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AI PATENTING AND EMPLOYMENT: EVIDENCE FROM THE WORLD'S TOP R&D INVESTORS

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Abstract

This paper considers 42 corporations which are among the biggest world's R&D investors and account for more than two thirds of AI patents worldwide. Their post-patenting performance is examined by focusing on employment changes and by comparing them with the outcomes of 42 similar companies, operating in the same sectors and recording high levels of R&D expenditures as well, but not involved in AI patenting to a significant extent. The main findings are that in Computers & electronics the companies with the highest shares of AI patents have experienced remarkable employment reductions, while IT services companies have recorded high rates of employment growth, only a bit higher if significantly involved in AI patenting. For companies belonging to Automobiles & parts the evidence is not clear cut, although some of those with significant shares of AI patents have documented a marked decrease of employees.

Keywords: Artificial intelligence, Patents, Employment changes, Large corporations.

JEL codes: O31, O33, J23

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AI Patenting and Employment: Evidence from the World's Top R&D Investors[*]

Alessandro Sterlacchini

1. Introduction

The term Artificial Intelligence (AI) encompasses a wide set of advanced technologies – such as machine learning, autonomous robotics and vehicles, computer vision, language processing, and neural networks – characterized by autonomous learning capabilities with limited or no human interactions. Over the last twenty years there has been a dramatic increase in the introduction and diffusion of robotics and, more recently, AI systems. Both processes have given rise to new opportunities for productivity growth and markets' development, but also strong concerns with respect to their negative impact on employment. Along with the reduction of low-skilled and routine jobs due to the adoption of robotics, software and communication technologies, AI is likely to displace also qualified workers. Several high-skilled or non-routine tasks and related occupations are deemed to be jeopardized by the adoption of AI systems (Frey and Osborne, 2017) and this appears to be the case of the US labour market (Webb, 2020).

According to the long-standing debate on the employment impact of technological change, the unemployment due to labour-saving innovations could be compensated by more demand stimulated by costs and prices' reduction as well as by the development of new business activities. In the same vein, Acemoglu and Restrepo (2019a) argue that also the displacement effect due to the recent wave of automation (robots plus AI) could be countervailed by a productivity effect or by the expansion of new tasks and related occupations. However, the creation of new tasks "is not just manna from heaven" (ibid. p, 207) and, moreover, may be hindered by the presence of inadequate skills. The same scholars also contend that labour market frictions may hamper a significant productivity effect so that if AI is mainly used for automation purposes (rather than the creation of new tasks) it can have a negative impact on aggregate employment. On the other hand, by considering AI a general-purpose technology (GPT), Brynjolfsson et al. (2019) argue that its currently disappointing impact on productivity

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shouldn't be surprising: indeed, as for previous GPTs, the full effects of AI can materialize only after the deployment of several complementary innovations, organizational changes, and human capital investments, especially to address potential skill mismatches.

Both the purported benefits and potential harms of AI (Acemoglu, 2021) cannot be based on conjectures but need to be assessed by empirical evidence. During the last years, most of the analyses on the employment effects of robots and AI have been performed across industries, geographical areas, and, to a lesser extent, firms. Moreover, almost all of them have used data on the adoption of automation systems while the performance of supplying industries and firms has been relatively neglected. Only very recently, some firm-level studies have attempted to fill this gap by employing patent data concerned with inventions related to AI and robots.

The present paper shares with the above studies the use of firm-level data for AI patents with the aim of assessing the employment changes in the supply side of the recent waves of automation. However, instead of using comprehensive data bases for the firms involved in such patents, the analysis is concerned with 42 large corporations which, on the one hand, are among the biggest R&D spenders of the world and, on the other, account for about 38% of AI patents worldwide. Their post-patenting performance is examined by focusing on employment changes and by comparing them with the outcomes of 42 similar companies, operating in the same sectors and recording a high level of R&D expenditures as well, but not involved in AI patenting to a significant extent.

The main findings are that in Computers & electronics the companies with the highest shares of AI patents have experienced remarkable employment reductions, while IT services companies, no matter their involvement in AI, have recorded high rates of employment growth, only a bit higher if significantly involved in AI patenting. For companies belonging to Automobiles & parts the evidence is not clear cut, although some of those with significant shares of AI patents have documented a marked decrease of employees. In any case, both the short time span considered and the limited number of examined companies do not allow to infer that there is a causal linkage between AI patenting and employment changes. However, the findings based on the behaviour of very large corporations provide additional and interesting insights which usefully complement those achieved by recurring to large firm-level databases.

The work is organized as follows. Section 2 reviews some recent studies on the productivity and employment effects of robots and AI with a particular focus of firm-level analyses. Section 3 describes the methodology and the AI patents database, concerned with the world's top R&D investors, developed by the OECD and the Joint Research Centre of the European Commission. Section 4 illustrates the extent of AI patenting of the top companies belonging to Computers & electronics, IT services and Automobiles & parts. Section 5 compares their post-patenting employment changes with that of similar companies which did not record a significant engagement in AI patenting in previous years. Comments to the achieved results and concluding remarks are contained in the final section.

2. The impacts of robots and AI: a survey of recent empirical contributions

The analysis of the effects of automation on employment goes back a long way and it would be much far from the purposes of this work to retrace here its controversial findings. More modestly and usefully, this section provides a concise survey of some empirical studies on robots and AI that have come out in recent years.

The recent wave of studies on the economic impacts of robots was moved by the work of Graetz and Michaels (2018) who have used newly released data by the International Federation of Robotics (IFR). As adoption measure they compute the number of robots per million of hours worked and examine its effect on economic outcomes by considering 14 industries in 17 advanced countries over the years 1993-2007. According to their estimates, the increasing rates of robot usage have a positive impact on the growth of labour productivity and a negative one on the share low-skilled workers although not significantly affecting the level of total employment. Acemoglu and Restrepo (2020) make use of the same IFR data to assess the intensity and the variation of robot adoption across US commuting zones (CZ). Using data from 1990 to 2007, they estimate that the change in robot exposure significantly reduces both employment and wages. By applying similar data and methodology, Aghion et al. (2019) find that also across French employment zones the effect of robot adoption is negative for aggregate employment, while Dauth et al. (2021) show that in German local labour markets robots reduce jobs in manufacturing, but this displacement is fully compensated by more jobs in services.

Moving to firm-level studies on robot and AI adoption, Aghion et al. (2020) employ different proxies, rather than direct measures, for automation at the firm or plant-level: the firm balance sheet value of industrial equipment and machines, the plant-level consumption of electricity for motors used in the production chain and the firm-level imports of industrial machines. Using these indicators for French firms and plants, they estimate a positive employment impact of automation, even for unskilled workers. However, these findings should be taken with caution especially, though not only, with respect to the first and last measure which also encompass capital investments and machines that have little or nothing to do with automation but may allow firms to rise their production capacity and, thus, even employment.

Alguacil et al. (2020) employ a direct though simple measure taken from a survey carried out in Spain every four years, from 1994 to 2014, in which firms are asked, among many other things, if they have adopted robots or not. Such dummy variable is used to distinguish between "treated" and "untreated" firms with the main purpose of assessing whether the former have recorded better export performances. Along with finding a positive impact of robots on foreign trade, the authors show that their adoption is associated with an employment reduction. By using the same database, Koch et al. (2021) find that the more productive firms have a higher probability to adopt robots and that, controlling for such a selection, their usage allows substantial output gains, reduces the share of labour costs, but also induces a net job creation.

Rammer et al. (2021), relying upon the German version of the Community Innovation Survey for the year 2018, consider AI technologies rather than robots. Along with a simple dichotomous variable for the AI adoption, the survey provides data for the use of different AI methods that are applied in different areas. They show that the firms more involved and experienced in AI have a higher share of sales due to new products, especially when the latter are classified as "new to the world". At the same time, a higher propensity to adopt AI technologies is associated with a greater intensity of process innovations leading to cost reductions.

The works reviewed so far, as well as most of those published on this topic, have used data on the adoption of robots and, in the last case, AI technologies. A few recent studies at firm-level have instead make use of patent data concerned with inventions related to AI and robots. This line of research fills a relevant gap of previous empirical analyses because to fully understand the impact of these technologies not only data on their adoption and diffusion but also on their supply are needed.

Damioli et al. (2021a) employ a worldwide dataset for firms with at least one patent application in the fields of AI and robotics over the period 2000-2016. The selection of patents, contained in the PATSTAT database of the European Patent Office, was based on text-mining searches of AI-related keywords on their titles and abstracts. Then, patent data were matched with company balance sheet information taken from the Bureau van Dijk ORBIS database. With a final unbalanced panel for 5257 companies, the authors perform a set of estimations to single out the effect of AI as well as non-AI patenting on firms' labour productivity. Their results show that a significant positive impact of AI patents on firms' productivity emerges only for the most recent sub-period (2009-2016), only in services as opposed to manufacturing, and particularly in Small and Medium-sized Enterprises.

With the same methodology and databases, Damioli et al. (2021b) estimate the impact of AI-patents on firms' employment. The full sample estimations indicate that both AI and non-AI patent applications positively affect firms' employees although the magnitude of the impacts is modest. However, by splitting the sample between manufacturing and services companies, it emerges that only for the latter the parameters of AI and non-AI patents are statistically significant and stronger in magnitude. Thus, the findings of the two studies by Damioli et al. suggest that among services companies the improvement of labour productivity due to AI patenting does not occur at the expenses of the employment.

Other recent papers have used firm-level data to examine the determinants of AI patents. Dernis et al. (2021) provides descriptive evidence on several characteristics of the companies that have been particularly active, between 2014 and 2018, in terms of patent applications protecting AI-related inventions. The latter are highly concentrated, as witnessed by the fact that the top five companies account for 14% of worldwide patents concerned with AI. This is confirmed by Igna and Venturini (2022): by considering EPO applications, they show that AI patents concentrate among a small group of (ex-ante) larger companies which exploit both first-mover advantages and cumulated competencies to reinforce their technological leadership and market power.

This paper shares with the last set of studies the choice of considering the supply rather than the usage of AI technologies. However, in the light of the very high level of concentration of AI patents, instead of using a large data base, the analysis is focussed upon the performance of the the top world's companies that are particularly involved in AI patenting.

3. AI patents of the top R&D investors of the world

The database exploited for our empirical analysis is the *EU Industrial R&D Investment Scoreboard* (henceforth *Scoreboard*) collected and published each year by the Joint Research Centre (JRC) of the European Commission. The *Scoreboard* provides information on net sales, employment, R&D and capital expenditures, and profits for the 2,500 companies investing the largest amounts of money in R&D worldwide[1]. According to the 2020 edition of the

[1] Details, as well as advantages and limitations, concerned with the ways in which company data are collected and elaborated for the *Scoreboard* can be found in European Commission et al. (2020). With respect to "net sales", they are defined as gross sales minus returns, allowances, and discounts.

Scoreboard (cf. European Commission et al., 2020), the total R&D expenditure of these companies is equivalent to about 90% of the world's business-funded R&D.

The JRC and the OECD have jointly developed a project for matching the *Scoreboard* data with those on AI patenting. The latter have been collected by a research team of OECD in collaboration with the Max Plank Institute (cf. Baruffaldi et al. 2020) by means of a mixed methodology based on patent classification codes and keywords searches and further validated by a set of experts and patent examiners. The findings of the matching procedure are contained in Chapter 5 (titled *Shaping AI development: The role of Top R&D investors*) of the report by Dernis et al. (2019).

It should be stressed that the AI patent search carried out by Baruffaldi et al. used "robots" as a keyword; however, robot-related patents are included only when such a keyword showed up in combination with classification codes or keywords concerned with AI systems (a technology field for this kind of patents is examined in Appendix 2). Most importantly, worldwide AI-related inventions were selected only if they are protected in at least two jurisdictions with at least one of them in one of the five major patent offices of the world[2]. This procedure, termed by the OECD "IP5 patent families", is more selective than that performed in previous studies (Webb et al., 2018; WIPO, 2019; Santarelli et al., 2021) which also included those protected in one jurisdiction only. Thus, as far as the extent of patent families is a good indicator of high-value inventions, it is possible to say that the patents selected by Baruffaldi et al. meet a relatively high level of quality (at least in the eyes of applicants). Moreover, the IP5 patent families' criterion makes patent data more comparable at the international level.

With respect to the sectoral distribution of AI patents of the top R&D investors filed in the period 2014-2016, Dernis et al. (2019) show that almost half of them belong to "Computers & electronics" followed by "Machinery", "IT services" and "Transport equipment". AI-related technologies are mainly developed by Japanese companies (43%) followed by those headquartered in the US (20%), EU28, China and South Korea. This geographical distribution is in line with that arising from WIPO (2019), while there are some differences in the sectoral ranking which are mainly due to the different criteria that are adopted to select AI patents (see above).

Most importantly for the purposes of the present paper, the dataset provided by the JRC-OECD project (available at http://oe.cd/ipstats) reports the list and the patent shares of the top

[2] The five IP offices are the EPO, the JPO for Japan, the KIPO for Korea, the USPTO, and the CNIPA for China.

50 companies (out of the 2,500 big R&D spenders of the *Scoreboard*) with AI patents in the period 2014-2016.

4. The top AI patenting companies …

In the following analysis, 42 out of the 50 top companies with AI patents are considered. The remaining ones (8) are excluded for different reasons but especially because, considering their main lines of business, it was impossible to include them into sectors sufficiently homogenous and large (in terms of number of companies) such as those reported in Table 1[3].

Table 1 – Top R&D investors with AI patents by sector*:

	Share of AI patents on those of the world's top R&D investors: 2014-2016[(a)]	Share on total AI patents worldwide: 2014-2018[(b)]
Computers & electronics: high patents' shares (7)	34.20	13.9
Computers & electronics: low patents' shares (18)**	18.80	8.8
Computers & electronics: total (25)	53.00	22.7
IT services (10)	13.13	9.8
Automobiles & parts (7)	6.43	5.1
Total (42)	72.56	37.6

*= Number of companies in brackets. **= Data in the second column refer to 13 companies only (see Table A1 in Appendix 1). Sources: (a) Dernis et al. (2019), (b) Dernis et al. (2021).

The first column shows that the examined companies (see the number in brackets after the sector label) account together for 72% of the total AI patents ascribed to the top R&D investors of the world. The lion share (53%) belongs to 25 companies included in Computers & electronics which are also distinguished into two groups: 7 companies with a percentage of total AI patents above the sectoral average (2.4%) and 18 with a lower share. The second place is achieved by 10 companies belonging to IT services followed by 7 Automobiles & parts companies.

[3] Among the excluded companies there are Amazon and Alibaba. Then, there are Boeing and Honeywell (mainly active in aerospace and defence systems), General Electric (aviation, healthcare, and energy), and Philips (lighting and personal care). The latter two can be hardly classified as Electronic & Electrical Equipment companies and included in the broad sector of Computers & Electronics (see Table 1 and Table A.1 in Appendix 1). Finally, for the Japanese Fanuc (automation products and services) and the Chinese Leshi (IT services) data on post-patenting performances were incomplete.

It should be stressed than the leading role of Computers & electronics is not simply due to the higher number of involved firms but also to the fact some of them record a remarkable share of AI patents. As shown by Table A.1 in Appendix 1, this is particularly the case of Canon (10.6 %) and Samsung Electronics (7.9%)[4]. The leading role of Asian companies in this sector and field of technology is confirmed by the fact that all the other 5 companies with greater shares of AI patens (around 3% on average) are Japanese. In IT services (cf. Table A.2) the percentages of AI patents are lower: only Alphabet (Google) records a share above 3% followed by the Japanese NEC (about 2%) and IBM (1.5%). Much lower percentages characterize Automobiles & parts companies as witnessed by the leading role of Toyota with just a 1.3% of AI patents (see Table A.3).

Table 1 also documents a further element stressing the relevance of the companies considered in this paper. The work by Dernis et al. (2021) provides data for the shares of the top 50 companies with AI patents but in this case the reference period is 2014-2018 and the reference population is the number of AI-related inventions in the world meeting the IP5 patent families' criterion. Not surprisingly, 37 out of the 42 examined companies are included in the world's top 50 companies with AI patents. Obviously, the shares reported in the second column of Table 1 are lower than the former. In any case, our set of companies accounts for about 38% of AI patents worldwide. The sectoral ranking does not change but it can be noticed an improvement of the relative positions of IT services and even Automobiles & parts, suggesting that the relevant companies, as opposed to those belonging to Computers & electronics, have remarkably increased their inventive activity in the field of AI during the years 2017 and 2018. This seems especially the case of Microsoft and IBM along with Alphabet and NEC (cf. Table A.2 in Appendix 1). In the Automobiles & parts sector Ford and General Motors slightly overtake Toyota (see Table A.3). Even in Computers & electronics the company ranking changes (Table A.1): the leading position is taken by Samsung Electronics, while Canon falls back to second place, closely followed by the Japanese Fujitsu.

[4] Contrary to what emerges from Dernis et al. (2019 and 2021), the WIPO report (2019) documents that IBM and Microsoft have the largest portfolio of AI patent applications worldwide. This proofs that the "IP5 patent families" criterion adopted in the first case is very selective and give rise to quite different findings. Indeed, the lower shares of IBM and especially Microsoft reported in Dernis et al. could be also due the fact that "pure" software patents are not always allowed outside the US.

5. … and their post-patenting performances

The further step of the analysis is the exam of the post-patenting performance – from 2016 to 2019 – of the top R&D spenders and AI patentees. Table 2 shows weighted average sectoral data for the number of employees in 2016, the employment and sales growth over 2016-2019 as well as the average intensities on sales of R&D and capital expenditures and profits.

Table 2 – Performances of the world's top R&D investors with significant and non-significant shares of AI patents: 2016-2019*

	Average employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Expenses/ Sales 2016-19	Profits/ Sales 2016-19
Computers & electronics						
High patent shares (7)	160986	-10.82	3.36	6.57	8.39	11.24
Low patent shares (18)	135383	3.91	17.97	7.73	6.50	9.67
Significant patent shares (25)	142552	-0.75	12.38	7.29	7.22	10.27
Non-significant patent shares (23)	*70572*	*8.50*	*15.76*	*6.86*	*4.56*	*13.51*
IT services						
Significant patent shares (10)	176837	15.60	32.83	8.82	8.87	20.38
Non-significant patent shares (9)	*50545*	*13.58*	*38.12*	*14.84*	*7.93*	*21.11*
Automobiles & parts						
Significant patent shares (7)	230553	-2.54	0.58	4.83	9.33	5.24
Non-significant patent shares (10)	*201116*	*8.48*	*9.60*	*5.33*	*5.23*	*5.62*

*= Number of companies in brackets.
Source. Own computations form the *EU Industrial R&D Investment Scoreboard* (2017-2020 issues).

The performances of the 42 examined corporations are compared with those of similar companies, that is belonging to the same sector and spending a relevant amount of money in R&D. The 42 companies selected for comparative purposes were always extracted from the *Scoreboard* moving from those that invest more in R&D to those that invest less and stopping when their employment size became too small compared with that of the companies of the same sector with AI patents. These companies, as opposed to former, did not record in the period 2014-2016 a significant share of AI patents according to the selection criteria adopted by Dernis et al. (2019). For this reason, they are labelled in Table 2 as having "non-significant patent shares". Tables A.4-A.10 in Appendix 1 report, along with those of the companies with "significant patent shares", the individual performances of the companies used for comparative purposes (23 in Computers & electronics, 9 in IT services and 10 in Automobiles & parts). It should be stressed that even the latter companies have applied for some patents related to AI in the same years. However, as shown in Appendix 2, in terms of number of patent applications the gap with respect to those classified as significantly involved in AI is remarkable so that the distinction does not appear to be arbitrary[5].

In what follows, the companies' performance between 2016 and 2019 are examined separately for each sector, with special focus on employment changes. It must be stressed that although the latter refer to a period subsequent to that of patent applications (2014-2016), one cannot infer they have been caused by the intensity of AI patenting. Indeed, the employment effects due to the exploitation of patent applications may occur over a much longer period. This is certainly true even though it should be considered that the publication of a patent application, which both in the EU and US legislation takes place within 18 months from the filing date, provisionally confers on the applicant the same rights as a granted patent[6]. On the one hand these provisions discourage competitors to exploit the same invention for commercial purposes while, on the other, incentivize the applicants to do that without waiting for the patent grant (also to benefit from first-mover advantages). Moreover, due to the cumulative nature of technological knowledge, it is possible to argue that companies showing a high propensity to AI patenting may have been investing in technologies aimed at automating production and business processes for a longer time. Accordingly, it should be reasonable and acceptable to consider an average time lag of about three years between the filing of AI patents' applications (2014-2016) and the employment changes (2016-2019). In principle, to allow a longer time-lag, also the year 2020 could have been taken into account; however, we have chosen not to do this since in this year the performance of most companies has been strongly affected by the negative shock caused by the Covid-19 pandemic.

[5] Obviously, even a firm with few patents could have introduced important, radical, or even disruptive inventions having a strong impact on employment when translated into innovations. However, this appears to be an exception rather than the rule since it can be assumed that the probability to introduce a breakthrough invention increases with the number of patents.

[6] Article 67(1) of the European Patent Convention states that from the date of its publication a European patent application provisionally confers on the applicant the same rights as would be conferred by a patent granted. Similarly, in the US the American Inventor's Protection Act of 1999 states that the owner of a published application receives provisional rights to pursue royalties or infringement damages for the period between the date of publication and date of patent grant. As Hegde et al. (2022, p. 7) point out "To be entitled to the royalties, the published claims must be "substantially identical" to the granted claims. These rules together limit the downside of early patent disclosure to inventor".

5.1 Computers & electronics

This sector plays a major role in our analysis for two main reasons. First it is composed by a relatively large number of companies (25 with significant and 23 with non-significant shares of AI patents) so that its post-patenting performance is less affected by the presence of possible outliers. Secondly, it includes companies with a quite different degree of involvement in AI patenting so that it was possible to distinguish between those with “high” and “low” shares of AI patents. As shown by Table 2, Computers & electronics companies with high shares of AI patents in 2014-1016 record a significant reduction of employment in 2016-2019 (about -11%) which does not appear justified by a parallel decrease of sales (although the latter augment, on average, by 3.4% only). In the same sector, instead, the companies with low AI patenting increase the number of employees by about 4% while those with non-significant patent shares by 8.5%. In both cases the employment growth is much lower than the growth rate of sales (18 and 16% respectively). Putting together the 25 companies significantly involved in AI patents, the rate of change of employment is -0.7% while their sales experience a significant increase.

In terms of R&D intensity and profitability the differences between the company groups are not remarkable. Only for capital expenditures, AI companies and especially those with high shares of patents record an intensity on sales higher than that of the company not significantly involved in AI patenting.

Tables A.4-A.6 in Appendix 1 show the performance of individual companies which are inserted in descending order with respect to the number of employees in 2016. All the 7 companies with high shares of AI patents have reduced the number of employees after 2016 (cf. Table A.4). Only for one company (Toshiba) this reduction is consistent with a decrease of sales; in four cases the employment decrease occurs despite the increase of sales, while in the remaining two companies the reduction of employees is much greater than that of sales. Instead, moving to the 18 companies with low shares of AI patents (table A.5), it is noticeable that the employment variations (positive in most of cases) are almost always consistent with those of sales: only LG Electronics records a small reduction of employees (-1.2%) in presence of a remarkable increase of sales (+11%) while the opposite happens to Qualcomm[7]. An even

[7] The performance of Qualcomm (characterized by an increase of employment with a negative change of sales and high rates of profitability) seems quite at odds with expectations. The situation is even more contradictory if the analysis starts from 2016. For this reason, the rate of changes of employment and sales are computed from 2017 to 2019. In any case, due to its relatively low size in terms of employment, the exclusion of Qualcomm would not change our findings.

greater consistency between the rates of change of employment and sales (again, in most case positive) emerges when the 23 companies with non-significant shares of AI patents are considered. In some instances, these positive variations are very high (above 30 and even 40%) but this mainly happens for companies with a lower size in terms of employment (see Table A.6).

5.2 IT services

Moving to IT services companies, Table 2 shows that those with significant patenting activities in the field of AI experience, between 2016 and 2019, an average growth rate of employment only a bit higher than that recorded by companies not significantly involved in AI patenting (15.6 vs. 13.6%). The latter group is instead characterized by a higher increase of sales and a greater intensity of R&D expenditures while, in terms of capital intensity and profitability, there are no significant differences with respect to the former "AI group".

Looking at individual companies, Table A.7 in Appendix 1 shows that among AI patenting companies, only IBM and Baidu (China) report an employment reduction, but in the former case this appears to be in line with a contemporaneous decline of sales. Looking at the companies with non-significant shares of AI patents (cf. Table A.8), the same occurs to Oracle (US) and Ericsson (Sweden) while only Hewlett Packard Enterprise (US) experiences an employment decline in presence of a sales' expansion[8]. It should be added that the latter group includes three US companies (Facebook, Servicenow, and Square) that have more than doubled their employment and sales in a three-year period. Due to their very small size in 2016, the impact of Servicenow and Square on the weighted averages is negligible. The same consideration does not apply to Facebook which starting with 17 thousand employees in 2016 has recorded an employment growth of 164% and an increase of sales of 140%. Its exclusion would have almost halved the average growth rates of employment and sales of the IT services companies with non-significant shares of AI patents. However, due to the inclusion of the Chinese Tencent among the AI companies (operating in a similar line of business and recording a 62% growth of employment and a 132% increase of sales) there were no valid reasons to exclude Facebook from our analysis.

[8] This inconsistency, which applies to Baidu too, would be much more evident by taking 2016 as the starting year. For this reason, the employment and sales changes of Hewlett Packard Enterprise and Baidu refer to the period 2017-2019.

5.3 *Automobiles & parts*

In this sector, over 2016-2019, the companies with significant shares of AI patents have reduced the number of employees by 2.5% while those not significantly involved in AI have recorded an increase of 8.5%. This different employment performance seems quite consistent with the growth of net sales: +0.6% only in the first group and + 9.6% in the second one. According to this sole finding, it would be difficult to interpret these different employment changes only in the light of the propensity to AI patenting.

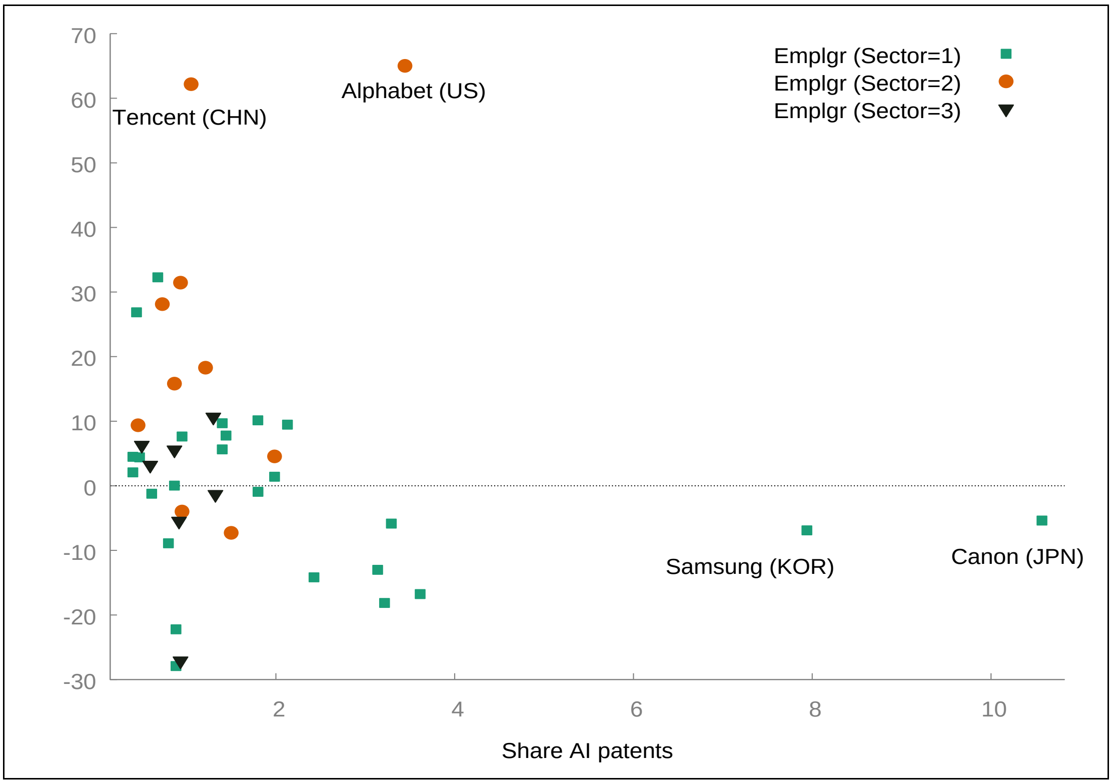
This consideration is reinforced by looking at the individual performance of Automobiles & parts companies. In fact, Table A.9 in Appendix 1 shows that marked employment reductions only emerge for the two US Automobiles companies (General Motors -24% and Ford -5.5%) and are consistent with a decline of sales (-23% and – 3.6% respectively). Only Toyota records a small negative change of employees (-1.3%) in presence of a sales' expansion (+9%). With respect to other variables, the Automobiles & parts companies with significant shares of AI patents are characterized by a greater intensity of capital expenses during 2016-2019, while both in terms of R&D and profitability the findings are in line with those arising from the comparative group.

5.4 *Regression analysis*

This additional section examines whether the above considerations concerned with employment variations find some support from a regression analysis based on data concerned with both types of companies, significantly and non-significantly involved in AI patenting. Before doing that, it is useful to focus on the first group of companies by showing a simple graphical analysis of the relationship between the shares of AI patents in 2014-2016 and the growth rates of employees over 2016-2019.

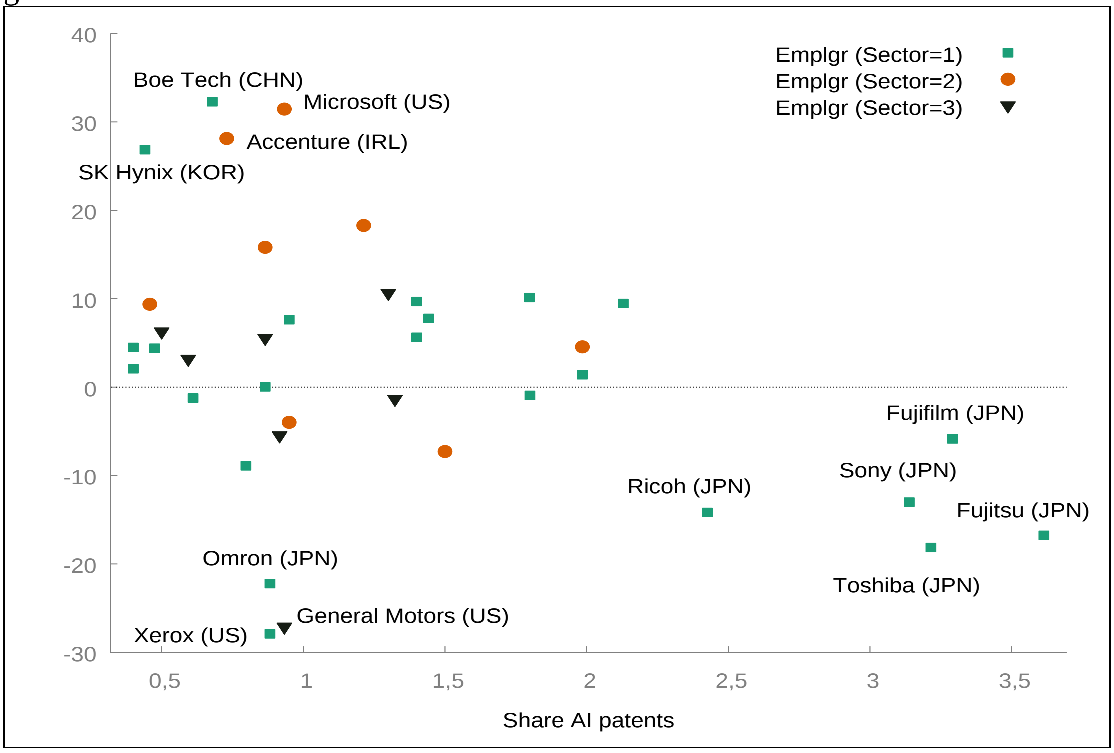
From both the scatter plots depicted in Figures 1.a and 1.b a negative relationship between the above variables emerges. By including all the AI companies, Figure 1.a suggests that such a finding is strongly influenced by four companies: on the one hand, Canon and Samsung (with very high shares of AI patents and negative variations of employment) while, on the other, Alphabet and Tencent (recording opposite performance).

Figure 1.a – All companies with significant shares of AI patents



Sector 1= Computers & electronics; Sector 2 = IT services; Sector 3= Automobiles & parts.

Figure 1.b – Companies with a share of AI patents lower than 4% and an employment growth lower with 40%.



Sector 1= Computers & electronics; Sector 2 = IT services; Sector 3= Automobiles & parts.

However, Figure 1.b shows that a negative relationship persists even when the above companies are excluded. A cluster of five companies with high shares of AI patents and negative employment growth emerges: all of them belong to Computers & electronics and have their headquarters in Japan. On the opposite side of the graph there are four companies: Microsoft and Accenture (headquarter in Ireland) which operate in IT services and Boe Technology (China) and SK Hynix (Korea) belonging to Computers & electronics. Finally, it is worth to notice the presence of three companies with low shares of AI patents and remarkable reductions of employees: General Motors for Automobiles and Omron (Japan) and Xerox (US) included in Computers & electronics.

To summarize, the negative relationship between AI patenting and employment appears to be shaped by the performance of Computers & electronics companies with high shares of AI patents and employment decreases, coupled with that of IT services companies characterised, instead, by lower shares of AI patents and very high rates of employment growth.

We now move to regression analyses aimed at comparing the employment growth of the above companies with that of those not significantly involved in AI patents. The low number of observations at our disposal (84 companies) prevent us to consider many possible explanatory variables. Hence, we just include in the regression the growth of sales over 2016-2019, the sectoral dummies, and three alternative indicators for the propensity to AI patenting:

a) a dummy variable called AI for companies with significant shares of AI patents;

b) two dichotomous variables termed “AI-high” and “AI-low” for companies having, respectively, a high and low (but significant) share of AI patents in the same period, with the former referring to 7 Computers & electronics companies (cf. Figures 1.a and 1.b and Table A.1 in Appendix 1);

c) a truncated variable for the share of AI patents (see Tables A.1-A.3) where a zero value is ascribed to the companies not significantly involved in AI patenting.

OLS estimations reported in Table 3.a show, as expected, a very significant positive correlation between employment and sales’ growth: the estimated parameter points to an elasticity of employment with respect to sales equal to 0.6. The dummy for having a significant share of AI patents has a negative and statistically significant impact on employment growth. Such a negative effect turns out to be stronger for companies with high shares of AI patents although it remains significant for those with low shares, always as opposed to the companies not involved in AI patenting. By using the shares of AI patents, instead of the dummies, the negative effect on employment is confirmed but the estimated parameter is significant only at a

10% level of confidence. Finally, the sectoral dummies, though not statistically significant, suggest that Computers & electronics companies record lower growth rates of employment while the opposite occurs to those active in IT services (Automobiles & parts being the reference sector).

Similar findings emerge by performing, in the light of the remarkable differences of company size, the same regressions with WLS, using the level of employees in 2016 as weight (cf. Table 3.b). The results for the sales' growth and the sectoral dummies are fully consistent with OLS estimations. The propensity to AI patenting exerts a negative impact on employment growth although, in this case, only the parameter of the AI-high dummy is statistically significant. Another difference with respect to OLS estimates is that the negative effect of the truncated variable for AI patents' shares is now statistically significant.

Table 3.a – OLS estimations. Dependent variable: employment growth 2016-2019.

	Coeff.	St.Err.		Coeff.	St.Err.		Coeff.	St.Err.	
Constant	2.766	2.439		2.609	2.486		0.154	1.934	
Sales growth 2016-19	0.669	0.081	***	0.667	0.082	***	0.686	0.083	***
AI 2014-2016	−7.366	3.186	**						
AI-high 2014-16				−9.700	3.797	***			
AI-low 2014-16				−6.957	3.411	**			
Share AI Pat 2014-16							−1.393	0.760	*
Computers	−3.922	2.593		−3.548	2.765		-3.858	2.680	
IT services	5.550	4.643		5.603	4.659		4.283	4.392	
Adjusted R^2	0.772			0.770			0.763		

Observations= 84. Standard errors robust to heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.b – WLS estimations (weight=Employment 2016). Dependent variable: employment growth 2016-2019.

	Coeff.	St.Err.		Coeff.	St.Err.		Coeff.	St.Err.	
Constant	0.941	2.425		0.598	2.407		-0.450	1.979	
Sales growth 2016-19	0.533	0.092	***	0.512	0.096	***	0.529	0.095	***
AI 2014-2016	-4.425	2.417	*						
AI-high 2014-16				-11.361	2.869	***			
AI-low 2014-16				-3.290	2.523				
Share AI Pat 2014-16							-1.282	0.497	**
Computers	-1.890	2.402		-0.308	2.493		-1.267	2.556	
IT services	7.182	4.159		7.061	4.175	*	6.303	3.881	
Adjusted R^2	0.570			0.583			0.575		

Observations= 84. Standard errors robust to heteroskedasticity. *** p<0.01, ** p<0.05, * p<0.1.

In alternative specifications, also the intensities of R&D and capital investments on sales in 2016 and country dummies (Japan, US, Other Asian countries, Europe) are included. The impact of the former variables is never statistically significant. The same apply to country dummies with a sole exception: when WLS estimations are performed the dummy for Other Asian countries (with Europe taken as reference category) is negatively associated with employment growth. In any case, the results reported in Table 3.b do not change.

To summarise, the regression analysis provides additional support to the negative relationship between AI patenting and employment growth. However, as already suggested by descriptive analyses, such a negative relationship appears to be mainly due to the behaviour of a limited set of companies characterised by high shares of AI patents. In any case, the estimated parameters for the propensity to AI patenting should be taken as measures of correlation rather than causal effects. In fact, even if the objection based on a too-short time lag between patent applications and employment changes is discarded (see the discussion below Table 2 in Section 5), our results could be affected by other problems, such as that of omitted variables, so that they cannot be interpreted as unbiased casual effects.

6. Comments and concluding remarks

The main finding that can be derived from the analysis of the top world's R&D investors is that in Computers & electronics (the sector for which we have the largest number of observations) a negative relationship emerges between employment variations and the shares of AI patents. For companies belonging to Automobiles & parts the evidence is less clear but what can be said is that the extent of AI patents is not correlated with employment increases. Instead, among IT services companies the extent of inventive activities in the field of AI is associated with high rates of employment growth, although only a bit higher than those achieved by the companies of the same sector not significantly involved in AI patenting.

A possible interpretation of these different results is the following. In the IT services sector patented inventions are mainly aimed at finding new applications to be commercialized in the growing market for AI solutions generated by firms operating in a wide range of industries. Hence, the investment in such inventive activities generates new business opportunities which can lead to a growth of sales and employees. In the Computers & electronics sector, it is instead likely that a substantial portion of AI-related inventions are undertaken with a view to exploit them also internally, within the same inventive firms. If this is the case, AI technologies could be implemented for automating a variety of tasks with a consequent displacement of workers.

To be reminded is that the above findings are achieved by comparing the employment performance of "AI companies" with that of companies that do not have significant shares of AI patents. Looking at the intensity of R&D expenditures on sales, the latter are not less innovative than the former. Instead, with the partial exception of IT services, "AI companies" prevail in terms of capital expenditures and this could signal a greater propensity to automate production processes. A further, though partial, piece of evidence supporting this conjecture has been provided in Appendix 2 by showing that in Computers & electronics and Automobiles & parts the companies more involved in AI patenting have applied for a remarkable number of patents concerned with inventions in which AI systems and robots are interconnected.

It must be stressed that the above considerations are mainly based upon descriptive evidence and, hence, cannot be interpreted as causal linkages. Although even the results of regression analyses point to a negative relationship between AI patents and employment the issue of causality remains unsolved.

Despite the above shortcomings, it appears hardly disputable that "The current trajectory in AI research is shaped by the visions of large tech companies, who are responsible for the majority of the spending on this technology. Many of these companies have business models centered on substituting algorithms for humans, which may make them focus excessively on using AI for automation." (Acemoglu, 2021, p. 25).

As far as the first part of the sentence is concerned, it should be reminded that all the companies examined in this paper are among the top R&D spenders of the world and those more involved in AI patenting account for more than two thirds of AI patents worldwide. So, although the emergence of newcomers will hopefully be substantial, it is indisputable that the future trends in AI, with their employment consequences, will be in the hands of a few top players. Accordingly, together with micro-econometric studies with large databases, it would be important and useful to monitor the behaviour of the top AI inventors, also by means of case studies[9].

[9] Babina et al. (2021) illustrate the cases of four US companies investing in AI: UnitedHealth Group, JPMorgan Chase, Caterpillar, and Qualcomm. In 2018 the employment size of the first three companies ranged from 100 (Caterpillar) to 300 thousand people (UnitedHealth) and their number of AI workers varied from 20 to 98.

With respect to the second part of the sentence, our findings show that among the companies with high shares of AI patents those belonging to Computers & electronics have experienced a remarkable reduction of employees. Aside from the difficulty of predicting if these outcomes will be kept in the future, the unavailability of data concerned with the adoption (rather than the introduction) of AI technologies[10] does not allow one to address the question of whether the job losses in some production activities could be countervailed by more jobs in other activities. In any case, as stressed in the literature survey of Section 2, such a compensation cannot be taken for granted; this open the further issue of what policy measures should be put to the fore to ensure a socially sustainable transition.

With respect to the limitations of the present paper, we have already pointed out the issues of the short time span between patenting and employment change and the lower number of examined companies. A further, and perhaps more severe shortcoming, is that the examined data derive from consolidated figures of very large groups and, sometimes, conglomerates which are active not only in different lines of business but even industries. Accordingly, much additional work should be done, especially by considering the different classes and sub-classes of AI patents (see, as an example, Appendix 2) also with a view to see whether the specific patent activities in which the companies are involved are consistent with their current lines of business and/or useful to foresee the development of new business activities. Hence, it would be necessary to employ disaggregate data on the economic performance of the major parent companies composing the group or the conglomerate.

Qualcomm, a company included in the present study (see Table A5 in Appendix 1), employed alone 660 AI workers out of 37 thousand employees. Rikap and Lundvall (2021) perform a pairwise comparison between US and Chinese giant corporations involved in the digital innovation race: Amazon-Alibaba, Google-Baidu, Apple-Huawei and Facebook-Tencent.

[10] As it was done in previous studies on ICT (cf. Stiroh, 2002) it could be interesting to try to classify the different industries in terms of AI-producers, AI-users, and non-AI. However, in this paper we contend that, in some industries, AI producers could be also intensive users of AI.

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Appendix 1: Company data

Table A.1 – Computers & electronics companies with significant shares of AI patents

	Share of AI patents on those of the world's top R&D investors: 2014-2016 (a)	Share on total AI patents worldwide: 2014-2018 (b)
Canon (Japan)	10.57	3.00
Samsung Electronics (Korea)	7.94	5.20
Fujitsu (Japan)	3.61	2.10
Fujifilm (Japan)	3.29	0.60
Toshiba (Japan)	3.22	1.30
Sony (Japan)	3.14	1.30
Ricoh (Japan)	2.43	0.40
Total 7 companies with AI shares higher that the average (2.14)	*34.20*	*13.90*
Qualcomm (US)	2.13	0.90
Olympus ((Japan)	1.99	0.60
Intel (US)	1.80	1.50
Hitachi (Japan)	1,80	0,80
Huawei (China	1.44	0.80
Siemens (Germany)	1,40	0,50
Mitsubishi Electric (Japan)	1,40	0,50
Kyocera (Japan)	0.95	n.a.
Xerox (US)	0.88	0.60
Omron (Japan)	0.88	0.50
Konica Minolta (Japan)	0.87	0.50
Casio Computer (Japan)	0.80	0.30
Boe Technology Group (China)	0.68	0.50
LG Electronics (Korea)	0.61	0.80
Seiko Epson (Japan)	0.48	n.a.
SK Hynix (Korea)	0.44	n.a.
Brother Industries (Japan)	0,40	n.a.
Hon Hay Precision Ind. (Taiwan)	0,40	n.a.
Total 18 companies with AI shares lower that the average	*18.80*	*8.80*
Total	53.00	22.70

Sources: (a) Dernis et al. (2019), (b) Dernis et al. (2021).

Table A.2 – IT services companies with significant shares of AI patents

	Share of AI patents on those of the world's top R&D investors: 2014-2016	Share on total AI patents worldwide: 2014-2018
Alphabet (US)	3.44	2.20
NEC (Japan)	1.99	1.00
IBM (US)	1.50	1.10
Softbank (Japan)	1.21	n.a.
Tencent (China)	1.05	0.70
Baidu (China)	0.95	1.20
Microsoft (US)	0.93	1.80
Tata Consulting Services (India)	0.87	0.80
Accenture (Ireland)	0.73	1.00
Wipro (India)	0.46	n.a.
Total	13.13	9.80

Sources: see Table A.1

Table A.3 – Automobiles & parts companies with significant shares of AI patents

	Share of AI patents on those of the world's top R&D investors: 2014-2016	Share on total AI patents worldwide: 2014-2018
Toyota (Japan)	1.32	0.90
Denso (Japan)	1.30	0.60
General Motors (US)	0.93	1.00
Ford (US)	0.92	1.00
Hyundai (Korea)	0.87	0.50
Honda (Japan)	0.59	0.40
Robert Bosh (Germany)	0.50	0.70
Total	6.43	5.10

Sources: see Table A.1

Table A.4 – Computers & electronics companies (7) with high shares of AI patents

	Employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Investment/ Sales 2016-19	Profits/Sales 2016-19
Samsung Electronics (Korea)	308745	-6.90	11.71	7.85	14.00	18.50
Canon (Japan)	197673	-5.38	6.10	8.30	5.37	7.13
Fujitsu (Japan)	155069	-16.77	-4.99	3.55	3.54	4.06
Toshiba (Japan)	153492	-18.14	-30.10	5.05	3.63	2.55
Sony (Japan)	128400	-13.01	9.11	5.71	4.11	8.28
Ricoh (Japan)	105023	-14.17	-0.57	4.83	3.79	0.49
Fujifilm (Japan)	78501	-5.85	0.13	6.74	3.08	7.40
Average	160986	-10.82	2.43	6.71	8.79	11.87

Source: Own computations form the *EU Industrial R&D Investment Scoreboard* (2017-2020 issues).

Table A.5 – Computers & electronics companies (18) with low shares of AI patents

	Employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Investment/ Sales 2016-19	Profits/Sales 2016-19
Hon Hay Precision Ind. (Taiwan)	873000	4.49	23.38	1.55	1.30	2.98
Siemens (Germany)	351000	9.69	9.05	6.78	2.93	8.28
Hitachi (Japan)	303887	-0.93	-3.89	3.46	3.83	7.32
Huawei (China	180000	7.78	63.78	14.81	4.17	10.42
Mitsubishi Electric (Japan)	138700	5.64	5.74	4.61	4.16	6.38
Intel (US)	100600	10.14	13.70	19.92	19.88	29.24
Seiko Epson ((Japan)	72420	4.40	2.27	4.95	6.69	5.83
Kyocera (Japan)	70153	7.63	12.88	4.24	5.94	6.36
Boe Technology Group (China)	49151	32.28	58.25	5.21	50.22	8.16
Konica Minolta (Japan)	43948	0.03	14.26	7.33	3.31	4.44
LG Electronics (Korea)	40610	-1.23	11.09	5.77	5.04	3.72
Xerox (US)	37453	-27.91	-10.14	3.78	0.95	9.96
Brother Industries (Japan)	36929	2.08	8.36	6.66	2.81	10.52
Omron (Japan)	36008	-22.22	-14.26	6.69	4.42	8.90
Olympus ((Japan)	34687	1.40	7.06	10.26	5.66	10.08
Qualcomm (US)*	33800	9.47	-6.26	25.50	3.67	16.75
SK Hynix (Korea)	22264	26.86	53.61	9.25	41.76	35.43
Casio Computer (Japan)	12287	-8.90	-5.48	2.35	1.92	9.85
Average	135383	3.91	17.97	7.73	6.50	9,67

*= 2017-19. Source: see Table A.4

Table A.6 – Computers & electronics companies (23) with non-significant shares of AI patents

	Employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Investment/ Sales 2016-19	Profits/Sales 2016-19
Panasonic (Japan)	257500	0.73	2.44	6.61	4.18	4.60
Sumitomo Electric (Japan)	248330	14.33	10.87	4.01	5.90	4.90
Dell Technologies (US)	138000	19.57	40.28	5.51	1.78	-0.99
Apple (US)	116000	18.10	13.21	5.33	5.19	26.47
Nokia (Finland)	101000	-2.65	-1.27	19.73	2.63	-0.37
TDK (Japan)	99693	7.47	16.19	8.21	13.39	7.13
ZTE (China)	81468	-14.00	-16.35	13.50	2.22	3.25
Western Digital (US)	68000	-9.12	-10.61	13.18	4.04	15.06
Murata manufacturing (Japan)	59985	23.55	35.68	6.66	18.37	15.75
Lenovo (China)	52000	21.15	10.58	2.53	0.99	1.90
HP (US)	49000	14.29	14.29	2.44	0.94	7.60
Taiwan Semiconductor (Taiwan)	46968	9.22	13.62	8.16	35.51	37.92
STMicroelectronics (Netherlands)	43480	4.77	28.76	15.60	12.57	10.40
Sharp (Japan)	41898	26.20	11.24	4.57	4.11	2.63
Seagate Technology (Ireland)	41000	2.44	4.16	9.93	4.28	12.58
NXP Semiconductors (Netherlands)	40400	-27.23	-12.30	17.30	5.62	18.45
Micron Technology (US)	31400	17.83	77.13	9.33	34.08	32.58
Texas Instruments (US)	29900	-0.44	0.94	10.23	5.42	40.30
Renesas (Japan)	18884	0.39	53.15	16.92	9.52	8.69
ASML Holding (Netherlands)	16647	49.58	73.96	14.23	4.83	26.07
Broadcom (Singapore)	15700	21.02	60.14	19.44	2.63	15.58
Applied Materials (US)	15600	41.03	26.62	12.94	2.90	24.62
Nvidia (US)	10299	33.75	48.26	21.61	4.68	29.97
Average	70572	8.50	15.76	6.86	4.56	13.51

Source: see Table A.4

Table A.7 – IT services companies (10) with significant AI patents

	Employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Investment/ Sales 2016-19	Profits/Sales 2016-19
Tata Consulting Services (India)	387223	15.82	19.03	0.22	1.55	15.82
Accenture (Ireland)	384000	28.13	16.53	1.88	1.43	13.82
IBM (US)	380300	-7.28	-9.42	6.47	4.15	15.73
Wipro (India)	160000	9.38	7.24	0.66	3.96	16.34
Microsoft (US)	124000	31.45	49.19	13.64	10.45	32.60
NEC (Japan)	107729	4.56	77.56	4.09	2.08	3.28
Alphabet (US)	72053	65.02	68.24	15.33	14.40	24.00
Softbank (Japan)	68402	18.28	7.27	1.44	12.34	5.17
Baidu (China)*	39643	-3.98	26,01	15.66	6.66	13.06
Tencent (China)	38775	62.18	131.76	7.65	5.83	31.09
Average	176213	16.02	35.30	8.37	8.67	19.14

*= 2017-19. Source: see Table A.4

Table A.8 – IT services companies (9) with non-significant AI patents

	Employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Investment/ Sales 2016-19	Profits/Sales 2016-19
Oracle (US)	138000	-2.17	-2.84	15.61	4.49	35.74
Ericsson (Sweden)	111464	-10.81	-6.67	15.94	2.22	-2.47
SAP (Germany)	84183	19.18	24.89	14.59	4.65	20.64
Hewlett Packard Enterprise (US)*	66000	-6.67	7.73	5.63	10.06	7.62
Salesforce (US)	25000	96.00	91.17	15.08	4.54	2.66
Facebook (US)	17000	164.36	140.02	19.53	19.77	45.07
Workday (US)	6600	84.85	116.86	42.84	10.89	-16.46
Servicenow (US)	4801	116.02	133.51	20.66	8.15	-2.76
Square (US)	1853	106.96	158.83	14.92	1.47	0.75
Average	50545	13.58	38.12	14.84	7.93	21.11

*= 2017-19. Source: see Table A.4.

Table A.9 – Automobiles & parts companies (7) with significant AI patents

	Employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Investment/ Sales 2016-19	Profits/Sales 2016-19
Robert Bosh (Germany)	389281	6.28	2.28	7.79	6.11	5.38
Toyota (Japan)	364445	-1.34	8.93	3.54	12.36	7.93
General Motors (US)	225000	-27.11	-22.60	5.04	17.81	4.91
Honda (Japan)	211915	3.19	7.12	5.08	2.83	5.06
Ford (US)	201000	-5.47	-3.63	4.94	4.72	2.03
Denso (Japan)	154493	10.64	14.33	9.23	7.52	5.57
Hyundai (Korea)	67737	5.56	10.52	2.59	4.85	4.05
Average	230553	-2.54	0.58	4.83	9.33	5.24

*= 2017-19. Source: see Table A.4

Table A.10 – Automobiles & parts companies (10) with non-significant AI patents

	Employees 2016	Employment growth 2016-19	Sales growth 2016-19	R&D/Sales 2016-19	Capital Investment/ Sales 2016-19	Profits/Sales 2016-19
Volkswagen (Germany)	626700	7.10	16.28	5.86	5.78	5.47
Daimler (Germany)	282488	5.72	12.71	5.29	4.16	6.60
Fiat Chrysler (Netherlands)	234499	-18.23	-1.06	3.70	5.58	5.43
Reanult (France)	181344	-0.98	-5.50	5.94	4.58	5.10
Peugeot (France)	170156	22.70	38.31	4.76	3.41	5.52
Nissan (Japan)	137250	-0.81	-15.34	4.59	4.39	1.93
BMW (Germany)	115842	15.48	10.67	6.23	7.00	9.03
Aisin Seiki (Japan)	110357	8.32	8.01	4.97	8.17	4.64
Valeo (France)	91800	24.95	17.91	8.68	5.97	6.27
Mahle (Germany)	70720	8.90	4.90	6.15	4.72	4.16
Average	202116	8.48	9.60	5.33	5.23	5.62

*= 2017-19. Source: see Table A.4

Appendix 2: Checking the distinction of companies with significant and non-significant shares of AI patents.

This additional exam is based upon a search on Espacenet for a set of AI-related patent applications filed by all the companies considered in this paper and published in the years 2016 and 2017 (that is, usually, one or two years after the filing or priority date). The two IPC (broad) codes that have been applied for this selection are among the major used by Baruffaldi et al. (2020) to identify AI patents:

- G06K9 - Methods or arrangements for reading or recognising printed or written characters or for recognising patterns.
- GO6N - Computer systems based on biological models[11].

Together with the above I also consider the IPC (specific) code B25J9/16 - Programme controls, which includes inventions that very often connect robots to AI systems emulating the decision-making ability of a human expert. An example of patent application classified in this field (cf. USPTO publication number US2016008976A1) is provided in the following box.

Robot program modification system *Abstract* A robot program modification system comprises a robot control apparatus and a program modification apparatus. The robot control apparatus has an information acquisition unit which executes an operation program and acquires robot detection information from a robot, and a communication unit which transmits the robot detection information to the program modification apparatus. The program modification apparatus has a simulation unit which performs simulation on the basis of the operation program, and a program modification unit which modifies the operation program on the basis of the robot detection information so that a result of the simulation satisfies an evaluation basis decided in advance.

Table A.11 shows the number of patent applications in the selected IPC codes and ascribed to the companies characterised by a higher propensity to be involved in AI patenting is not comparable with that of the companies used for comparative purposes. The gap is huge looking at Computers & electronics and IT services while in Automobiles & parts the difference, though evident, is less pronounced. According to this further check, the distinction, adopted in

[11] Biological models reproduce genetic activities as well as those of brain (intelligence and consciousness). The G06N class includes, among others, patents in the fields of machine learning, fuzzy logic, and probabilistic/neural networks.

the paper, between companies with significant and non-significant share of AI patents does not appear to be discretionary.

It is interesting to notice that, although the Automobiles & parts companies with AI are only seven, they record a remarkable number of patent applications with the G06K9 codes. This is not surprising because most of the patented inventions in this field are concerned with systems and apparatus for assisting the driving of vehicles as well as with autonomous vehicles.

Table A.11 - Worldwide patent applications published in 2016-2017.

	G06K9 Methods or arrangements for reading or recognising printed or written characters or for recognising patterns	GO6N Computer systems based on biological models	B25J9/16 Programme controls
Computers & electronics			
High shares of AI patents (7)	3575	445	178
Low shares of AI patents (18)	3124	767	289
Non-significant shares of AI patents (23)	1132	178	30
IT services			
Significant shares of AI patents (10)	2568	2016	126
Non-significant shares of AI patents (9)	248	270	0
Automobiles & parts			
Significant shares of AI patents (7)	1004	125	129
Non-significant shares of AI patents (10)	215	9	12

Source: search on Espacenet by using the selected IPC codes and the name of the companies as assignees.

Another interesting finding highlighted by Table A.11 is that a non-negligible number of patent applications of the companies with significant shares of AI patents are classified with the B25J9/16 code which identifies inventions in which robots and AI systems are inter-connected. In this very specific field, and with the partial exception of those belonging to Automobiles & parts, the companies with non-significant shares of AI patents are absent (IT services) or scanty present (Computers & electronics).