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Micro evidence from the supply side

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Abstract[*] [**]

This study is based on a worldwide longitudinal dataset of 3,500 front-runner companies that patented AI technologies over the period 2000-2016. Our results support the labor-friendly nature of product innovation in the AI supply industries.

Keywords: Innovation, artificial intelligence, patents, employment.
JEL: O33, O31, O30

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1. Introduction

Nowadays, the arrival of Artificial Intelligence (AI) has raised a fear of a new wave of 'technological unemployment' (for an historical analysis of labor-saving innovations, see Staccioli and Virgillito, 2021; for a survey, see Calvino and Virgillito, 2018; for a theoretical reprise, see Acemoglu and Restrepo, 2018).

In this vein, according to Brynjolfsson and McAfee (2014), the root of the current employment problems is a "Great Restructuring" having an ever-bigger impact on jobs, and skills (see also Frey and Osborne, 2017; Arntz *et al*., 2017; Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020).

However, one of the limitations of the current debate is its sole focus on the demand side (that is the adoption of AI and robots as labor-saving process innovations in the downstream industries), while there is an obvious gap to be filled with regard to the supply side, that is the possible job-creation effect of AI technologies, conceived as product innovations in the upstream sectors.[1]

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

2. Methodology, data and variables

2.1 Methodology

Similarly to the prior relevant microeconometric literature (see Van Reenen, 1997; Lachenmaier and Rottmann, 2011; Bogliacino *et al.,* 2012; Van Roy *et al.,* 2018), we derive our empirical specification from a stochastic version of a dynamic standard labor demand, augmented with an innovation proxy:

$$\begin{aligned} &\boldsymbol{l_{i,t} = \alpha\, l_{i,t-1} + \beta_1\, y_{i,t} + \beta_2\, w_{i,t} + \beta_3\, I_{i,t} + \beta_4\, innov_{i,t} + \mu_i + \varepsilon_{i,t}} \\ &\boldsymbol{with}\text{: } \boldsymbol{\beta_4 innov_{i,t} = \gamma\, Pat^{AI}_{i,t} + \delta\, Pat^{Non-AI}_{i,t}} \ \ \boldsymbol{and}\ \ i = 1, .., n; \quad t = 1, .., T \end{aligned} \tag{1}$$

Lower case letters denote natural logarithms, l corresponds to labor, y to output, w to wages, and I to gross investments; as measure for innovation, we use AI and non-AI patent families ($Pat^{AI}_{i,t}$ and $Pat^{Non-AI}_{i,t}$). Lastly, μ is an unobserved firm-specific and time-invariant effect and ε the usual error term.

Dynamic labor demand specifications as in (1) suffer from simultaneity and endogeneity problems, which may lead to biased estimations.[2] 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,

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[1] Think, for instance, to the electronic industry where robots are produced, or to the scientific services where AI algorithms are conceived.

[2] In particular, pooled ordinary least squares (POLS) lead to an overestimate of the coefficient of the lagged dependent variable, while fixed effect (FE) lead to an underestimate of such coefficient. However, Table 1 also reports POLS and FE results.

all the explanatory variables are considered as potentially endogenous and instrumented when needed. 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).

2.2 Data

To identify AI patents, we rely on Damioli *et al.* (2021, Table 5), who follow a comprehensive approach by applying a keyword-based approach consisting in the search for specific terms in the title or the abstract of patents.[3]

This text-mining search has been conducted on the Spring 2018 edition of the EPO-PATSTAT database, covering more than 90 patent authorities including all the major countries. We grouped retrieved patents in patent families to avoid double counting of the same or similar inventions filed in different patent offices. 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 a worldwide coverage and includes firms belonging to manufacturing and service sectors.

2.3 Variables

Our dependent variable is the number of employees in head counts. Explanatory variables include firm turnover, labor cost per employee and gross investments measured as the annual change in fixed assets. We expect a positive impact on labor demand of turnover and gross investments and a negative impact of labor 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; however, we also take into account innovative efforts in non-AI related fields through the number of non-AI patent families.

Since patents can differ both in economic and technological value, other indicators have been proposed to correct for the quality of patents, such as forward citation-weighted patents and family size (Harhoff *et al.*, 2003; Hall *et al.*, 2005; Van Roy *et al.*, 2018). Weighting AI patents with forward citations is particularly controversial, since the take-off of AI technologies has taken place recently (Cockburn *et al.*, 2019). We therefore resume to using patent family size, *i.e.* the number of countries in which an invention is protected by a patent.[4]

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[3] An analogous approach to select AI patents has been pursued in Cockburn *et al*. (2019).

[4] 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 et al., 2003; Lanjouw and Schankerman, 2004).

3. Results

Table 1 reports the estimation coefficients for POLS, FE and SYS-GMM models, first using patent family counting and then using patent family size.[5].

Lagged employment is highly significant in all six different estimations tested. Unsurprisingly, labor 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 *et al.,* 2012; Van Roy *et al.,* 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, labor cost significantly inhibits, as expected, labor 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 elasticity of about 3-4%. This finding supports the employment friendly nature of product innovation in general, and provides novel evidence for the emerging AI technologies. However, when patent family size is used, only AI innovations imply a significant positive effect on employment.

4. Conclusions

In contrast with a literature solely devoted to assess the possible labor-saving impact of automation in the user sectors, this paper investigates the possible labor-friendly nature of AI technologies, seen as product innovations in the supply industries.

Indeed, our estimates support this hypothesis. Moreover, the AI positive employment impact is larger and more significant when compared to the job creation effect of other innovation activities.

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[5] The outcome of the Wald test on the overall significance of the regressions and the LM 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 (2009a and 2009b) demonstrated that, for large samples, the Hansen test tends to over-reject the null. Therefore, the model was re-estimated on random sub-samples comprising 10% of the baseline observations and the null was never rejected (results available upon request).

Table 1. Dependent variable: Employment.

	POLS		Fixed effects		Sys. GMM	
Employment t-1	0.854***	0.857***	0.495***	0.500***	0.523***	0.532***
	(0.010)	(0.010)	(0.027)	(0.028)	(0.034)	(0.035)
Turnover	0.107***	0.109***	0.208***	0.210***	0.257***	0.264***
	(0.009)	(0.009)	(0.028)	(0.028)	(0.041)	(0.041)
Gross investments	0.100***	0.100***	0.058***	0.059***	0.033**	0.033**
	(0.012)	(0.012)	(0.009)	(0.009)	(0.015)	(0.015)
Labor cost per employee	-0.094***	-0.094***	-0.231***	-0.231***	-0.518***	-0.528***
	(0.007)	(0.007)	(0.016)	(0.016)	(0.035)	(0.036)
AI patent families	0.002		0.020***		0.034***	
	(0.006)		(0.006)		(0.013)	
Non-AI patent families	0.017***		0.035***		0.028***	
	(0.002)		(0.004)		(0.009)	
AI patent family size		0.022***		0.024***		0.028***
		(0.006)		(0.006)		(0.010)
Non-AI patent family size		0.024***		0.030***		0.014
		(0.005)		(0.006)		(0.009)
Constant	0.611***	0.559***	1.346***	1.304***	6.194***	1.312
	(0.121)	(0.122)	(0.354)	(0.355)	(0.037)	(0.863)
R-squared	0.986	0.986	0.636	0.634		
F test			(22, 3509) 213.2***	(22, 3509) 190.1***		
Hansen					6.560e+08***	2.880e+13***
Wald test					92449***	555160***
AR(1)					-11.16***	-11.04***
AR(2)					-1.992**	-2.116**
AR(3)					-0.585	-0.430
Nr. of instruments					108	108
Observations	26,137	26,137	26,137	26,137	26,137	26,137
Number of firms	3,510	3,510	3,510	3,510	3,510	3,510

Notes: all models include year dummies; POLS and SYS-GMM models also include industry and country dummies. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

References

Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 108(6), 1488-1542.

Acemoglu, D., & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6), 2188-2244.

Arntz M., Gregory, T., & Zierahn, U. (2017). Revisiting the risk of automation. *Economics Letters*, 159, 157-160.

Blundell, R., & Bond, S. (2000). GMM estimation with persistent panel data: an application to production functions. *Econometrics Reviews*, 19, 321-340.

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

Bogliacino, F., Piva, M., & Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European data. *Economics Letters*, 116(1), 56-59.

Brynjolfsson, E, & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W.W. Norton, New York.

Calvino, F., & Virgillito, M.E. (2018). The innovation employment nexus: A critical survey of theory and empirics. *Journal of Economic Surveys*, 32, 83-117.

Cockburn, I., Henderson, R., & Stern, S. (2019). The Impact of Artificial Intelligence on Innovation. In: A. Agrawal, J. Gans, & A. Goldfarb (Eds.) *The economics of artificial intelligence: an agenda*. University of Chicago Press and NBER.

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

Frey, C., & Osborne, M. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280.

Graetz, G., & Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics*, 100(5), 753–768.

Hall, B., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of economics*, 16-38.

Harhoff, D., Scherer, F. M., & Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research policy*, 32(8), 1343-1363.

Lachenmaier, S., & Rottmann, H. (2011). Effects of innovation on employment: A dynamic panel analysis. *International Journal of Industrial Organization*, 29(2), 210-220.

Lanjouw, J., & Schankerman, M. (2004). Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators. *Economic Journal*, 114(495), 441-465.

Roodman, D. (2009a). How to Do xtabond2: An Introduction to "Difference" and "System" GMM in Stata. *Stata Journal*, 9, 86-136.

Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics*, 71, 135-158.

Staccioli, J., Virgillito, M.E. (2021), Back to the past: the historical roots of labor-saving automation, *Eurasian Business Review*, 11(1), 27–57.

Van Reenen, J. (1997). Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms, *Journal of Labor Economics*, 15(2), 255-284.

Van Roy, V., Vertesy, D., & Vivarelli, M. (2018). Technology and employment: Mass unemployment or job creation? Empirical evidence from European patenting firms. *Research Policy*, 47(9), 1762-1776.

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