

## AI technologies and employment: micro evidence from the supply side

Giacomo Damioli, Vincent Van Roy, Daniel Vertesy & Marco Vivarelli

**To cite this article:** Giacomo Damioli, Vincent Van Roy, Daniel Vertesy & Marco Vivarelli (2023) AI technologies and employment: micro evidence from the supply side, Applied Economics Letters, 30:6, 816-821, DOI: [10.1080/13504851.2021.2024129](https://doi.org/10.1080/13504851.2021.2024129)

**To link to this article:** <https://doi.org/10.1080/13504851.2021.2024129>



© 2022 European Union. Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 20 Feb 2022.



Submit your article to this journal [↗](#)



Article views: 7503



View related articles [↗](#)






View Crossmark data [↗](#)



Citing articles: 26 View citing articles [↗](#)

## AI technologies and employment: micro evidence from the supply side

Giacomo Damioli <sup>a</sup>, Vincent Van Roy <sup>b</sup>, Daniel Vertesy <sup>c,d</sup> and Marco Vivarelli <sup>d,e,f</sup>

<sup>a</sup>European Commission, Joint Research Centre (JRC), Ispra, Italy; <sup>b</sup>European Commission, Joint Research Centre (JRC), Sevilla, Spain;

<sup>c</sup>International Telecommunication Union, Geneva, Switzerland; <sup>d</sup>UNU-MERIT, Maastricht, Netherlands; <sup>e</sup>Università Cattolica del Sacro Cuore, Milan, Italy; <sup>f</sup>IZA, Bonn, Germany

### ABSTRACT

In this work we investigate the possible job-creation impact of artificial intelligence (AI) technologies, focusing on the supply side, where the development of these technologies can be conceived as product innovations in upstream sectors. The empirical analysis is based on a worldwide longitudinal sample (obtained by merging the EPO PATSTAT and BvD-ORBIS databases) of more than 3,500 front-runner companies that patented AI-related inventions over the period 2000–2016. Based on system GMM estimates of dynamic panel models, our results show a positive and significant impact of AI patent families on employment, supporting the labour-friendly nature of AI product innovation.

### KEYWORDS

Innovation; artificial intelligence; patents; employment

### JEL CLASSIFICATION

O33; O31; O30

## I. Introduction

Artificial Intelligence (AI) typically refers to the capability of a system to perform human-like cognitive functions (learning, understanding, reasoning, and interacting) with the aim of obtaining rational outcomes (Ertel 2018; Russell and Norvig 2016).

Indeed, the recent application of AI technologies in production has raised fears of a new wave of ‘technological unemployment’ (for a historical analysis of labour-saving innovations, see Staccioli and Virgillito 2021; for a survey, see Calvino and Virgillito 2018; for a theoretical framework, see Acemoglu and Restrepo 2018). In this vein, according to Brynjolfsson and McAfee (2014), at the root of current employment problems lies a ‘Great Restructuring’ which is having an ever-bigger impact on jobs and skills (see also Frey and Osborne 2017; Arntz, Gregory, and Zierahn 2017; Graetz and Michaels 2018; Acemoglu and Restrepo 2020).

However, if we adopt a Schumpeterian perspective (see Schumpeter 1912), technological change cannot be reduced to labour-saving process innovation. Indeed, the extant literature only focuses on the possibly negative employment impact of AI and (particularly) robots conceived as process innovations, while there is no evidence so far about the possible

positive employment effect of these new technologies, considered as product innovations in the supply sectors. This is unfortunate since product innovations are theoretically considered drivers of job creation (see Katsoulacos 1984; Vivarelli 1995; Edquist, Hommen, and McKelvey 2001), and several empirical studies have provided evidence in support of their labour-friendly nature (see Van Reenen 1997; Bogliacino and Pianta 2010; Bogliacino, Piva, and Vivarelli 2012; Van Roy, Vertesy, and Vivarelli 2018). In this framework, AI products not only entail the emergence of entire new sectors or a substantial expansion of existing ones<sup>1</sup> but also the creation of brand-new employment opportunities such as those related to data processing, transactional procedures, customization, remote collaboration, and so on.

The aim of this study is indeed to assess the possible job-creation impact of AI technologies, focusing on the providers of the new knowledge base.

## II. Methodology, data, and variables

### Methodology

Similarly to prior relevant microeconomic literature (see Van Reenen 1997; Lachenmaier and Rottmann 2011; Bogliacino, Piva, and Vivarelli 2012; Van Roy, Vertesy, and Vivarelli

**CONTACT** Giacomo Damioli  [Giacomo.damioli@ec.europa.eu](mailto:Giacomo.damioli@ec.europa.eu)  European Commission, Joint Research Centre (JRC), Ispra, Italy

This article has been republished with minor changes. These changes do not impact the academic content of the article.

<sup>1</sup>Think, for instance, of the electronic industry where robots are produced, or scientific services where AI algorithms are conceived.

© 2022 European Union. Published by Informa UK Limited, trading as Taylor & Francis Group.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

2018), we derive our empirical specification from a stochastic version of a dynamic standard labour demand, augmented with an innovation proxy:

$$l_{i,t} = \alpha l_{i,t-1} + \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 I_{i,t} + \beta_4 innov_{i,t} + \mu_i + \varepsilon_{i,t}$$

with:  $\beta_4 innov_{i,t} = \gamma Pat_{i,t}^{AI} + \delta Pat_{i,t}^{Non-AI}$  and  $i = 1, \dots, n; t = 1, \dots, T$

(1)

Lower case letters denote natural logarithms,  $l$  corresponds to labour,  $y$  to output,  $w$  to wages, and  $I$  to gross investments; we use AI and non-AI patent families ( $Pat_{(i,t)}^{(AI)}$  and  $Pat_{(i,t)}^{(Non-AI)}$ ) as a measure of innovation. Lastly,  $\mu$  is an unobserved firm-specific and time-invariant effect and the usual error term. It is important to include non-AI technologies in model specifications in order to isolate the specific employment impact of AI technologies. Moreover, their exclusion may generate an omitted variable issue potentially leading to a spurious upward bias of the effects associated with AI variables arising from the positive correlation between AI and (omitted) non-AI variables (equal to 0.35 for patent families and 0.18 for patent family size in our sample).

Dynamic labour demand specifications as in Equation 1 suffer from simultaneity and endogeneity problems, which may lead to biased estimations. To tackle both problems, we use a system GMM approach as developed by Blundell and Bond (1998; 2000). Since possible problems of endogeneity are not confined to the lagged dependent variable, all the explanatory variables are considered to be potentially endogenous and instrumented when needed. As a high instrument count may imply a downward bias in the two-step system GMM standard errors (see Roodman 2009b, pp. 140–141), we use the one-step system GMM estimator. The lag limits of the instruments were chosen both to satisfy the outcomes of the autocorrelation tests and to limit instrument proliferation, as highlighted in Roodman (2009a, 2009b).

## Data

To identify AI patents, we rely on Damoli *et al.* (2021), who follow a comprehensive, keyword-based approach consisting of the search for specific terms in the title or the abstract of patents.<sup>2</sup>

Text-mining searches following the methodology of Van Roy, Vertesy, and Damoli (2020) have been conducted to retrieve the keywords in either the patent title or the abstract of the Spring 2018 edition of the Worldwide Patent Statistical Database (PATSTAT) released by the European Patent Office (EPO). Containing bibliographical and legal event patent data from around 100 million patent filings covering more than 90 issuing authorities, including all the major offices, the EPO's PATSTAT has become a point of reference in the field of patent statistics. We grouped retrieved patents in patent families based on PATSTAT extended family identifiers. A patent family is a collection of patent applications covering the same or similar technical content. The use of patent families therefore ensures avoiding double counting of the same or similar inventions filed in different patent offices across countries. We then obtained key company characteristics of AI patent applicants through the BvD-ORBIS databases.

After excluding observations with missing values and outliers in both levels and growth rates, our final dataset covers 3,510 firms (resulting in 26,137 observations) active in AI patenting over the years 2000–2016. It provides worldwide coverage and includes firms belonging to manufacturing and service sectors.

## Variables

Our dependent variable is the number of employees in head counts. Explanatory variables include firm turnover, labour cost per employee, and gross investments measured as the annual change in fixed assets. We expect a positive impact on labour demand of turnover and gross investments, and a negative impact of labour cost. The models also control for industry-, year-, and country-specific differences in employment dynamics.

The key explanatory variable of interest is the number of AI patent families filed by a firm in a year, which measures the development and adoption of AI technology. In order to isolate

<sup>2</sup>An analogous approach to selecting AI patents was adopted by Cockburn, Henderson, and Stern (2019).

the distinctive impact of AI technologies, we also take into account innovative efforts in non-AI related fields through a number of non-AI patent families.

Since patents can differ in both economic and technological values, other indicators have been proposed to correct for the quality of patents, such as forward citation-weighted patents and family size (Harhoff, Scherer, and Vopel 2003; Hall, Jaffe, and Trajtenberg 2005; Van Roy, Vertesy, and Vivarelli 2018). Weighting AI patents with forward citations is particularly controversial in the present setting since the take-off of AI technologies has occurred recently (Cockburn, Henderson, and Stern 2019). We therefore use patent family size, which is the number of countries in which an invention is protected by a patent family. Given the huge costs of acquiring patents in multiple jurisdictions, patent family size is often used to approximate the value that applicants attribute to the invention (see Harhoff, Scherer, and Vopel 2003; Lanjouw and Schankerman 2004). A firm-level measure of patent family size was computed by taking the average size of all

applications filed by a company in a given year, separately for AI and non-AI patents, to provide a quality-augmented measure of innovation efforts of a firm.

**Table A1** in the Appendix reports the summary statistics of the dependent and explanatory variables used in the estimations. Firms in the sample report an average of over 4,200 employees due to the presence of big corporations (by contrast the median equals 99 employees). The development of AI technologies is much lower than the development of their non-AI counterparts: on average, each firm files approximately 1 AI patent family and 100 non-AI patent families every 3 years.

### III. Results

Table 1 reports the estimation coefficients in seven model specifications, in which AI and non-AI variables are included separately and together. The outcomes of the tests on autocorrelation dynamics are reassuring. With regard to the Hansen test on adequate instruments, the null hypothesis is rejected. Blundell and Bond (2000) and Roodman

**Table 1.** Results from GMM-SYS analysis. **Notes:** one-step GMM robust standard errors are reported in parentheses. All variables are taken in log. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . For the level equation, we used differenced values of the explanatory variables as instruments, i.e. thrice-lagged differences in labour demand, AI and non-AI patent families, gross investments, and cost of labour. The level equations also include a set of sector, country, and year dummies. In the equations in differences, we employed thrice-lagged values of the above-mentioned right-hand side variables as instruments. The lag limits of the instruments were chosen both to satisfy the outcomes of the autocorrelation tests and to limit instrument proliferation, as highlighted in Roodman (2009a, 2009b).

[illegible]

(2009a, 2009b) demonstrated that the Hansen test tends to over-reject the null in large samples. Therefore, the model was re-estimated on random sub-samples comprising 10% of the baseline observations and the null was never rejected.<sup>3</sup>

The magnitude and significance of the coefficients remain reassuringly unchanged in all specifications. Lagged employment is highly significant: unsurprisingly, labour demand is persistent and autoregressive, confirming its path dependency. With regard to the control variables, results are in line with prior studies (Van Reenen 1997; Bogliacino, Piva, and Vivarelli 2012; Van Roy, Vertesy, and Vivarelli 2018): the positive effect of turnover is substantial and highly significant, while the effect of gross investments is more contained, but still significant at the 5% level; finally, as expected, labour cost significantly inhibits labour demand.

Regarding our key innovation variables, positive and highly significant coefficients of AI and non-AI patent families are detected: they both imply a similarly moderate employment short-term elasticity of about 3–4%. The positive effect of AI technologies in models (6) and (7), which control for non-AI patents, indicates that the labour friendly nature of AI technologies is additional to other (non-AI) firm innovation activities. As such, this finding confirms the employment-friendly nature of product innovation in general, and provides novel evidence for the emerging AI technologies. In particular, when patent family size is used, only AI innovations imply a significant positive effect on employment.

#### IV. Conclusions

In contrast with the extant literature solely devoted to assessing the possible labour-saving impact of automation in the user sectors, this article investigates the possible labour-friendly nature of AI technologies, seen as product innovations in the supply industries.

Our estimates support this hypothesis. Moreover, the positive employment impact of AI is larger and more significant when compared to the job creation effect of other innovation activities. However, the labour-friendly employment effect of patenting in AI technologies is small in magnitude (the estimated elasticity being equal to 3–4%) and is unlikely to be

able to compensate for the possible labour-saving impact in the downstream user industries (see the studies cited in Section 1).

Obviously, our findings cannot be generalized at a more aggregate and macroeconomic level; further research is needed to assess the employment impact of the new knowledge base at the level of the entire economy, taking into account innovators, non-innovators, and user firms. Finally, a further avenue of future research should focus on the possible role of SMEs in labour-friendly AI product innovation, a focus that is beyond the scope of the present contribution.

#### Acknowledgments

We are very grateful to two anonymous referees for extensive comments that helped to improve the article considerably. We also thank the participants of the Workshop ‘The Economics and Management of AI Technologies’ (Bureau d’Economie Théorique et Appliquée, Université de Strasbourg) and of the GLO Virtual Seminar. Giacomo Damioli acknowledges the financial support from the European Union’s Horizon 2020 Framework Programme under the ‘Innova Measure IV’ project (Grant agreement no. 857088). Marco Vivarelli acknowledges support by the Italian Ministero dell’Istruzione, dell’Università e della Ricerca (PRIN-2017, project 201799ZJSN: ‘Technological change, industry evolution and employment dynamics’; principal investigator: Marco Vivarelli).

#### Disclaimer statement

The scientific output expressed here 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 that might be made of this study.

#### Disclosure statement

No potential conflict of interest was reported by the author(s).

#### Funding

This work was supported by the Horizon 2020 Framework Programme [857088]; Ministero dell’Istruzione, dell’Università e della Ricerca [201799ZJSN].

<sup>3</sup>Results are available upon request.



## ORCID

Giacomo Damioli  <http://orcid.org/0000-0001-8308-8367>  
 Vincent Van Roy  <http://orcid.org/0000-0003-4056-3273>  
 Daniel Vertesy  <http://orcid.org/0000-0002-3359-7988>  
 Marco Vivarelli  <http://orcid.org/0000-0002-8746-9324>

## References

- Acemoglu, D., and P. Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108 (6): 1488–1542. doi:10.1257/aer.20160696.
- Acemoglu, D., and P. Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–2244. doi:10.1086/705716.
- Arntz, M., T. Gregory, and U. Zierahn. 2017. "Revisiting the Risk of Automation." *Economics Letters* 159: 157–160. doi:10.1016/j.econlet.2017.07.001.
- Blundell, R., and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87: 115–143. doi:10.1016/S0304-4076(98)00009-8.
- Blundell, R., and S. Bond. 2000. "GMM Estimation with Persistent Panel Data: An Application to Production Functions." *Econometrics Reviews* 19: 321–340. doi:10.1080/07474930008800475.
- Bogliacino, F., and M. Pianta. 2010. "Innovation and Employment: A Reinvestigation Using Revised Pavitt Classes." *Research Policy* 39 (6): 799–809. doi:10.1016/j.respol.2010.02.017.
- Bogliacino, F., M. Piva, and M. Vivarelli. 2012. "R&D and Employment: An Application of the LSDVC Estimator Using European Data." *Economics Letters* 116 (1): 56–59. doi:10.1016/j.econlet.2012.01.010.
- Brynjolfsson, E., and A. McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York: W.W. Norton.
- Calvino, F., and M. E. Virgillito. 2018. "The Innovation Employment Nexus: A Critical Survey of Theory and Empirics." *Journal of Economic Surveys* 32: 83–117. doi:10.1111/joes.12190.
- Cockburn, I., R. Henderson, and S. Stern. 2019. "The Impact of Artificial Intelligence on Innovation." In *The Economics of Artificial Intelligence: An Agenda*, edited by A. Agrawal, J. Gans, and A. Goldfarb. University of Chicago Press and NBER.
- Damioli, G., V. Van Roy, and D. Vertesy. 2021. "The Impact of Artificial Intelligence on Labor Productivity." *Eurasian Business Review* 11 (1): 1–25. doi:10.1007/s40821-020-00172-8.
- Edquist, C., L. Hommen, and M. McKelvey. 2001. *Innovation and Employment: Product versus Process Innovation*. Cheltenham: Elgar.
- Ertel, W. 2018. *Introduction to Artificial Intelligence: Undergraduate Topics in Computer Science*. New York: Springer International Publishing.
- Frey, C., and M. Osborne. 2017. "The Future of Employment: How Susceptible are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114: 254–280. doi:10.1016/j.techfore.2016.08.019.
- Graetz, G., and G. Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics* 100 (5): 753–768. doi:10.1162/rest\_a\_00754.
- Hall, B., A. Jaffe, and M. Trajtenberg. 2005. "Market Value and Patent Citations." *RAND Journal of Economics* 16–38.
- Harhoff, D., F. M. Scherer, and K. Vopel. 2003. "Citations, Family Size, Opposition and the Value of Patent Rights." *Research Policy* 32 (8): 1343–1363. doi:10.1016/S0048-7333(02)00124-5.
- Katsoulacos, Y. S. 1984. "Product Innovation and Employment." *European Economic Review* 26: 83–108. doi:10.1016/0014-2921(84)90023-0.
- Lachenmaier, S., and H. Rottmann. 2011. "Effects of Innovation on Employment: A Dynamic Panel Analysis." *International Journal of Industrial Organization* 29 (2): 210–220. doi:10.1016/j.ijindorg.2010.05.004.
- Lanjouw, J., and M. Schankerman. 2004. "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators." *Economic Journal* 114 (495): 441–465. doi:10.1111/j.1468-0297.2004.00216.x.
- Roodman, D. 2009a. "How to Do Xtabond2: An Introduction to "Difference" and "System" GMM in Stata." *Stata Journal* 9: 86–136. doi:10.1177/1536867X0900900106.
- Roodman, D. 2009b. "A Note on the Theme of Too Many Instruments." *Oxford Bulletin of Economics and Statistics* 71: 135–158. doi:10.1111/j.1468-0084.2008.00542.x.
- Russell, S., and P. Norvig. 2016. *Artificial Intelligence: A Modern Approach*. Malaysia: Pearson Education Limited.
- Schumpeter, J. A. 1912. *The Theory of Economic Development*. (Mass.) Engl. Ed. 1968, Cambridge: Harvard University Press.
- Staccioli, J., and M. E. Virgillito. 2021. "Back to the Past: The Historical Roots of Labor-saving Automation." *Eurasian Business Review* 11 (1): 27–57. doi:10.1007/s40821-020-00179-1.
- Van Reenen, J. 1997. "Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms." *Journal of Labor Economics* 15 (2): 255–284. doi:10.1086/209833.
- Van Roy, V., D. Vertesy, and G. Damioli. 2020. "AI and Robotics Innovation." In *Handbook of Labor, Human Resources and Population Economics*, edited by K. Zimmermann, 1–35.
- Van Roy, V., D. Vertesy, and M. Vivarelli. 2018. "Technology and Employment: Mass Unemployment or Job Creation? Empirical Evidence from European Patenting Firms." *Research Policy* 47 (9): 1762–1776. doi:10.1016/j.respol.2018.06.008.
- Vivarelli, M. 1995. *The Economics of Technology and Employment: Theory and Empirical Evidence*. Elgar, Cheltenham. (reprinted 1997).

## Appendix

**Table A1.** Definition and summary statistics of the variables used in analysis. **Notes:** the sample includes 26,137 observations and 3,510 firms. The variable definition describes how variables are used in the empirical models. All variables are defined at firm-year level. The summary statistics are expressed as follows: employment is the number of employees; turnover, cost of labour per employee, and fixed assets are expressed in EURs; gross investments are shown as yearly percentage changes.

Variable name	Variable definition	Summary statistics			
		Mean	SD	Min	Max
Employment		4,247	16,501	1	218,598
	Natural logarithm of the number of employees expressed in head counts				
Turnover		1.3	5.3	0	71.4
	Natural logarithm of the turnover expressed in billion EURs				
Gross investments		23.5	80.6	−100.0	894.2
	Natural logarithm of fixed assets expressed in EURs in t – natural logarithm of fixed assets expressed in EURs in t-1				
Cost of labour per employee		34,945.8	32,298.8	2.3	422,000.0
	Natural logarithm of labour cost per employee (labour cost expressed in EURs/number of employees)				
AI patent families		0.3	1.6	0	78.0
	Natural logarithm of the number of AI patent families				
Non-AI patent families		30.0	107.9	0	1,391.0
	Natural logarithm of the number of non-AI patent families				
AI patent family size		0.3	1.0	0	51.5
	Natural logarithm of the average size of AI patent families				
Non-AI patent family size		1.5	2.2	0	44.5
	Natural logarithm of the average size of non-AI patent families				