The impact of AI on labour productivity

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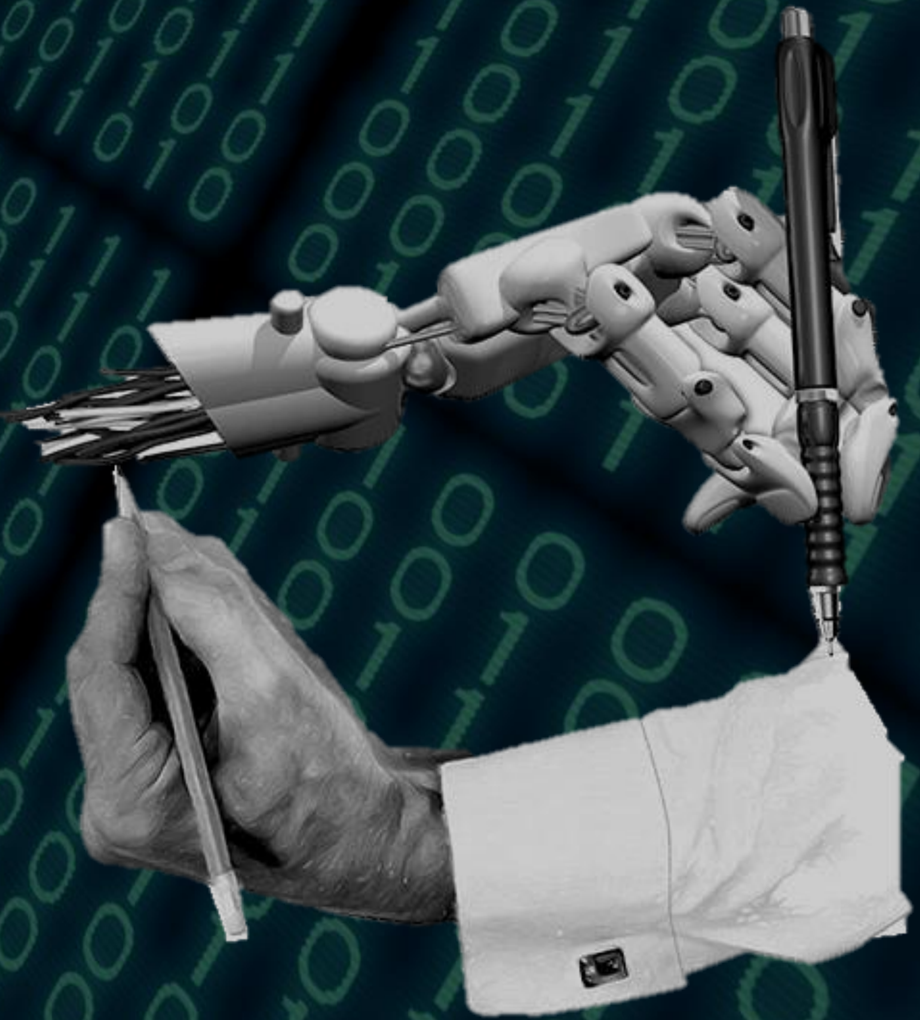
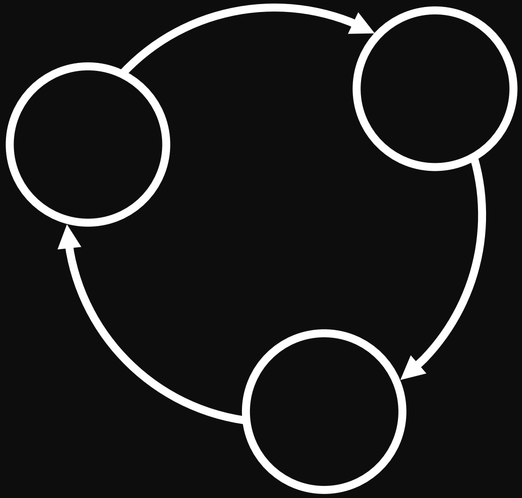


The quest to measure AI innovation and its impact



Measure impact

- Efficiency or productivity improvements
- Impact on tasks; on local / global organization and distribution of work (supply chains, etc.) …and social activities
- Magnitude of labour replacement vs. labour creation effects?
- Unevenness of impact (skill-biased, geographical, etc.), inequalities created…

→ inform policy making

- When, where, why, how to intervene?
- Risks and consequences & how to speed up beneficial / mitigate negative impact?
- Awareness of limitations

Define AI

- Constantly evolving knowledge base
- Core + broadening applications
- No established definition
  → tech classes, keywords, use AI to find AI
  (include automation/robotics application?)
- Actors: companies, public research institutions, universities
- Users: awareness; pay with their data;

Measure activity

- Measurement linked to actor: science / technology side?
- Companies' expenditure on /stock of intangibles, software, data, ICT services, human resources, R&D;
- Companies' technological capabilities: software code/algorithms (proprietary / public?), patents; new products, improved processes
- Challenge: how can we see through secrecy?

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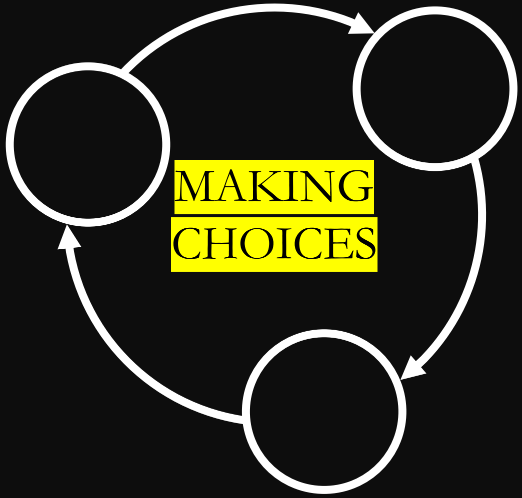

Define AI

- Constantly evolving knowledge base
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  → tech classes, keywords, assisted by ML; (include automation/robotics application)
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Our reasoning:

- AI as global innovative activity is already measurable (= beyond scale of case studies);
- Direct effect = 1st step to understand economic impact
- Scarce evidence (Raj and Seamans, 2019)

◀ Evidence of AI's recent take-off as a S&T activity

…in recent years!

Number of AI papers on arXiv, 2010-2019
Source: arXiv, 2019.

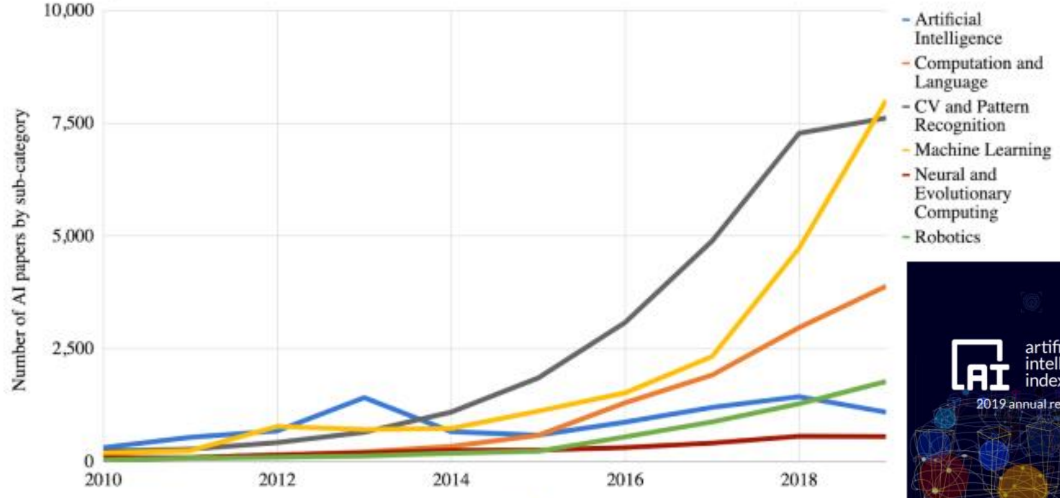


Fig. 1.6.

Growth in large conference attendance, relative to 2012
Source: Conference provided data.

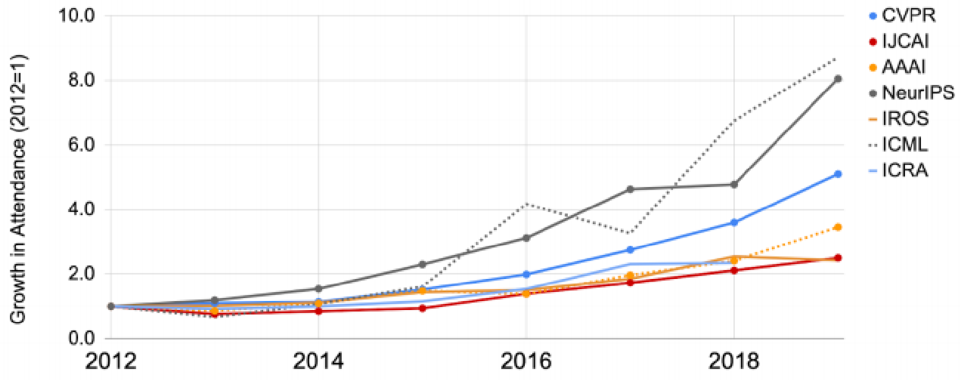
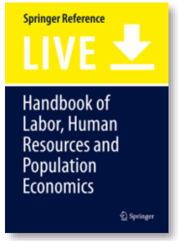
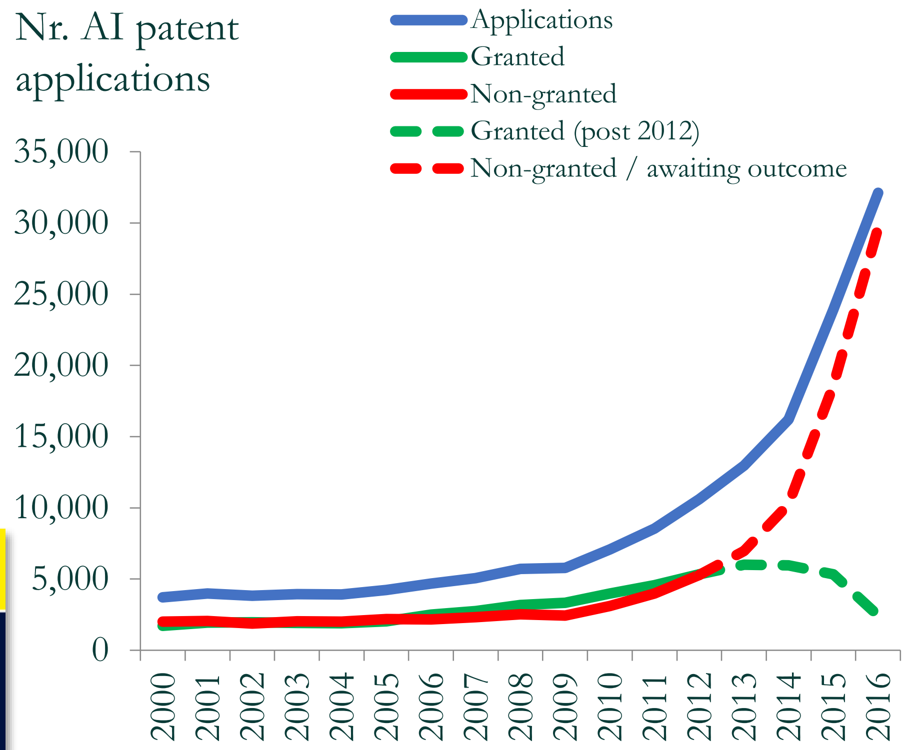


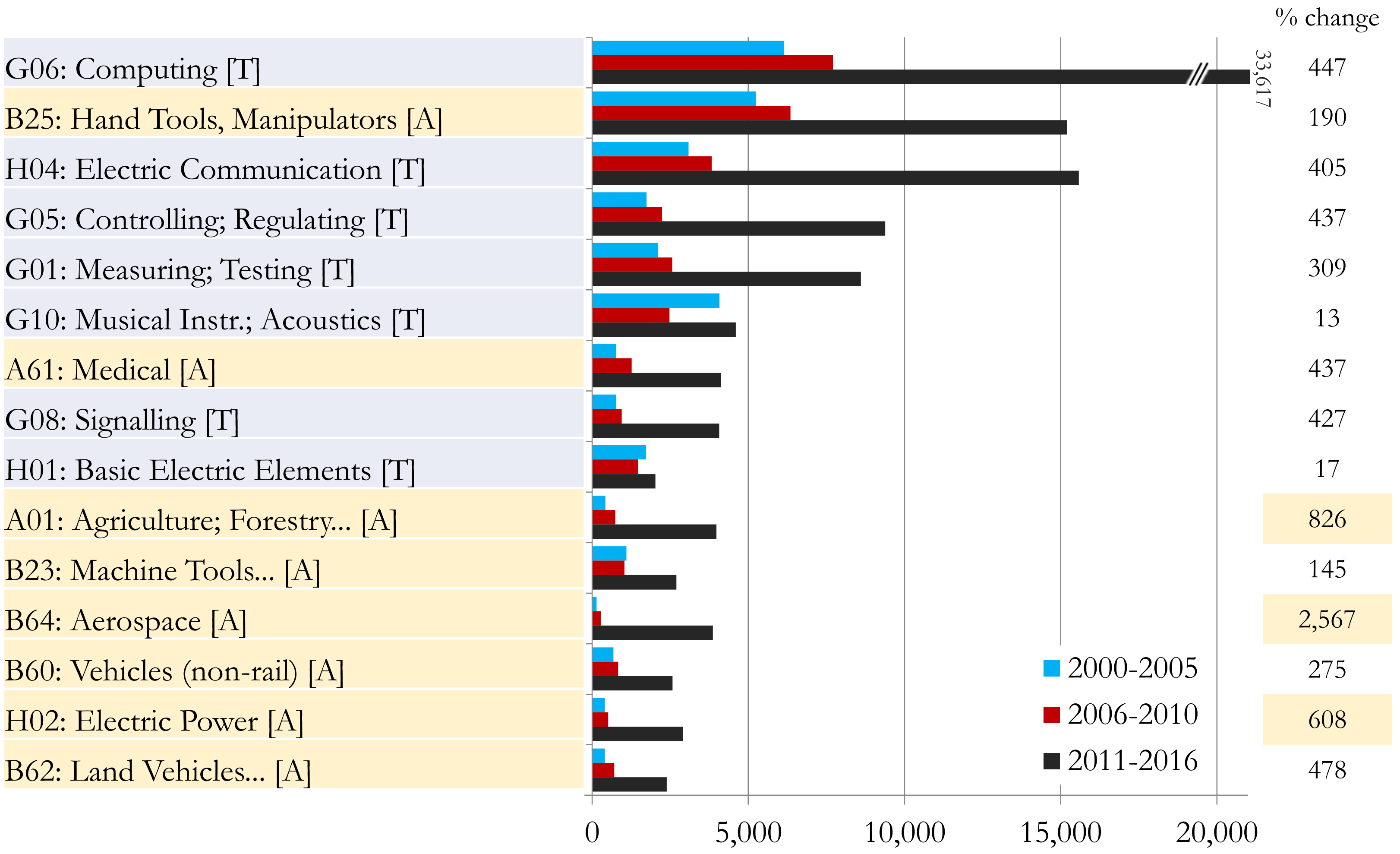
Fig. 2.1b





◀ Diffusion of AI: transversal applicability across sectors

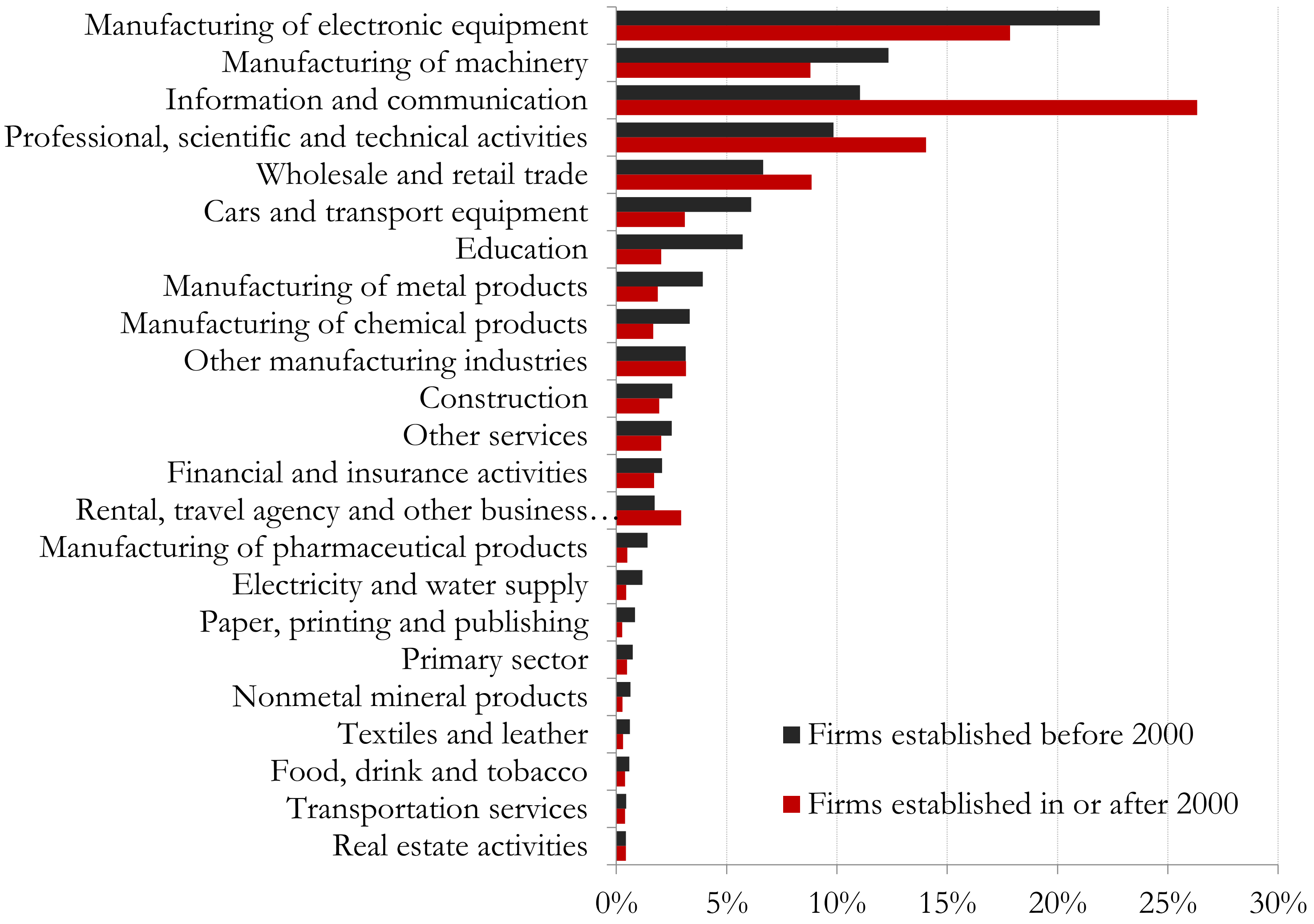
The Top 15 3-digit IPC technology classes with the largest nr. of AI patent applications, 2000-2016



Source: authors' calculations based on TIM / EPO PATSTAT data

◀ AI applied across the economy

Sectoral distribution of AI patent applicants, 2000-2016



What is the impact of AI innovation on productivity?

- Theories are inconclusive
  (+) more precise forecasts, accelerated innovation ↔ (-) productivity paradox; lag-time, aggregate demand drop

- Few, if any, firm-level evidence
  Use of industrial robots associated with productivity increase (Graetz and Michaels, 2018, EC 2016)
  AI patents positively associated with sales and productivity growth (Alderucci *et al* 2020)
  Patenting 4th Industrial Revolutions techs positively associated with productivity (Benassi *et al* 2020)

- Potential differences by…:
  Time period (before / after financial-economic crisis)
  Whether the company is patenting other technologies
  Company size
  Sector

What is the impact of AI tech development on firms' productivity?

Key findings of the paper

- Developing AI technology boosts inventor firms' labour productivity:
  Doubling AI patenting → 3% productivity growth
- Effect driven by SMEs and the service sector, as well as developments of recent years
- We control (inter alia) for patents in other (non-AI) technologies
- Measure causality based on a dynamic panel estimates on over 5,000 companies worldwide that filed a patent in AI between 2000 and 2016

Exploited company financials & patents data

- Covers 5,200+ AI inventor companies, their key balance sheet data and portfolio of non-AI patents (EPO PATSTAT – JRC TIM & ORBIS)

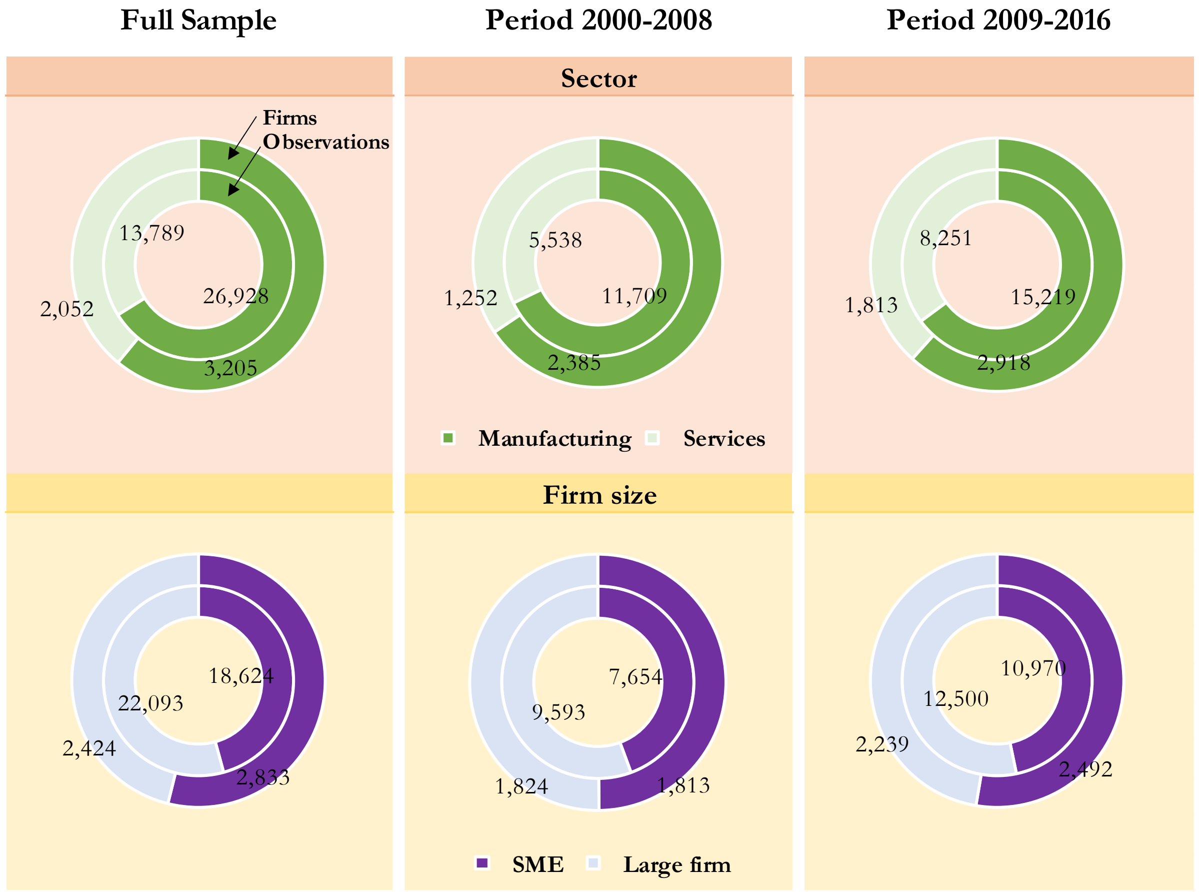
Sectors:

- Services: ~60%
  (mostly telecom, professional/ sci/tech services)
- Manufacturing:
  80% high-tech, 20% low-tech

Size:
~50% SMEs

Location:

- Asia: ~ 2/3 (JP, KR, CN,…)
- Europe: ~ 1/4 (DE, UK, FR,…)
- US: ~ 1/10 (Orbis…)



Applied a knowledge-stock augmented growth model

- Change in L.prod is a function of past L.prod, and change in capital, labour and knowledge stock

- Patents serve as proxies for technological capabilities (knowledge stock)
  - Other measures, i.e. R&D is an aggregate in balance sheet, while patents are more specific
  - Patent portfolio reflects technological capability of firm (based on past innovative efforts)
  - Limitations apply

- Simultaneity and endogeneity tackled using generalized method of moments (GMM) approach for estimation;
  - 2x lagged differences
  - Country, sector and year controls

Empirical results I

- Doubling AI patenting → 3% productivity growth
- Non-AI patent stock: ~2% effect
- Half of the productivity gap disappears through convergence

- Period breakdown:
  Increasing importance of AI over time
  (first period: less mature technology; less experience to exploit it)

	Labour productivity		
	Full model	Period 2000-2008	Period 2009-2016
AI patent applications	0.032***	0.011	0.030**
	(0.011)	(0.014)	(0.015)
Non-AI patent applications	0.019***	0.024*	0.029***
	(0.007)	(0.013)	(0.010)
Labour productivity t-1	0.544***	0.621***	0.517***
	(0.054)	(0.060)	(0.092)
Employment growth	-0.470***	-0.480***	-0.497***
	(0.032)	(0.036)	(0.052)
Fixed capital growth	0.088***	0.123***	0.080***
	(0.022)	(0.024)	(0.029)
Firm size	0.013	-0.082	0.083
	(0.047)	(0.057)	(0.071)
Industry and country dummies	included	included	included
Year dummies	included	included	included
Observations	40,717	17,247	23,470
Number of firms	5,257	3,637	4,731
Wald test	4648.64***	28906.45***	5375.37***
AR(1)	-8.78***	-6.69***	-6.50***
AR(2)	-1.22	-0.68	-0.34
Nr. of instruments	107	94	97
Hansen test	11.59**	15.81***	851.67***

Note: Standard errors in parentheses. Significance levels are represented as: *** p<0.01, ** p<0.05, * p<0.1. All variables are expressed in natural logarithms.
The models presented in the table are based on system GMM estimations with collapse option to reduce the number of instruments.

Empirical results II

	Labour productivity						
	Full model	Sector		Manufacturing		Firm type	
		Manufacturing	Services	High-tech	Low-tech	SMEs	Large firms
AI patent applications	0.030**	0.006	0.077**	0.003	-0.005	0.069*	0.007
	(0.015)	(0.014)	(0.034)	(0.016)	(0.029)	(0.040)	(0.011)
Non-AI patent applications	0.029***	0.035***	0.022	0.033***	0.039	0.014	0.033***
	(0.010)	(0.011)	(0.021)	(0.012)	(0.027)	(0.017)	(0.010)
Labour productivity t-1	0.517***	0.567***	0.491***	0.551***	0.603***	0.447***	0.581***
	(0.092)	(0.086)	(0.175)	(0.090)	(0.129)	(0.105)	(0.180)
Employment growth	-0.497***	-0.491***	-0.548***	-0.456***	-0.622***	-0.436***	-0.540***
	(0.052)	(0.056)	(0.097)	(0.056)	(0.106)	(0.074)	(0.086)
Fixed capital growth	0.080***	0.088***	0.072	0.099***	0.064	0.039	0.129**
	(0.029)	(0.030)	(0.055)	(0.026)	(0.068)	(0.043)	(0.050)
Firm size	0.083	0.069	0.163	0.022	0.248	0.086	-0.049
	(0.071)	(0.088)	(0.126)	(0.087)	(0.154)	(0.146)	(0.098)
Industry and country dummies	included	included	included	included	included	included	included
Year dummies	included	included	included	included	included	included	included
Observations	23,470	15,219	8,251	12,069	3,150	9,780	13,690
Number of firms	4,731	2,918	1,813	2,345	573	2,359	2,566
Wald test	5375.37***	3853.71***	48300.52***	4033.07***	1796.96***	41176.39***	5531.24***
AR(1)	-6.50***	-6.29***	-3.53***	-5.79***	-3.27***	-5.71***	-3.45***
AR(2)	-0.34	-0.56	0.08	-0.76	0.38	0.25	-2.00
Nr. of instruments	97	76	78	67	60	86	90
Hansen test	851.67***	16.65***	373.42***	16.71***	8.59	2.99***	2304.37***

AI only significant among service firms and SMEs

- Note: SMEs tend to be relatively more specialized in AI than large firms

Physical capital growth and non-AI patents only significant for [HT] manufacturing and large companies

Alderucci et al: similarly find no impact on mfg, only on services

Conclusions

Results suggest…

- the presence of technological opportunities in activities characterized by lower capital intensity
- Smaller, more agile firms may have been able to exploit AI faster than complex, larger companies;
- AI appears to have reached a critical mass in its maturity after 2009

Limitations apply

- Patents are rough measure of knowledge capital (secrecy, other IPR forms, i.e. software copyrights etc.); due to the recency of AI patents, 'quality' measures (i.e., citations) could not be applied (yet);
- We measure short-term, direct effect (on inventor company) – spillovers are yet to measure
- Cherry-picking effect: selection of highly innovative companies (those with at least 1 AI patent)
- Uncertainty in the definition of AI (no precise, universally applied definition)
- Broad approach to AI – inclusion of robotics… possible impacts; difficult to disentangle
- ORBIS limitations: missing info on K, Value Added, etc. No info on skills/tasks

Implications… / Next steps

Possible future studies:

- Should continue to expand evidence base…
- Look at employment effects
- Broader social / economic impacts: on developers / users
- Heterogeneity in geography; differences in regulatory frameworks

Points for reflection:

- How to better measure AI development / use?
    - i.e. collaborations and JVs, also with other actors: PROs
- Large companies: AI as a source of "rejuvenation"? Threat of [data / AI] monopolies?
- IPR in the context of AI: patents are tip of the iceberg, algorithms remain secret…

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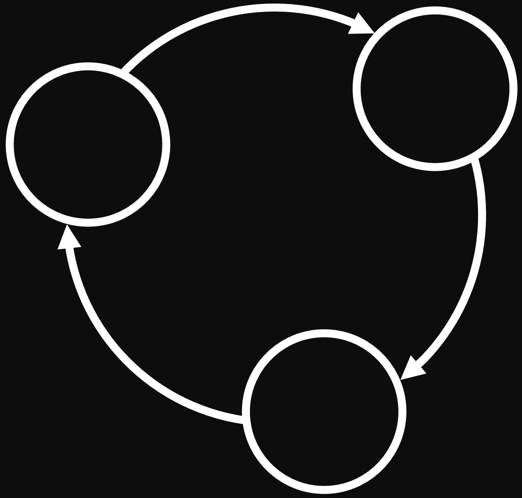

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Thank you!

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References

Acemoglu, A.D., & Restrepo, P. (2019a). Automation and New Tasks: How Technology Displaces and Reinstates Labor'. Journal of Economic Perspectives 33 (2), 3–30.

Aghion, P, & Howitt, P. (1992). A Model of Growth through Creative Destruction. Econometrica, 60 (2), 323–51.

Agrawal, A., Gans, J.S., & Goldfarb, A. (2019a). Prediction, judgment, and complexity: a theory of decision-making and artificial intelligence. In: A. Agrawal, J. Gans, & A. Goldfarb (Eds.) The economics of artificial intelligence: an agenda. University of Chicago Press and NBER.

Alderucci, D., Branstetter, L., Hovy, E., Runge, A. & Zolas, N. (2020). Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata. Paper presented at the Allied Social Science Associations - ASSA 2020 Annual Meeting.

Autor, D., & Dorn, D. (2013) The growth of low-skill service jobs and the polarization of the U.S. labor market. The American Economic Review, 103 (5), 1553-1597.

Autor, D, Levy, F., & Murnane, R. (2003). The skill content of recent technological change: an empirical exploration. The Quarterly Journal of Economics, 118 (4), 1279-1311.

Barbieri, L., Mussida, C., Piva, M., & Vivarelli, M. (2020). Testing the Employment and Skill Impact of New Technologies. In K. Zimmermann (Eds.) Handbook of Labor, Human Resources and Population Economics, 1-27.

Bartelsman, E.J., Falk, M., Hagsten, E., & Polder, M. (2019). Productivity, Technological Innovations and Broadband Connectivity: Firm-Level Evidence for Ten European Countries. Eurasian Business Review, 9, 25-48.

Belderbos, R., Lokshin, B., & Sadowski, B. (2015). The returns to foreign R&D. Journal of International Business Studies, 46 (4), 491-504.

Belderbos, R., Van Roy, V., & Duvivier, F. (2013). International and domestic technology transfers and productivity growth: firm level evidence. Industrial and corporate change, 22 (1), 1-32.

Bloom, N, Jones, C. I., & Van Reenen, J. (2020). Are Ideas Getting Harder to Find? American Economic Review, 110 (4), 1104–1144.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 microdata. Economics Letters, 116 (1), 56-59.

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. In: A. Agrawal, J. Gans, & A. Goldfarb (Eds.) The economics of artificial intelligence: an agenda. University of Chicago Press and NBER.

Brynjolfsson, E. (1993). The productivity paradox of information technology. Communications of the ACM, 36 (12), 66–77.

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.

De Prato G, Lopez Cobo M et al. (2018). The AI Techno-Economic Segment Analysis. Selected Indicators. European Commission, Joint Research Centre, Seville.

European Commission (2016a). Analysis of the Impact of Robotic Systems on Employment in the European Union. Luxembourg, Publications Office of the European Union. European Commission (2018). Artificial Intelligence: A European Perspective. European Commission, Joint Research Centre, Seville. doi:10.2760/936974.

Gordon, R. J. (2018). Why Has Economic Growth Slowed When Innovation Appears to be Accelerating? NBER Working Paper 24554. National Bureau for Economic Research.

Gordon, R. J. (2016). The rise and fall of American growth: The US standard of living since the Civil War. Princeton: Princeton University Press.

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

Gries, T., & Naudié, W. (2018). Artificial Intelligence, Jobs, Inequality and Productivity: Does Aggregate Demand Matter? IZA DP No. 12005, Bonn.

Hall, B., Mairesse, J., & Mohnen, P. (2012). Measuring the returns to R&D. In B. Hall, & N. Rosenberg (Eds), Handbooks in economics: Economics of innovation. Vol. 2, 1033–1082. Amsterdam:North-Holland.

Jones, B.F. (2009). The Burden of Knowledge and the 'Death of the Renaissance Man': Is Innovation Getting Harder? Review of Economic Studies, 76 (1), 283–317.

Lokshin, B., Belderbos, R., & Carree, M. (2008). The productivity effects of internal and external R&D: Evidence from a dynamic panel data model. Oxford Bulletin of Economics and Statistics, 70 (3), 399–413.

Piva, M., & Vivarelli, M. (2005). Innovation and employment: Evidence from Italian microdata. Journal of Economics, 86 (1), 65-83.

Romer, P.M. (1990). Endogenous Technological Change. Journal of Political Economy, 98 (5), S71–102.

Seamans, R. & Raj, M. (20182019). AI, Labor, Productivity and the Need for Firm-Level Data. In: A. Agrawal, J. Gans, & A. Goldfarb (Eds.) The economics of artificial intelligence: an agenda. University of Chicago Press and NBER.

Solow, R.M. (1957). Technical Change and the Aggregate Production Function. Review of Economics and Statistics, 39 (3): 312–20.

Van Roy, V., Vertesy, D., & Damioli, G. (2020). AI and Robotics Innovation. In K. Zimmermann (Eds.) Handbook of Labor, Human Resources and Population Economics, 1-35.

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

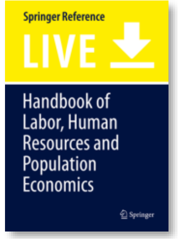
Vivarelli, M. (1995). The Economics of Technology and Employment: Theory and Empirical Evidence. Edward Elgar, Aldershot.

Vivarelli, M. (2013). Technology, employment and skills: an interpretative framework. Eurasian Business Review, 3 (1), 66-89.

Theory inconclusive

- Tech change in general:
  - + impact on productivity: Source of growth (Solow, 1957; Romer, 1990; Aghion and Howitt, 1992)
  - More nuanced view with respect to employment: skill-biased tech change (wage polarization); unemployment due to automation; yet, increased demand & productivity effect may outweigh displacement effect (see Autor et al, 2003; Barbieri et al, 2020; Autor and Dorn, 2013; Vivarelli, 1995, 2013; Josten and Lordan, 2019; Acemoglu and Restrepo, 2019);
- AI: positive impact on productivity:
  - More precise forecasts – reduction of uncertainty (Agrawal et al, 2019a)
  - Accelerated innovation (Bartelsman et al, 2019; Cockburn et al, 2019); automated recombination of existing techs (Agrawal et al, 2019b);
- Productivity paradox: productivity slowdown despite digital revolution!
  - Explain with lag time (for diffusion, complementary innovations and upskilling of workers) (Brynjolfsson et al, 2017)
  - Over-optimism: it's less than electricity or the internal combustion engine (Gordon, 2016, 2018);
  - Ideas are harder to find (Bloom et al, 2020); more complex to organize (Jones, 2009)
  - Aggregate demand: declining earnings, greater inequality due to automation & AI (Gries and Naudé, 2018)

Empirical evidence so far…



- Scanty for now… maybe it is too soon? – Not anymore! (Van Roy et al, 2020)
- Most of the studies focus on robots
  - Industrial robots increased productivity of countries by 15% (Graetz and Michaels, 2018; using IFR data for 1993-2007, 17 countries)
  - Companies using industrial robots see higher labour productivity (EC, 2016; study of 3000 companies);
- One on AI:
  - Alderucci et al (2020) study US companies that filed AI-related patents with a control group using US Census Bureau data (1997-2016) and find that the invention of the first AI patent is related to subsequent increases in sales, employment and within-firm earnings inequality. They do not measure causal effect. On labour productivity: 4.15% increase; positive for services but negative for manufacturing firms.

- The challenge:

  [1] Capture AI + [2] Capture firms that develop the tech (or use it) + [3] Capture actual tasks/process

Description of the variables

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

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

Exploited company financials & patents data

- Covers 5,200+ AI inventor companies, their key balance sheet data and portfolio of non-AI patents (EPO PATSTAT – JRC TIM & ORBIS)

Descriptives

Variable name	**Full Sample**		**Period 2000-2008**		**Period 2009-2016**	
	N = 40,717		N = 17,247		N = 23,470	
	Mean	SD	Mean	SD	Mean	SD
Labour productivity (Turnover/Employee)	280,319	312,349	261,061	293,628	294,471	324,699
AI patent applications	0.48	2.60	0.37	2.00	0.56	2.97
Non-AI patent appl.	61.18	160.81	65.11	171.52	58.29	152.40
Labour productivity growth	10.03	44.16	9.91	44.73	10.12	43.74
Employment growth	5.76	27.11	6.82	28.91	4.98	25.68
Fixed capital growth	17.68	62.94	16.81	64.43	18.31	61.81
Firm size	5,995	16,561	5,670	15,466	6,233	17,318

Distribution of firms across sectors

	Full sample				Period 2000-2008				Period 2009-2016			
	Observations		Firms		Observations		Firms		Observations		Firms	
	Numbers	Perc.	Numbers	Perc.	Numbers	Perc.	Numbers	Perc.	Numbers	Perc.	Numbers	Perc.
Sector												
Manufacturing	26,928	66.13	3,205	60.97	11,709	67.89	2,385	65.58	15,219	64.84	2,918	61.68
Services	13,789	33.87	2,052	39.03	5,538	32.11	1,252	34.42	8,251	35.16	1,813	38.32
Manufacturing												
High-tech	21,263	78.96	2,578	80.44	9,194	78.52	1,920	80.50	12,069	79.30	2,345	80.36
Low-tech	5,665	21.04	627	19.56	2,515	21.48	465	19.50	3,150	20.70	573	19.64
Firm size												
SME	18,624	45.74	2,833	53.89	7,654	44.38	1,813	49.85	10,970	46.74	2,492	52.67
Large firm	22,093	54.26	2,424	46.11	9,593	55.62	1,824	50.15	12,500	53.26	2,239	47.33
Total	40,717	100.00	5,257	100.00	17,247	100.00	3,637	100.00	23,470	100.00	4,731	100.00

Firm distribution across sectors and countries

	Observations		Firms	
	Numbers	Perc.	Numbers	Perc.
Manufacturing	**26,928**	**66.13**	**3,205**	**60.97**
Primary	279	0.69	29	0.55
Food	209	0.51	30	0.57
Textile	273	0.67	31	0.59
Paper	322	0.79	32	0.61
Chemistry	1,620	3.98	166	3.16
Pharmaceutical	708	1.74	71	1.35
Minerals	356	0.87	36	0.68
Metal	2,038	5.01	213	4.05
Electronics	10,221	25.10	1,353	25.74
Machinery	6,602	16.21	750	14.27
Transport	2,782	6.83	305	5.80
Other Manufacturing	1,518	3.73	189	3.60
Services	**13,789**	**33.87**	**2,052**	**39.03**
Construction	1290	3.17	162	3.08
Electricity/Water	465	1.14	58	1.10
Retail trade	2,174	5.34	305	5.80
Transport Services	167	0.41	19	0.36
Hotel & Catering	59	0.14	6	0.11
Telecommunication	5,554	13.64	856	16.28
Finance	163	0.40	28	0.53
Real Estate & Rental	881	2.16	123	2.34
Scientific	2,709	6.65	426	8.10
Administration/Education	115	0.28	26	0.49
Other services	212	0.52	43	0.82
Total	**40,717**	**100.00**	**5,257**	**100.00**

	Observations		Firms	
	Numbers	Perc.	Numbers	Perc.
Asia	**26,626**	**65.39**	**3,531**	**67.17**
Japan	11,432	28.08	888	16.89
South-Korea	9,406	23.10	1,468	27.92
China	4,456	10.94	991	18.85
Taiwan	1,065	2.62	149	2.83
Rest of Asia	267	0.66	35	0.67
Europe	**10,175**	**24.99**	**1,252**	**23.82**
Germany	2,381	5.85	337	6.41
United Kingdom	1,494	3.67	150	2.85
France	1,402	3.44	174	3.31
Italy	1,075	2.64	117	2.23
Sweden	679	1.67	62	1.18
Spain	632	1.55	73	1.39
Belgium	348	0.85	30	0.57
Denmark	322	0.79	27	0.51
Finland	209	0.51	30	0.57
Netherlands	168	0.41	24	0.46
Romania	153	0.38	16	0.30
Austria	132	0.32	29	0.55
Poland	131	0.32	20	0.38
Czech Republic	126	0.31	18	0.34
Switzerland	107	0.26	7	0.13
Rest of Europe	816	2.00	138	2.63
United States	**3,774**	**9.27**	**449**	**8.54**
Rest of World	**142**	**0.35**	**25**	**0.48**
Total	**40,717**	**100**	**5,257**	**100**

Our model

- Derived from a knowledge-stock augmented Cobb-Douglas growth model (e.g., Lokshin et al. 2008; Hall et al. 2012; Belderbos et al. 2013, 2015)

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

- Tackle simultaneity and endogeneity issues in a dynamic panel using the GMM approach (Blundell and Bond, 1998, 2000)
    - all the explanatory variables considered potentially endogenous to L.Prod, and instrumented in all models (Piva and Vivarelli 2005; Lokshin et al. 2008; Bogliacino et al. 2012; Van Roy et al. 2018)
    - 2x-lagged differences used for L.Prod, AI and non-AI patent applications, employment growth, fixed capital growth, and firm size
    - sector, country and year dummies included in level equation

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

Labour prod at time *t*

Growth in labour input

Growth in fixed capital

Growth in knowledge stock

function of AI & non-AI **patent applications**

Patents vs. R&D:

- R&D is an aggregate in balance sheet, while patents are more specific
- **Patent portfolio reflects technological capability** of firm (based on past innovative efforts)
- Usual caveats apply…