11.59**

Standard errors in parentheses. Significance levels are represented as: *** p < 0.01, ** p < 0.05, * p < 0.1. All variables are expressed in natural logarithms

The GMM models presented in the table use twice-lagged instruments, and apply the collapse option to reduce the number of instruments

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Compliance with ethical standards

Conflict of interest The scientific output expressed here are those of the authors and does not imply a policy position of the European Commission or the International Telecommunication Union and their Member States. Neither the European Commission nor any person acting on behalf of the Commission is responsible for the use which might be made of this study.

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