TECHNOLOGY, DEMAND AND EMPLOYMENT

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NEW TECHNOLOGIES AND EMPLOYMENT

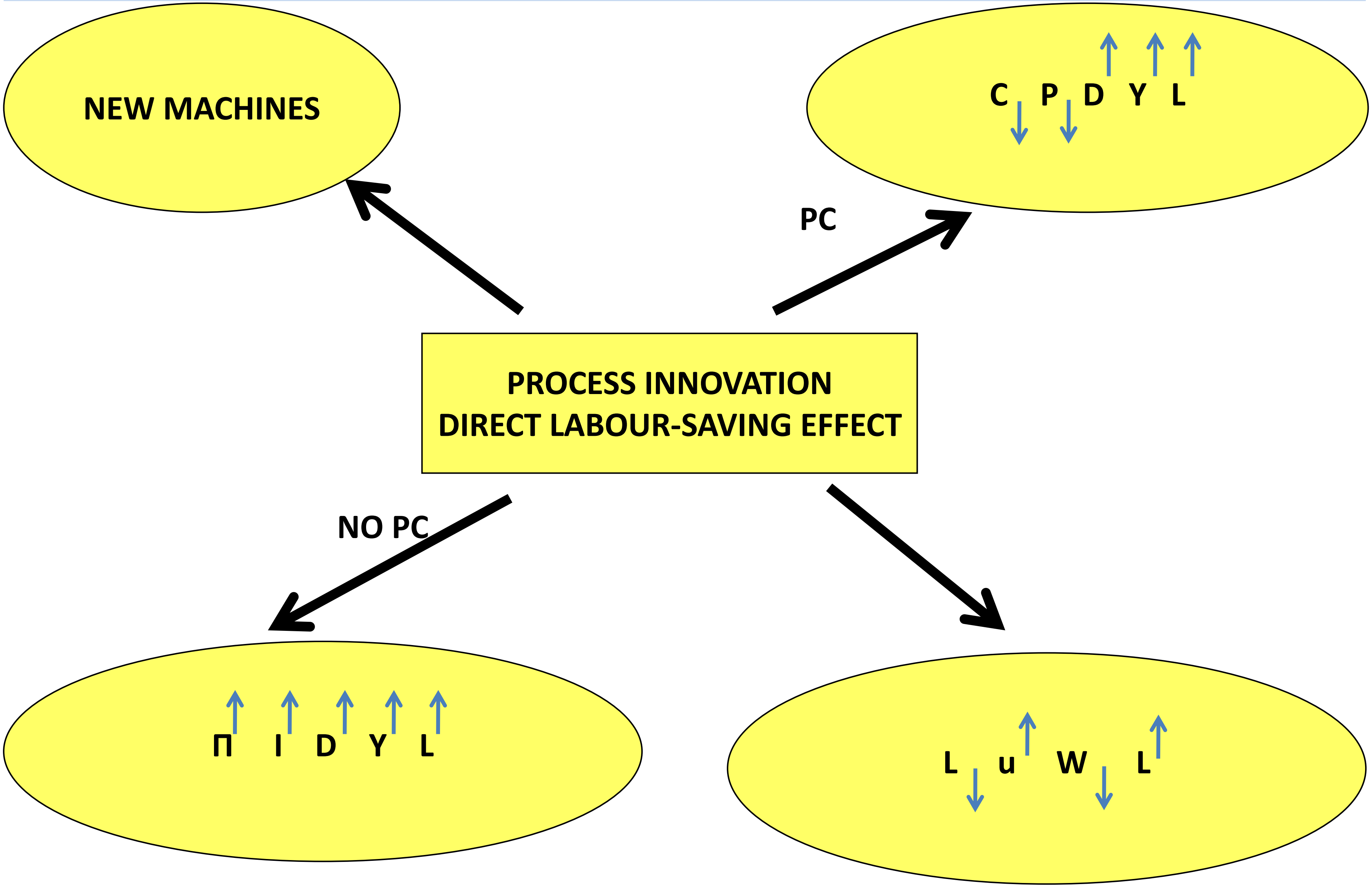
- The widespread diffusion of automation and, more recently, the arrival of GenAI has raised again a fear of a new wave of '**technological unemployment**'; here below the literature pillars from the last decade.
- According to Brynjolfsson and McAfee (2011 and 2014), the root of the employment problems is not the Great Recession (triggered by the financial crisis in the late '00, but rather a "Great Restructuring" characterized by an exponential growth in computers' processing speed having an ever-bigger impact on jobs, skills, and the whole economy: "**This time is different**".
- Moreover, not only agricultural and manufacturing employment appears at risk, but employees in services (Uber, airbnb, Amazon) - including **cognitive skills** - are no longer safe. Frey and Osborne (2017) predict that 47% of the occupational categories are at high risk of being automated, including a wide range of service/white-collar/cognitive tasks such as accountancy, logistics, legal works, translation and technical writing, etc.
- Compared with these comprehensive pictures, **mainstream economists** (particularly Acemoglu and Restrepo) put forward on the one hand an overall long-run and general equilibrium optimism (see below) and on the other hand a narrow empirical focus on the labour-saving impact of the solely robots on the user sectors, mainly car factories accounting for 40% of robot usage (Acemoglu and Restrepo, 2018 and 2019).

RICARDO’S SURPRISE? NOT AT ALL
A LONG TRADITION OF MAINSTREAM ECONOMICS OPTIMISM

“….the opinion, entertained by the labouring class, that the employment of machinery is frequently detrimental to their interests, is not founded on prejudice and error, but is conformable to the correct principles of political economy” (Ricardo, 1951, vol 1, p. 387; third edition, 1821)

However, technological unemployment is considered an exception, occurring only when production does not grow, otherwise a “**compensation**” always occurs:

THE MAINSTREAM COMPENSATION THEORY



CLASSICAL AND CONTROVERSIAL ISSUE (1)

- *"Machines cannot be constructed without considerable labour, which gives occupation to the hands they throw out of employ."* (Say, 1967, p. 87; first ed. 1803);

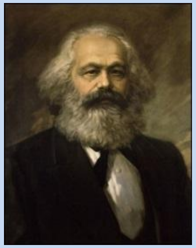
HOWEVER:

"…the machine can only be employed profitably, if it…is the (annual) product of fewer men than it replaces." (Marx, 1969, p. 552; first ed. 1905-1910);

- *"The introduction of machines is found to reduce prices in a surprising manner. And if they have the effect of taking bread from hundreds, formerly employed in performing their simple operations, they have that also of giving bread to thousands."* (Steuart, 1966, vol. II, p. 256; first ed. 1767);

HOWEVER:

"..the increased demand for commodities by some consumers, will be balanced by a cessation of demand on the part of others, namely, the labourers who were superseded by the improvement." (Mill, 1976, p.97; first ed. 1848)



CLASSICAL AND CONTROVERSIAL ISSUE (2)

- “*I have before observed, too, that the increase of net incomes, estimated in commodities, which is always the consequence of improved machinery, will lead to new saving and accumulation*” (Ricardo, 1951, vol 1, p. 396; third edition, 1821) ;

<u>HOWEVER</u>:

“*The accumulation of capital, though originally appearing as its quantitative extension only, is effected, as we have seen, under a progressive qualitative change in its composition, under a constant increase of its constant, at the expense of its variable constituent*.” (Marx, 1961, vol. 1; p. 628; first ed. 1867).

MAINSTREAM ECONOMICS PUTS FORWARD A TRICKLE-DOWN «FAIRY TALE»

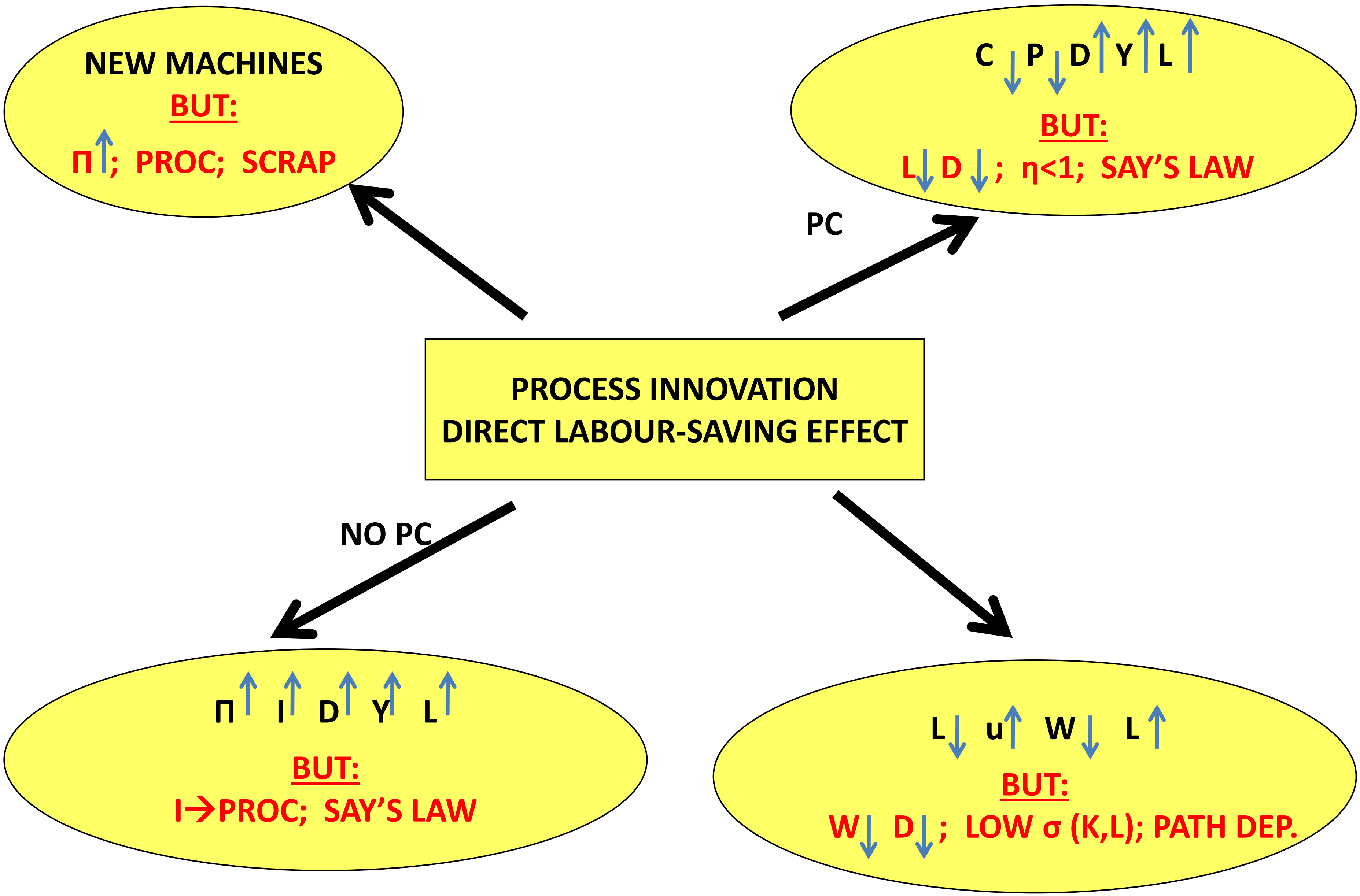
Examples of "fairy tales": Neary, 1981; Stoneman, 1983; Kautsolacos, 1984; Hall and Heffernan, 1985; Waterson and Stoneman, 1985; Dobbs *et al*., 1987; Layard *et al.*, 1991.

"This neo-classical general equilibrium framework can be said to correspond most closely to present-day traditional economic views on technical change and employment. Technological change may indeed result in some temporary unemployment, but with efficiently operating labour and capital markets there is no basic economic problem arising from the introduction of new technology"

(Freeman, C. and Soete, L., ***Work for All or Mass Unemployment***, London: Pinter, 1994, p.25)

In the real world, non competitive markets, price rigidities, pessimistic expectations may severely hinder and delay the compensation of the initial job losses.

THE CRITIQUE



INDUCED-BIAS TECHNOLOGICAL CHANGE AND WAGE FLEXIBILITY

*"An important conclusion follows from this overall assessment of '**induced innovation**'. It is that there is inherent plausibility in the Hicks inducement theory, biasing the long term direction of technical change in a labour-saving direction. Attempts to generate a **reversal** of this trend by temporary small reductions in the relative price of labour are **extremely unlikely to be effective**"*

(Freeman, C. and Soete, 1987, **Technical Change and Full Employment**, Oxford, Basil Blackwell, p.46)

THE OTHER SIDE OF THE COIN: PRODUCT INNOVATION

As emphasized by Schumpeter (1912) in his seminal contribution, technological change cannot be reduced to the sole process innovation (potentially labour-saving). Indeed, the introduction of **new products** entails the raise of new branches of production and stimulate additional consumption. Enlarged production and higher consumption translate into higher demand and therefore higher employment.

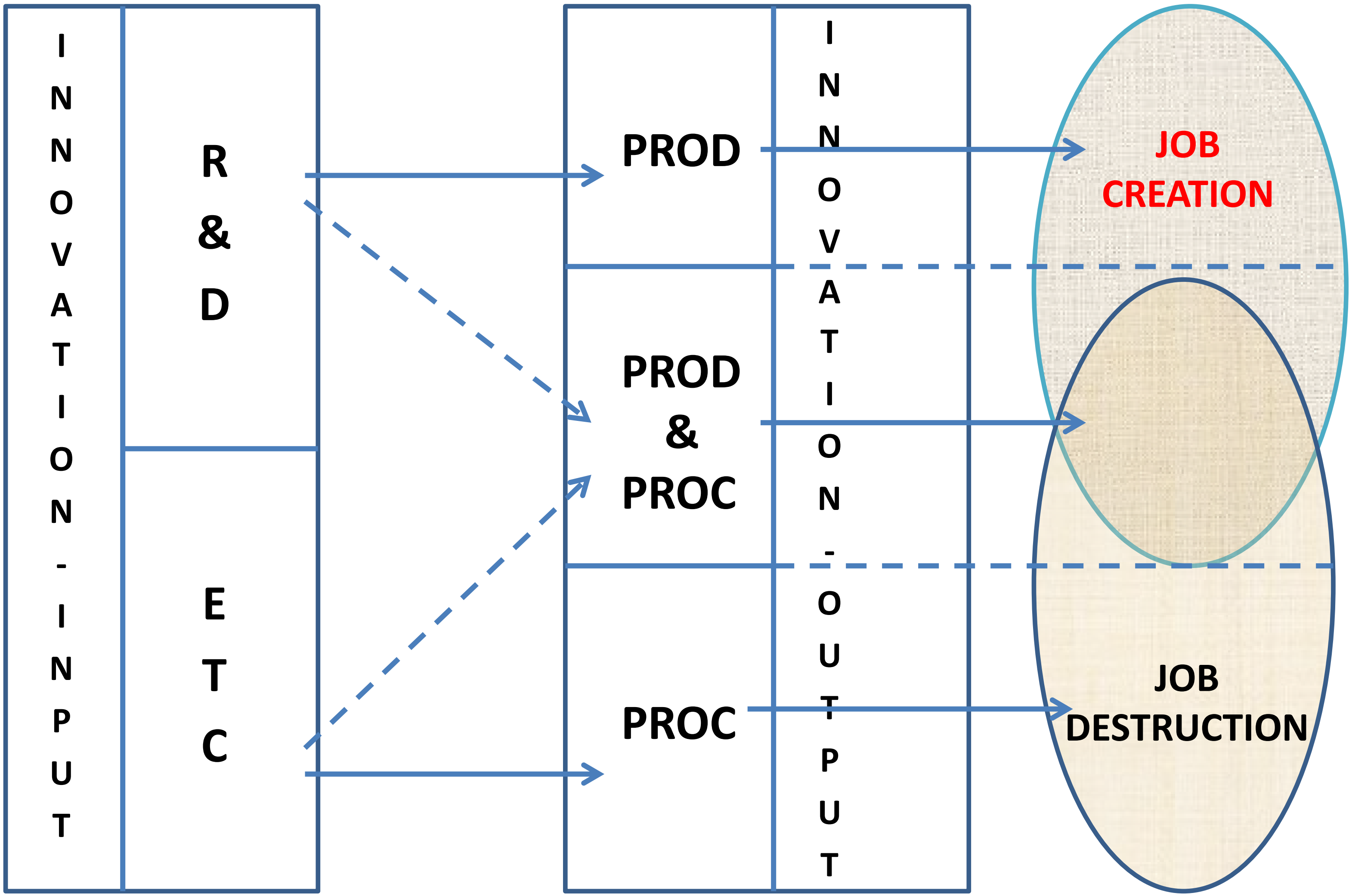
The **labour-friendly nature of product innovation** was even (and earlier) recognized by the most strict critic of the compensation theory:

“ Entirely new branches of production, creating new fields of labour, are also formed, as the direct result either of machinery or of the general industrial changes brought about by it. But the places occupied by these branches in the general production is, even in the most developed countries, far from important” (Marx, 1961, vol. 1; p. 445 first ed. 1867).

EVEN THE LABOUR-FRIENDLY NATURE OF PRODUCT INNOVATION SHOULD NOT BE OVER-EMPHASIZED

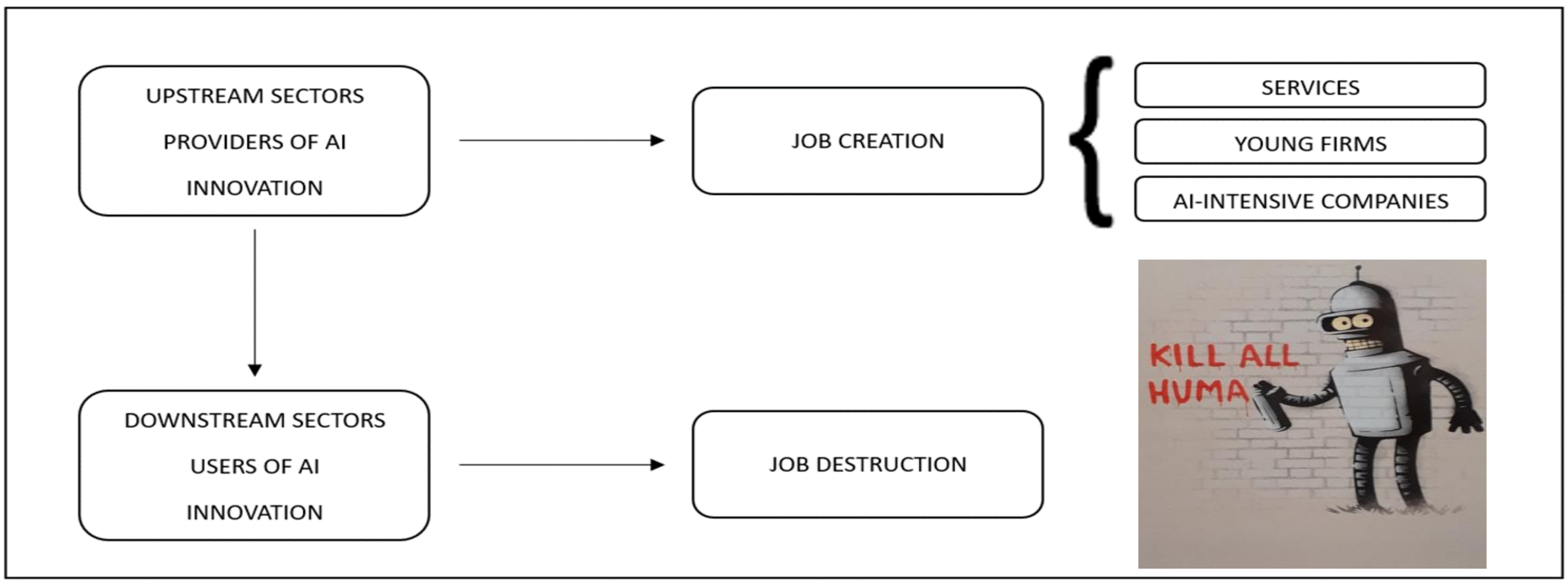
- First, the intensity of its impact depends on the **weight** that new products have in the baskets of consumption and on the **income elasticities** of their demand.
- Second, those which are new products for those producing them might well represent efficiency enhancing **processes for their users** (for instance: computers and robots)
- Third, in order to exert a compensating effect, new products should not exclusively replace obsolete ones. If new products just cannibalize the sales of old ones, the net result might be ambiguous. In other words, at the consumer level the "**welfare effect**" should be compared with the "**substitution effect**" (Katsoulacos, 1984 and 1986; Vivarelli, 1995)
- Fourth, product innovators may face a demand increase via market expansion, while the market shares of **non-innovators** may be eroded since old products become obsolete.
- Finally, new products may be produced more efficiently, due to the widespread evidence on the **complementarity** between product and process innovation.

THE EMPIRICAL SETTING: HOW TO PROXY TECHNOLOGY IS CRUCIAL
ETC (INCLUDING ROBOTS AND ALGORITHMS) AS A MISSING LINK IN MAINSTREAM ECONOMICS



THE EMPIRICAL SETTING: VERTICAL LINKS ARE CRUCIAL

- The current debate on the employment impact of AI is solely focusing on the demand side (that is the adoption of AI and robots as labour-saving **process innovations** in the downstream industries), while there is an obvious gap to be filled with regard to the **supply side**, where AI technologies can be conceived as **product innovations** (see above).
- Damioli, Van Roy, Vertesy and Vivarelli, (2024),test the **possible job-creation impact of AI** technologies, focusing on the supply side, namely the providers of the new knowledge base in the



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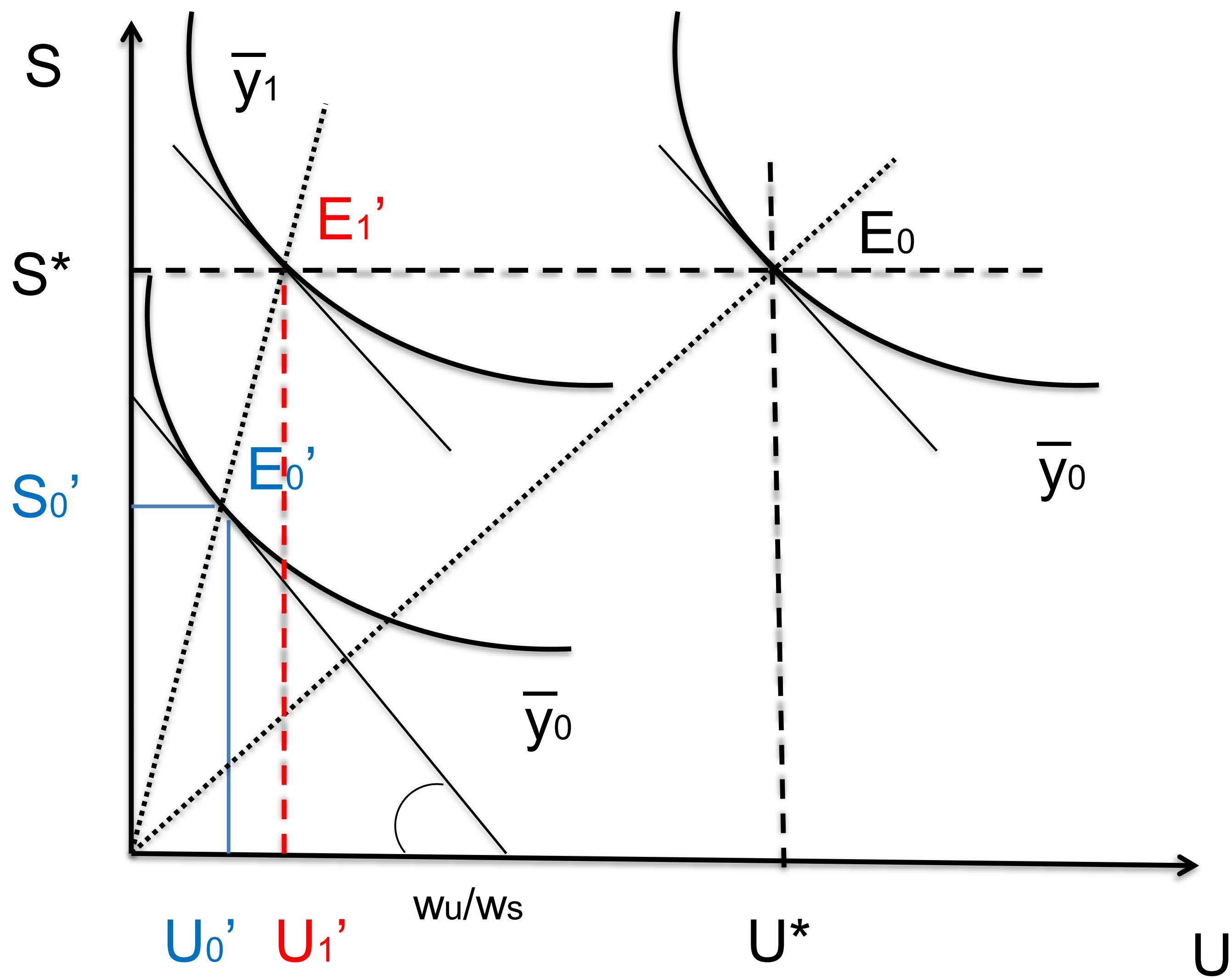
THANK YOU

- SKILLS

SKILL-BIASED TECHNOLOGICAL CHANGE MAY RENDER COMPENSATION IMPOSSIBLE



WHEN TECHNOLOGICAL CHANGE IS ALSO SKILL-BIASED EDUCATION AND TRAINING POLICIES ARE CRUCIAL

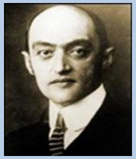
LEVELS OF FULL EMPLOYMENT	TECHNOLOGY AT TIME t0 FULL EMPLOYMENT EQUILIBRIUM OUTPUT: 120 OUTPUT/LABOUR: 1 SKILLED/UNSKILLED: 1:1	TECHNOLOGY AT TIME t1 (LABOUR-SAVING AND SKILL-BIASED) OUTPUT: 120 OUTPUT/LABOUR: 2:1 SKILLED/UNSKILLED: 2:1	OUTPUT COMPENSATION VIA PRICE AND INCOME MECHANISMS OUTPUT: 180 OUTPUT/LABOUR: 2:1 SKILLED/UNSKILLED: 2:1
EMPLOYMENT	120	60	90
SKILLED: 60	60 EMPLOYED	40 EMPLOYED 20 UNEMPLOYED	60 EMPLOYED (MAXIMUM LEVEL)
UNSKILLED: 60	60 EMPLOYED	20 EMPLOYED 40 UNEMPLOYED	30 EMPLOYED 30 UNEMPLOYED
UNEMPLOYMENT	0	60	**30**

A SHORTAGE IN SKILLED LABOUR IMPLIES UNEMPL0YMENT AMONG UNSKILLED LABOUR

TWO POSSIBLE SOLUTIONS:

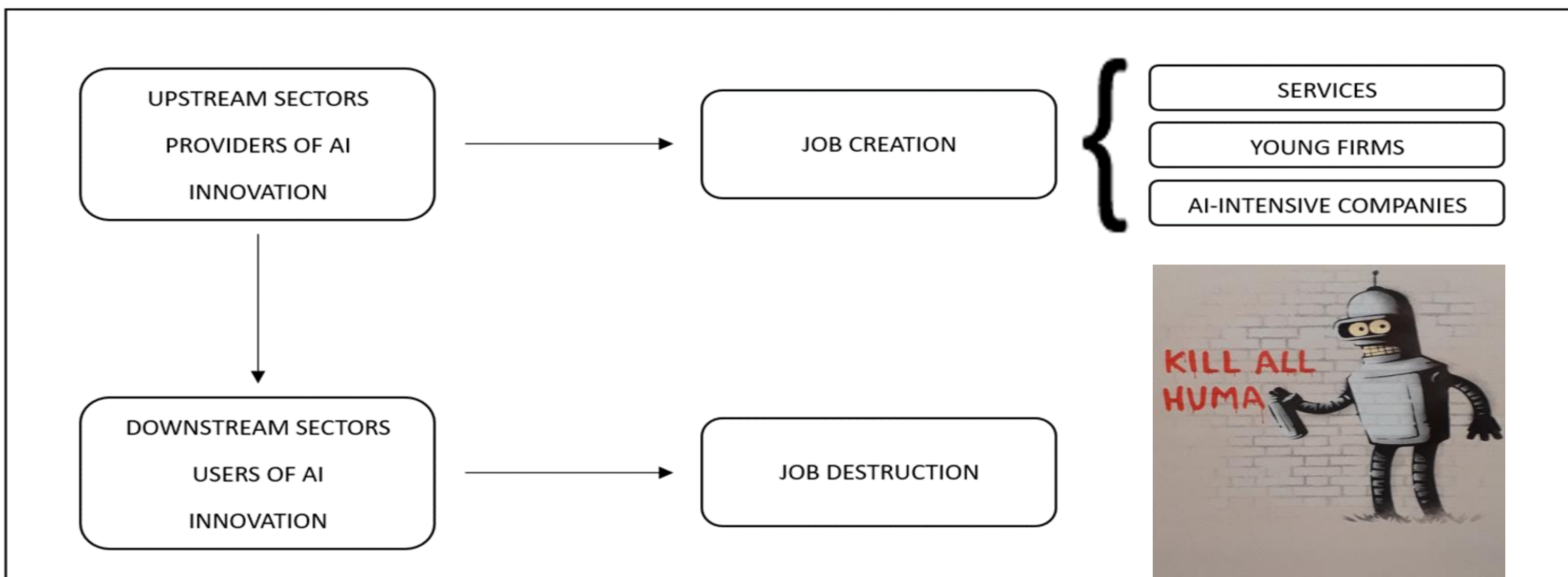
AMERICAN (FLEXIBILITY IN RELATIVE WAGES) *VS* NORDIC (TRAINING AND RETRAINING)

- **AI LABOR FRIENDLY**



AIMS AND SCOPE

- **Motivation:** The current debate and the extant economics literature (see above) is solely focusing on the demand side (that is the adoption of AI and robots as labour-saving **process innovations** in the downstream industries), while there is an obvious gap to be filled with regard to the **supply side**, where AI technologies can be conceived as **product innovations (Schumpeter)**.
- **Purpose:** to test the **possible job-creation impact of AI** technologies, focusing on the supply side, namely the providers of the new knowledge base in the upstream sectors:



THE ECONOMETRIC SPECIFICATION

$$l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 gi_{i,t} + \beta_4 Inno_{i,t} + (\varepsilon_i + \nu_{i,t}) \qquad i = 1,..,n; \; t = 1,..,T$$

Taking into account **viscosity in the labor demand** (Arellano and Bond, 1991; Van Reenen, 1997), we move to the proper dynamic specification:

$$l_{i,t} = \alpha l_{i,t-1} + \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 gi_{i,t} + \beta_4 Inno_{i,t} + (\varepsilon_i + \nu_{i,t})$$

As common in the literature (see Van Reenen, 1997; Lachenmaier and Rottmann, 2011; Bogliacino, Piva and Vivarelli, 2012), this specification can be seen as a dynamic labor demand augmented by an innovation proxy.

Panel methodologies:

- **POLS** with time and sector dummies (endogeneity, unobservables not solved)
- **FE/RE** according to the Hausman's test, with time dummies (endogeneity not solved)
- **GMM-SYS** better than GMM-DIF because of strong persistence and dominant cross sectional variability; see Blundell and Bond, 1998 (preferred methodology, when feasible)
- Moreover, **endogeneity** may also affect other covariates in the model (for instance, it may well be the case that wage, investment and employment decisions are jointly and simultaneously adopted). Hence, all the explanatory variables will be cautiously considered as potentially endogenous to labour demand and instrumented when necessary, using up to thrice lagged instruments.
- Since all the variables are expressed in log, the estimated coefficients can be interpreted as **elasticities**.

CLEANING ORBIS DATA

Step 1: identify and treat clerical errors and typos for key financial variables (**employees**, **turnover**, **fixed assets** and **cost of employees** variables [i.e.: ‘000 errors]);
for **nr. employees**, impute values missing between two known time points not more than 4 years apart (typically unfilled values). Did not impute K or wage data due to high annual fluctuation.
(followed Hallak and Harasztosi, 2019)

Step 2: Remove outlier *year-on-year growth rates* in key financial vars (by size class, typically <1% of tails, following Van Roy et al, 2018). Thresholds:

Step 3: Trim top 1 percentile in terms of *levels* for Empl, Turn, K, Empl.cost/empl., patent appl

VARIABLES

Variable name	Variable definition
Employment	Natural logarithm of the number of employees expressed in head counts
Turnover	Natural logarithm of the turnover expressed in EURs
Gross investments	Natural logarithm of fixed assets expressed in EURs in t - natural logarithm of fixed assets expressed in EURs in t-1
Labour cost per employee	Natural logarithm of labour cost per employee (labour cost expressed in EURs/number of employees)
AI patent families	Natural logarithm of the number of AI patent families
Non-AI patent families	Natural logarithm of the number of non-AI patent families
AI patent family size	Natural logarithm of the average size of AI patent families
Non-AI patent family size	Natural logarithm of the average size of non-AI patent families

DESCRIPTIVE STATISTICS

Variable name	Mean	SD	Min	Max
Employment	5,161	23,328	1	552,810
Turnover	1.46E+09	7.84E+09	10000	3.48E+11
Gross investments	22.5	78.3	-97.8	894.1
Cost of labour per employee	34,586	32,050	2.3	422,000
AI patent families	0.3	1.6	0	78
Non-AI patent families	32.4	148.4	0	6,601
AI patent family size	0.3	1.04052	0	51.5
Non-AI patent family size	1.500	2.214945	0	44.5

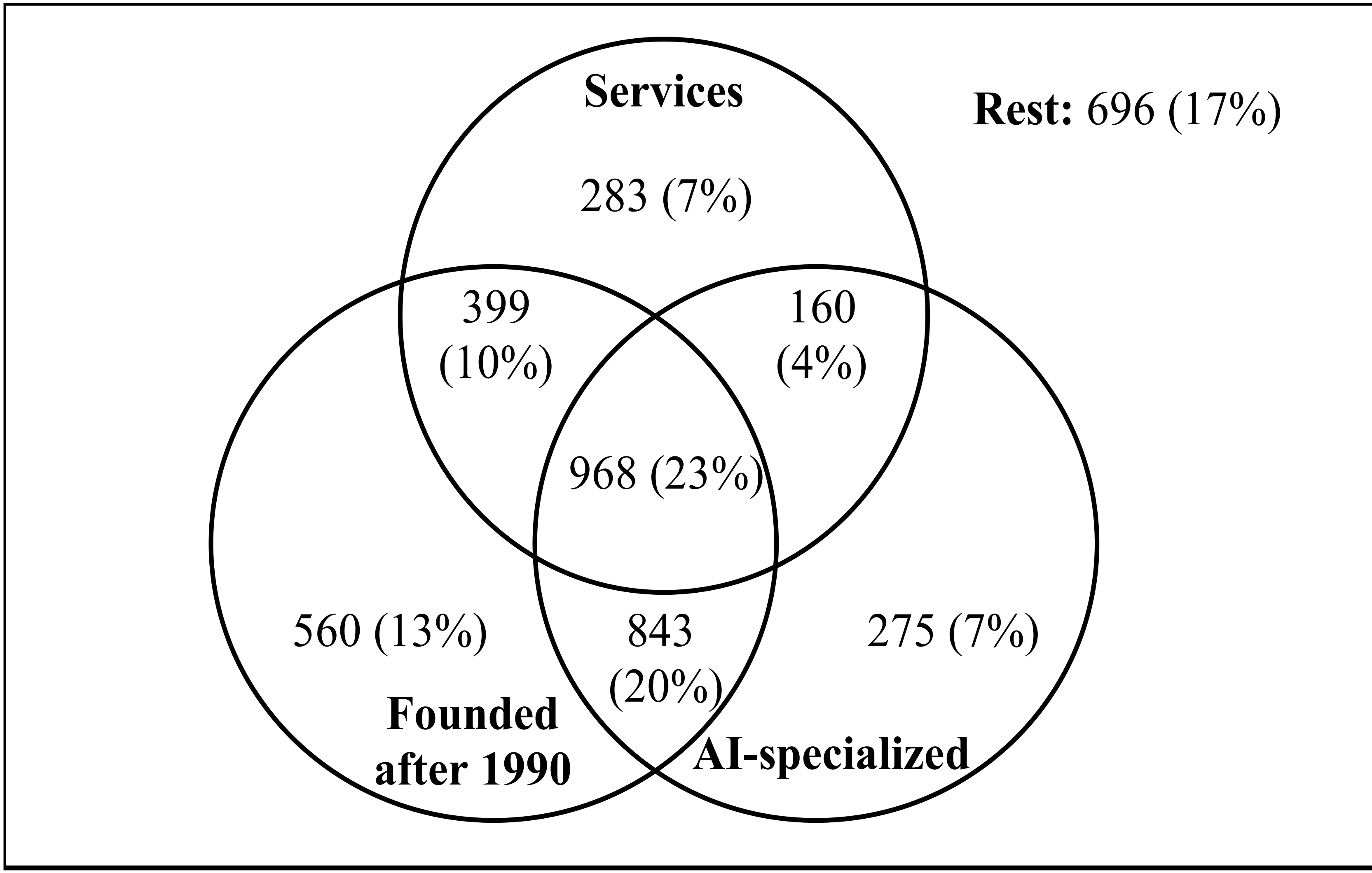
Notes: the full sample includes **28,840** observations and **4,184 firms**. Employment is the number of employees. Turnover, cost of labour per employee, fixed assets are expressed in EURs. Gross investments are shown as yearly percentage changes.

DISTRIBUTION ACROSS SECTORS, AGE AND AI INTENSITY

	Full sample			
	Observations		Firms	
	Numbers	Perc.	Numbers	Perc.
Sector				
Services	11,713	40.61	1,810	43.26
Manufacturing	17,127	59.39	2,374	56.74
Age of firm				
Founded before 1990	11,077	38.41	1,414	33.80
Founded after 1990	17,763	61.59	2,770	66.20
AI intensity				
AI-specialized	14,327	49.68	2,246	53.68
Non-AI-specialized	14,513	50.32	1,938	46.32
Total	28,840	100.00	4,184	100.00

Notes: Age is defined based on the year of foundation or consolidation of the firm. AI-specialized companies are those with the share of AI patents over total patents in the period which is above the median.

DISTRIBUTION OF FIRMS ACROSS SUB-SAMPLES



DISTRIBUTION ACROSS INDUSTRIES

	Observations		Firms	
	Numbers	Perc.	Numbers	Perc.
Manufacturing	17,127	59.4	2,374	56.7
Primary	260	0.9	34	0.8
Food	70	0.2	13	0.3
Textile	130	0.5	20	0.5
Paper	135	0.5	18	0.4
Chemistry	896	3.1	113	2.7
Pharmaceutical	385	1.3	42	1.0
Minerals	171	0.6	24	0.6
Metal	1,263	4.4	171	4.1
Electronics	6,337	**22.0**	944	22.6
Machinery	4,672	**16.2**	627	15.0
Transport	1,712	5.9	214	5.1
Other Manufacturing	1,096	3.8	154	3.7
Services	11,713	40.6	1,810	43.3
Construction	1,001	3.5	159	3.8
Electricity/Water	187	0.7	26	0.6
Retail trade	1,827	6.3	274	6.6
Transport Services	113	0.4	19	0.5
Hotel & Catering	38	0.1	7	0.2
Telecommunication	4,641	**16.1**	721	17.2
Finance	144	0.5	21	0.5
Real Estate & Rental	105	0.4	22	0.5
Scientific	2,698	**9.4**	402	9.6
Administration/Education	794	2.8	127	3.0
Other services	165	0.6	32	0.8
Total	28,840	100	4,184	100

DISTRIBUTION ACROSS COUNTRIES

	Observations		Firms	
	Numbers	Perc.	Numbers	Perc.
Asia	16,409	56.9	2,560	61.2
South Korea	11,453	**39.7**	1,729	41.3
Japan	3,070	**10.6**	564	13.5
Taiwan	1,275	4.4	171	4.1
China	402	1.4	66	1.6
Rest of Asia	209	0.7	30	0.7
Europe	11,038	38.3	1,331	31.8
Germany	2,496	**8.7**	329	7.9
France	2,063	**7.2**	224	5.4
United Kingdom	1,593	5.5	161	3.8
Italy	1,397	4.8	162	3.9
Spain	784	2.7	98	2.3
Sweden	561	1.9	66	1.6
Rest of Europe	2,144	7.4	291	7.0
United States	1,023	**3.5**	239	5.7
Rest of World	370	1.3	54	1.3
Total	28,840	100	4,184	100

RESULTS (1)

	Baseline		Industry			
			Services		Manufacturing	
Employment t-1	0.447***	0.452***	0.482***	0.492***	0.415***	0.420***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	0.368***	0.372***	0.305***	0.313***	0.307***	0.304***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gross investments	0.033*	0.033*	0.027*	0.027*	0.035	0.036
	(0.092)	(0.092)	(0.058)	(0.053)	(0.304)	(0.293)
Labour cost per employee	-0.475***	-0.481***	-0.412***	-0.422***	-0.515***	-0.521***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI patent families	**0.023****		**0.033***		**0.012**	
	(0.042)		**(0.093)**		**(0.421)**	
Non-AI patent families	**0.022*****		**0.045*****		**0.003**	
	(0.010)		**(0.001)**		**(0.797)**	
AI pat. family size		**0.016***		**0.033****		**0.004**
		(0.051)		**(0.011)**		**(0.726)**
Non-AI pat. family size		**0.008**		**0.027****		**-0.010**
		(0.356)		**(0.043)**		**(0.299)**

Notes: All variables are taken in natural logs, apart from gross investments, which are expressed as the log difference of fixed assets between time t and t-1. All models include industry, country and year dummies.

p-values derived from one-step GMM robust standard errors are reported in parentheses. Instrumental variables compromise 3-year lags. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

RESULTS (2)

	Baseline		Age of firm			
			Founded before 1990		Founded after 1990	
Employment t-1	0.447***	0.452***	0.270***	0.275***	0.473***	0.478***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	0.368***	0.372***	0.491***	0.481***	0.292***	0.305***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gross investments	0.033*	0.033*	0.091	0.093	0.023*	0.023*
	(0.092)	(0.092)	(0.148)	(0.136)	(0.083)	(0.085)
Labour cost per employee	-0.475***	-0.481***	-0.591***	-0.606***	-0.430***	-0.433***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI patent families	**0.023****		**0.009**		**0.032****	
	(0.042)		**(0.610)**		**(0.031)**	
Non-AI patent families	**0.022*****		**0.009**		**0.033*****	
	(0.010)		**(0.582)**		**(0.002)**	
AI pat. family size		**0.016***		**0.000**		**0.026****
		(0.051)		**(0.994)**		**(0.015)**
Non-AI pat. family size		**0.008**		**0.005**		**0.009**
		(0.356)		**(0.751)**		**(0.383)**

Notes: All variables are taken in natural logs, apart from gross investments, which are expressed as the log difference of fixed assets between time t and t-1. All models include industry, country and year dummies.
p-values derived from one-step GMM robust standard errors are reported in parentheses. Instrumental variables compromise 3-year lags. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

RESULTS (3)

	Baseline		AI intensity			
			AI specialized			
Employment t-1	0.447***	0.452***	0.544***	0.547***	0.343***	0.344***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Turnover	0.368***	0.372***	0.263***	0.267***	0.432***	0.435***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gross investments	0.033*	0.033*	0.028**	0.027**	0.052	0.054
	(0.092)	(0.092)	(0.013)	(0.016)	(0.229)	(0.220)
Labour cost per employee	-0.475***	-0.481***	-0.471***	-0.472***	-0.472***	-0.478***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI patent families	**0.023****		**0.032****		**0.016**	
	(0.042)		**(0.031)**		**(0.449)**	
Non-AI patent families	**0.022*****		**0.037*****		**0.003**	
	(0.010)		**(0.000)**		**(0.803)**	
AI pat. family size		**0.016***		**0.025***		**0.005**
		(0.051)		**(0.061)**		**(0.678)**
Non-AI pat. family size		**0.008**		**0.028*****		**-0.015**
		(0.356)		**(0.003)**		**(0.298)**

Notes: All variables are taken in natural logs, apart from gross investments, which are expressed as the log difference of fixed assets between time t and t-1. All models include industry, country and year dummies.
p-values derived from one-step GMM robust standard errors are reported in parentheses. Instrumental variables compromise 3-year lags. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

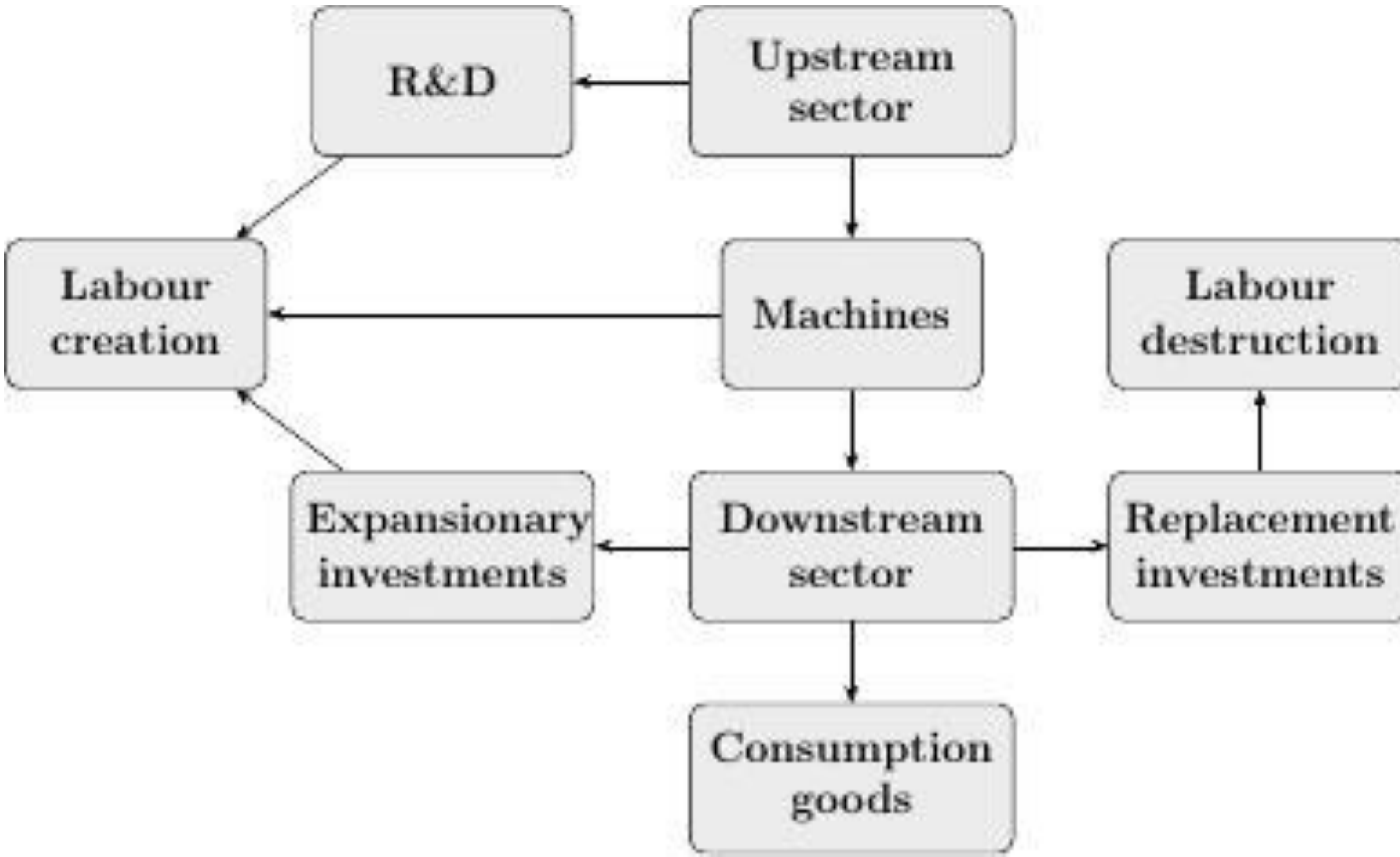
KEY FINDINGS

- Our findings indeed reveal a **positive and significant impact of AI patent applications on employment**, supporting the labour-friendly nature of product innovation in the supply industries.
- However, this job-creation effect is **small in magnitude** (3/4%) and unlikely able to compensate the labour-saving effect in the downstream industries.
- The positive employment impact is limited to **service sectors and younger firms**, that is in the leading actors of AI revolution.
- Some evidence of **increasing returns** seem to emerge: indeed, the innovative companies which are more focused on AI technologies are those obtaining the larger effects in terms of job creation.
- These pieces of evidence suggest that the technological leaders within the emergence of the AI paradigm can realize (modest) labour-friendly outcomes; however, **heterogeneity** is also detected, with manufacturing, older and less innovative companies unable to couple product innovation with job creation.
- However, if AI will develop into a **new technological paradigm** (see above) with an increasing role played by new, young and AI intensive companies, **the detected job creation effect might dramatically increase in magnitude**, as was the case in previous technological revolutions.

RESEARCH POLICY

A GUIDELINE TO EMPIRICAL TESTS

Dosi, G., Piva, M., Virgillito, M., Vivarelli, M. (2021), «Embodied and disembodied technological change: the sectoral patterns of job-creation and job-destruction", Research Policy, 50 (4), 10419



THE UPSTREAM SECTOR

(1) $A_{q,t+1} = \left(1 - e^{-\gamma R\&D_t}\right)_q \left[A_{q,t}\left(1 + x^A_{q,t}\right)\right]$ (machine improvement)

(2) $RD_{1,t} = \nu S_{1,t-1}$ (demand – pull innovation)

(3) $L^{R\&D}_{1,t} = \dfrac{\nu S_{1,t-1}}{w_{1,t}}$ (demand for R&D workers; mechanism via decrease in wages)

(4) $L^{Q}_{1,t} = \dfrac{Q_{1,t}}{b_1}$ (demand for production workers; **direct labour – saving effect**)

(5) $L_{1,t} = L^{R\&D}_{1,t} + L^{Q}_{1,t}$ (total demand for labour in the upstream sector 1)

Therefore: $\uparrow \Delta S_1 \Rightarrow \uparrow \Delta R\&D_1 \Rightarrow \uparrow \Delta L_1$

Prediction 1: Disembodied technical change (**product innovation**) via R&D expenditures has a positive impact on employment growth.

Prediction 2: Beyond R&D expenditures, employment in the upstream sector depends positively on output and negatively on wages.

THE DOWNSTREAM SECTOR

(6) $K_{2,t} = \sum_q \sum_{k=t-\tau}^{t} A_{q,k}\, q_k$ (downstream productive capacity)

(7) $EI_{2,t}^d = K_{2,t}^d - K_{2,t}$ (expansionary investment; **mechanism via new investments**; the desired capital stock K_2^d depends on the desired level of production $Q_{2,t}^d$)

(8) $L_{2,t}^d = \frac{Q_{2,t}^d}{K_{2,t}}$ (total demand for labour in the downstream sector)

(9) $\boldsymbol{p_{1,t} < \delta w_{2,t}(1/A_{q,t-\tau} - 1/A_{q,t})}$ (scrapping rule; **direct labour – saving effect + mechanism via decrease in prices** in the upstream sector and **via decrease in wages** in the downstream sector)

where: $c_{1,t} = \frac{w_{1,t}}{b_1}$ and $p_{1,t} = (1 + \mu_1)c_{1,t}$

*** Upstream product innovation (via new machines) shapes downstream process innovation**

(10) $I^{tot} = EI_{2,t} + SI_{2,t}$ (total investment in the downstream sector)

Therefore: $\uparrow \Delta Q_2 \Rightarrow \uparrow \Delta EI_2 \Rightarrow \uparrow \Delta L_2$; $\uparrow \Delta A_1 \Rightarrow \uparrow \Delta SI_2 \Rightarrow \downarrow \Delta L_2$

Prediction 3: *Expansionary investments have a positive impact on employment growth.*
Prediction 4: *Replacement investments have a negative impact on employment growth.*
Prediction 5: *beyond investments, employment in the downstream sector depends positively on output and negatively on wages.*

DATA

- **Sectoral** STAN OECD and ANBERD OECD data covering **19 European countries** over the period **1998-2016 (unbalanced panel).**
- Upstream and downstream sectors are singled out applying a refined Pavitt (1984) taxonomy, as in **Bogliacino and Pianta (2010).** The "Science-based" and "Specialized Suppliers" sectors are considered upstream, while the "Scale and information intensive" and the "Supplier dominated" industries are considered downstream.
- In order to split the two components of investments (EI and SI), we consider the **Consumption of Fixed Capital (CFCC) as the scrapping component (SI).** The extra investment given by **(GFCF – CFCC) - where GFCF is the Gross Fixed Capital Formation - represents the expansionary component**. When CFCC resulted to be higher than GFCF, we set expansionary investments equal to 0 to avoid unreliable negative values.

Table A3: Descriptive statistics

		Employees	Value Added	Cost of Labour per Employee	R&D	Consumption of Fixed Capital	Expansionary Investments
UP	Mean	81.29	8,850.32	58.36	701.14		
	St.dev.	136.42	14,405.51	41.59	1,280.53		
DOWN	Mean	184.04	14,275.35	43.93		1,948.61	1,289.75
	St.dev.	397.61	53,491.72	41.08		9,239.55	6,452.03

Note: While the Employees are expressed in thousands of persons engaged, the monetary variables are expressed in millions (thousands in the case of Cost of labour per employee) of constant PPP 2010 US dollars.

Table A1: Distribution of observations across countries

COUNTRY	SECTORS	OBSERVATIONS
AUSTRIA	41	525
BELGIUM	35	458
CZECH REPUBLIC	12	154
DENMARK	13	34
ESTONIA	14	32
FINLAND	12	405
FRANCE	13	72
GERMANY	35	488
HUNGARY	11	96
ITALY	35	502
NORWAY	13	130
POLAND	29	188
PORTUGAL	34	458
SLOVAKIA	40	486
SLOVENIA	37	525
SPAIN	13	124
SWEDEN	10	35
THE NETHERLANDS	40	174
UNITED KINGDOM	30	195
TOTAL	***467***	***5,081***

Table A2: Sectoral classification

UPSTREAM SECTORAL AGGREGATE: Science-Based and Specialized Suppliers	**2-digit NACE classification**
- Manufacture of chemicals and chemical products	20
- Manufacture of basic pharmaceutical products and pharmaceutical prep.	21
- Manufacture of computer, electronic and optical products	26
- Manufacture of electrical equipment	27
- Manufacture of machinery and equipment n.e.c.	28
- Manufacture of other transport equipment	30
- Repair and installation of machinery and equipment	33
- Telecommunications	61
- Computer programming, consultancy and related activities	62
- Scientific research and development	72
DOWNSTREAM SECTORAL AGGREGATE: Scale and Information Intensive and Suppliers Dominated	
- Manufacture of food products	10
- Manufacture of beverages	11
- Manufacture of tobacco products	12
- Manufacture of textiles	13
- Manufacture of wearing apparel	14
- Manufacture of leather and related products	15
- Manufacture of wood and of products of wood and cork, except furniture	16
- Manufacture of paper and paper products	17
- Printing and reproduction of recorded media	18
- Manufacture of coke and refined petroleum products	19
- Manufacture of rubber and plastic products	22
- Manufacture of other non-metallic mineral products	23
- Manufacture of basic metals	24
- Manufacture of fabricated metal products, except machinery and equipment	25
- Manufacture of motor vehicles, trailers and semi-trailers	29
- Manufacture of furniture + Other manufacturing	31-32
- Wholesale and retail trade, repair of motor vehicles and motorcycles	45
- Wholesale trade, except motor vehicles and motorcycles	46
- Retail trade, except motor vehicles and motorcycles	47
- Land transport and transport via pipelines	49
- Water transport	50
- Air transport	51
- Warehousing and support activities for transportation	52
- Postal and courier activities	53
- Accommodation and food service activities	55-56
- Publishing activities	58
- Information service activities	63
- Financial service activities, except insurance and pension funding	64
- Insurance, reinsurance and pension funding	65
- Activities auxiliary to financial services and insurance activities	66
- Veterinary activities	75
- Employment activities	78
- Travel agency, tour operator reservation services and related activities	79

SPECIFICATION AND METHODOLOGY

$$l_{i,t} = \alpha l_{i,t-1} + \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 R\&D_{i,t-1} + (\varepsilon_i + \nu_{i,t})$$ UPSTREAM

i = 1, … 177; t = 1998…2016

$$l_{i,t} = \alpha l_{i,t-1} + \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 \mathrm{EI}_{i,t-1} + \beta_4 SI_{i,t-1} + (\varepsilon_i + \nu_{i,t})$$ DOWNSTREAM

i = 1, … 297; t = 1998…2016

As common in the literature (see Van Reenen, 1997; Lachenmaier and Rottmann, 2011; Bogliacino, Piva and Vivarelli, 2012) The specifications above can be seen as **dynamic labor demands augmented by proxies of disembodied** (*R&D*) **and embodied technological change** (expansionary investments, *EI*, and scrapping, *SI*).

The specifications above have been tested through : Pooled Ordinary Least Squares (**POLS**) controlled for time effects; Fixed Effects (**FE**), in order to take into account country/sector unobservables; and the preferred **GMM-SYS** methodology to solve the obvious endogeneity problem brought about by the inclusion of the lagged dependent variable.

Moreover, **endogeneity** problems may also arise from other covariates in the model (for instance, it may well be the case that wage, investment and employment decisions are jointly and simultaneously adopted). Hence, all the explanatory variables will be cautiously considered as potentially endogenous to labour demand and instrumented when necessary, using up to thrice lagged instruments.

Since all the variables are expressed in log, the estimated coefficients can be interpreted as **elasticities**.

RESULTS

	UPSTREAM			DOWNSTREAM		
	POLS	**FE**	**GMM-SYS**	**POLS**	**FE**	**GMM-SYS**
Log(Employees)$_{-1}$	0.971*** (0.005)	0.689*** (0.038)	0.872*** (0.031)	0.967*** (0.007)	0.796*** (0.052)	0.964*** (0.019)
Log(Value Added)	0.025*** (0.005)	0.187*** (0.026)	0.110*** (0.028)	0.047*** (0.007)	0.104*** (0.024)	0.089*** (0.019)
Log(Cost of labour per Employee)	-0.041*** (0.007)	-0.201*** (0.026)	-0.139*** (0.035)	-0.310*** (0.007)	-0.095*** (0.028)	-0.015 (0.017)
Log(R&D)$_{-1}$	**0.004*** (0.001)**	**0.009* (0.005)**	**0.011* (0.006)**			
Log(Consumption of Fixed Capital)$_{-1}$				**-0.018*** (0.002)**	**-0.003 (0.010)**	**-0.064*** (0.011)**
Log(Expansionary Investments)$_{-1}$				**0.003*** (0.000)**	**0.004*** (0.001)**	**0.005* (0.002)**
Constant	0.044* (0.023)	0.377*** (0.092)	0.100 (0.064)	-0.004 (0.014)	0.324** (0.135)	-0.101*** (0.031)
Wald time-dummies **(p-value)**	6.8*** (0.000)	4.4*** (0.000)	93.8*** (0.000)	12.7*** (0.000)	11.3*** (0.000)	164.7*** (0.000)
Hansen test (p-value) **AR (p-value)**			0.138 AR(3) 0.40			0.092* AR(2) 0.68
R^2 (overall) **R^2 (within)**	0.99	 0.83		0.99	 0.89	
Obs.	1,732			3,349		
N. of sectors	170			297		

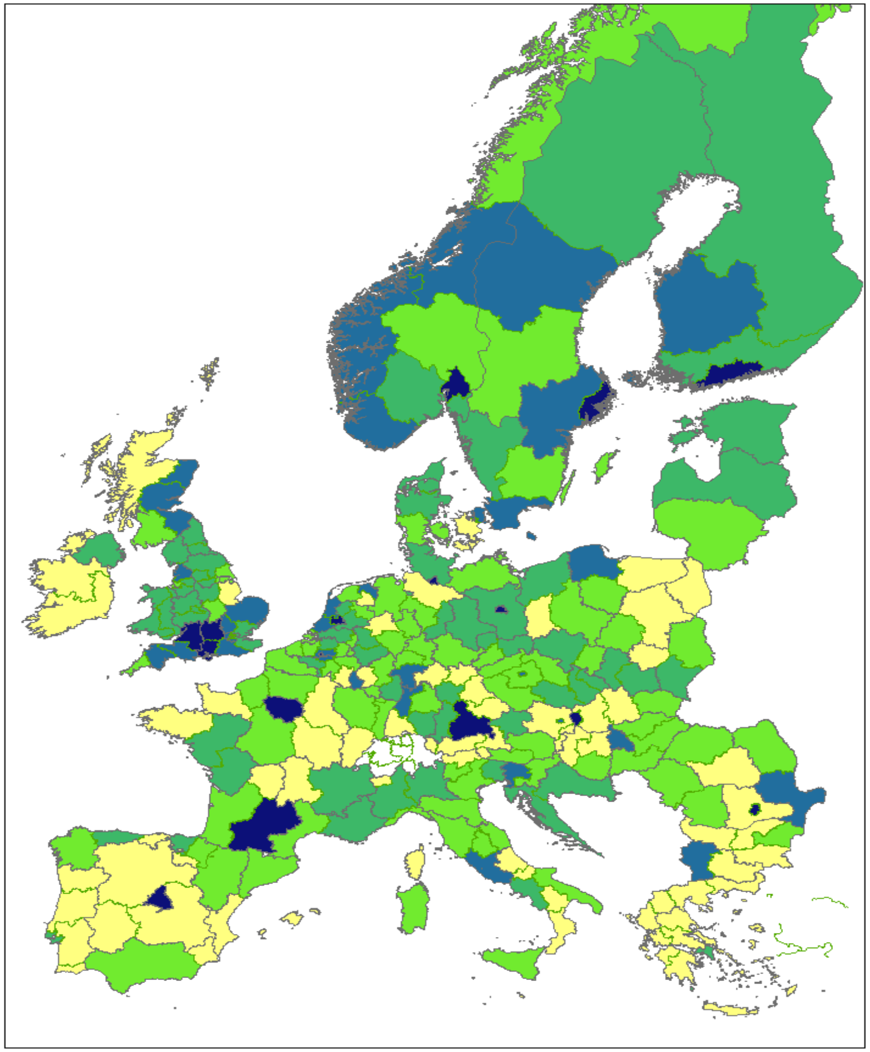
RESULTS (ZOOM)

$Log(R\&D)_{-1}$	0.004*** (0.001)	0.009* (0.005)	0.011* (0.006)			
$Log(Consumption\ of\ Fixed\ Capital)_{-1}$				-0.018*** (0.002)	-0.003 (0.010)	-0.064*** (0.011)
$Log(Expansionary\ Investments)_{-1}$				0.003*** (0.000)	0.004*** (0.001)	0.005* (0.002)

CONCLUSIONS AND POLICY IMPLICATIONS

- Increasing **value added** involves increasing employment, but this link is more robust in the upstream sectors where R&D investment and product innovation reinforces the employment/output elasticity → policy implication: expansionary policies may be more effective in the high-tech, rather than in the supplier dominated ones.
- **Cost of labor** turns out to negatively affect the demand for labor both in the upstream and the downstream sectors; although this (weak) evidence is consistent with a traditional labor market approach, in our framework this result is consistent with labor expulsion driven by faster adoption of more efficient vintages of machinery.
- Consistently with the model prediction, disembodied technical change (**R&D**) positively affects employment in the upstream sector, such as expansionary embodied technical change (**expansionary investment**) in the downstream one. Interestingly enough, both these labor-friendly effects are barely significant and negligible in magnitude.
- Consistently with the model prediction, replacement of machines (**scrapping**) induces a negative impact on labor demand (highly significant and larger in magnitude).
- These outcomes should make policy makers extremely cautious in considering new technologies as drivers of job creation. In fact, the introduction of new products in the science-based and emerging sectors might have a **very low employment multiplier**, while the diffusion of new technologies in the downstream sectors (the vast majority of industries) might have **negative employment impacts.**

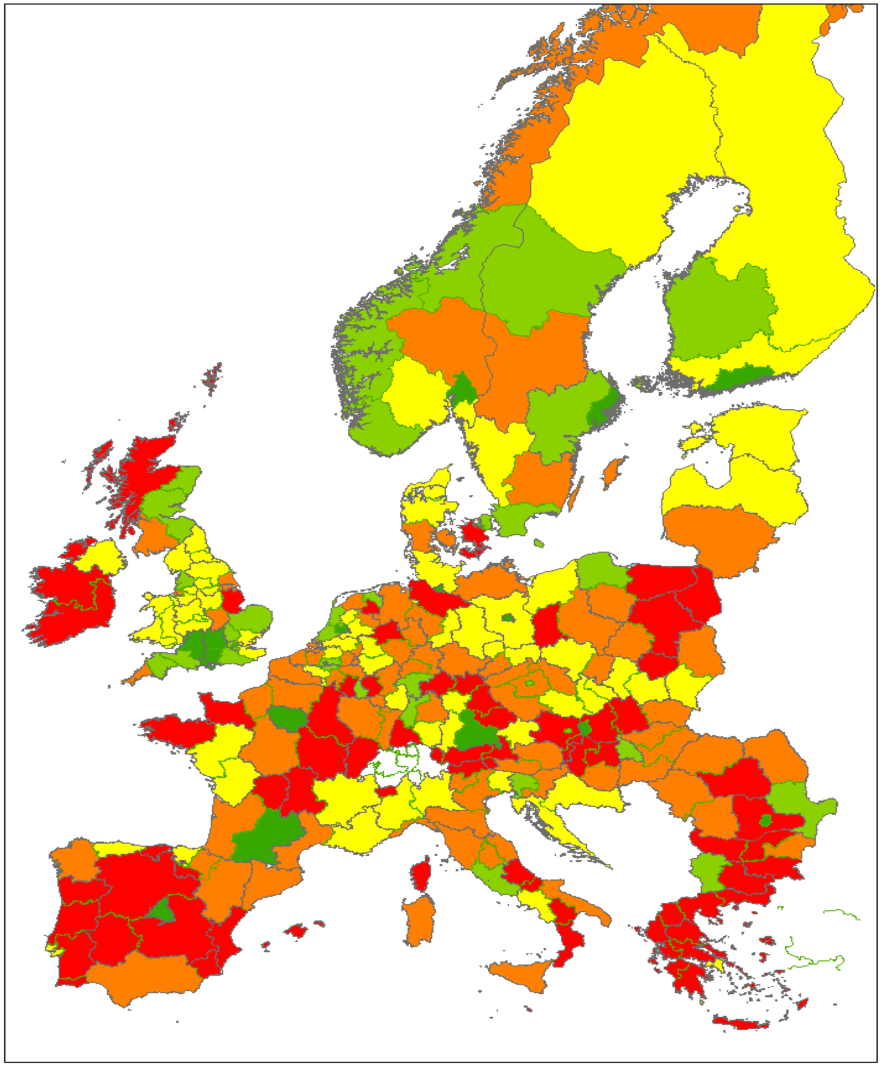
UPstream industries



$$\frac{Employees_{UP\ NUTS\ 2}}{Employees_{NUTS\ 2}}$$

0,03 - 4,06
4,07 - 6,44
6,45 - 9,40
9,41 - 13,08
13,09 - 21,35

DOWNstream industries



$$\frac{Employees_{DOWN\ NUTS\ 2}}{Employees_{NUTS\ 2}}$$

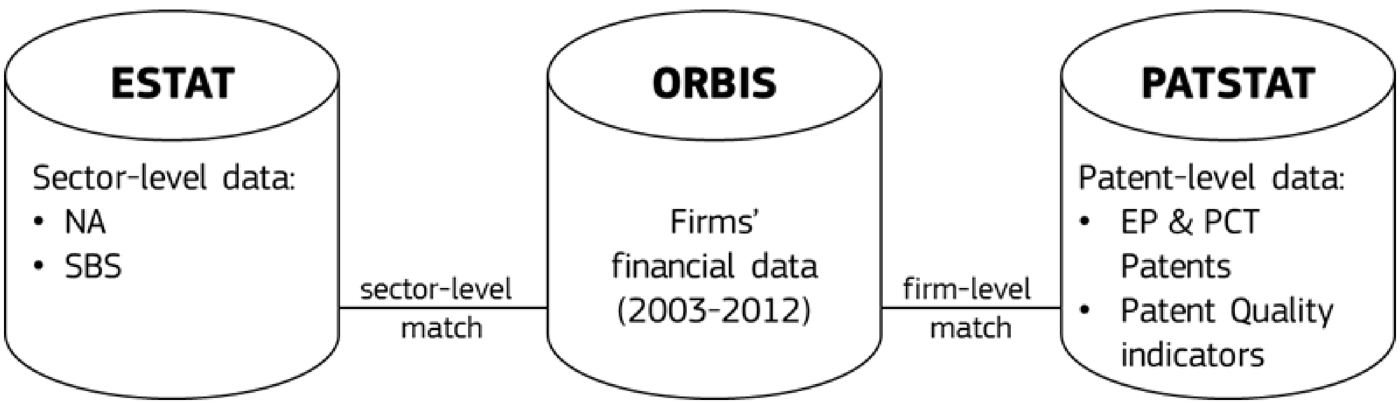
- 78,64 - 86,57
- 86,58 - 90,49
- 90,50 - 93,50
- 93,51 - 95,85
- 95,86 - 99,97

PREVIOUS EMPIRICAL EVIDENCE

We matched accounting company data originating from **ORBIS** with patent and patent quality information from the **OECD PATSTAT** dataset using firm-patent concordance tables developed by **EPO** and the Office for Harmonization in the Internal Market (**OHIM**), while sectoral deflators have been taken from **EUROSTAT** sources.

The matched dataset covers 63,561 EU-based, patenting firms from 27 EU Member States for the years **2003-2012** and belonging to manufacturing and service sectors.

We then: (1) excluded firms for which either sectoral belonging, employment, value added, fixed assets or cost of labor were missing or not positive (-60%); (2) we dropped outliers in both levels and growth (-4%); ending with a workable unbalanced panel of **19,978 companies (104,074 observations).**



$$Weighted\ patents_{i,t} = \sum_{p=1 \in i,t}^{n} \frac{1 + Forward\ citations_{p,t,f}}{Max.\ Forward\ citations_{t,f}}$$

SPECIFICATION

Dynamic demand for labour augmented with innovation:

$$l_{i,t} = \chi l_{i,t-1} + \alpha y_{i,t} + \beta w_{i,t} + \gamma\, invest_{i,t} + \delta\, innov_{i,t-3} + \left(\varepsilon_i + v_{i,t}\right)$$

<u>Where:</u>

l = employees
y = value added
w = gross wage per employee
invest = gross investment
innov = patent counts or citation-weighted patent counts
ε is the idiosyncratic individual and time-invariant firm's fixed effect and ***v*** the usual error term.
Lower case letters indicate **natural logarithms**

EMPIRICAL RESULTS (I)
FULL SAMPLE

	Employment	Employment
Employment t-1	0.673***	0.670***
	(0.016)	(0.016)
Value added	0.301***	0.302***
	(0.015)	(0.015)
Patents	0.051	
	(0.040)	
Weighted patents		0.050**
		(0.021)
Gross investments	0.135***	0.131***
	(0.037)	(0.037)
Labor cost per employee	-0.287***	-0.304***
	(0.095)	(0.096)
Constant	0.408***	0.425***
	(0.059)	(0.060)
Time, industry and country dummies	included	included
Observations	104074	104074
Number of firms	19978	19978
Wald test	6290000***	6350000***
AR(1)	-24.89***	-24.85***
AR(2)	2.9***	3.01***
AR(3)	0.97	0.78
Hansen test	537.25***	535.85***

EMPIRICAL RESULTS (II)
MANUFACTURING *VS* SERVICES

	Employment			
	Manufacturing		Services	
Employment t-1	0.687***	0.686***	0.589***	0.585***
	(0.015)	(0.015)	(0.030)	(0.030)
Value added	0.285***	0.284***	0.397***	0.399***
	(0.014)	(0.014)	(0.030)	(0.030)
Patents	0.045		0.098	
	(0.045)		(0.091)	
Weighted patents		0.048**		0.058
		(0.024)		(0.040)
Gross investments	0.041	0.043	0.170***	0.160***
	(0.036)	(0.036)	(0.052)	(0.051)
Labor cost per employee	-0.204**	-0.211**	-0.826***	-0.859***
	(0.102)	(0.103)	(0.156)	(0.152)
Constant	0.379***	0.394***	0.595***	0.619***
	(0.062)	(0.063)	(0.090)	(0.089)
Time, industry and country dummies	included	included	included	included
Observations	75546	75546	28528	28528
Number of firms	13841	13841	6137	6137
Wald test	5020000***	4980000***	318143.53***	329401.22***
AR(1)	-24.57***	-24.52***	-14.89***	-15.18***
AR(2)	2.18**	2.18**	1.81*	1.78*
AR(3)	1.08	1.09	0.45	0.44
Hansen test	419.25***	3373.05***	224.04***	225.45***

EMPIRICAL RESULTS (III)
HIGH-TECH *VS* LOW-TECH MANUFACTURING FIRMS

	Employment			
	High-tech R&D		Low-tech R&D	
Employment t-1	0.676***	0.671***	0.692***	0.694***
	(0.017)	(0.017)	(0.020)	(0.019)
Value added	0.291***	0.293***	0.289***	0.283***
	(0.016)	(0.016)	(0.018)	(0.018)
Patents	0.115***		-0.015	
	(0.043)		(0.079)	
Weighted patents		0.080***		0.001
		(0.025)		(0.038)
Gross investments	0.069**	0.063**	0.035	0.041
	(0.030)	(0.030)	(0.036)	(0.036)
Labor cost per employee	-0.375***	-0.408***	-0.255**	-0.229*
	(0.113)	(0.113)	(0.130)	(0.130)
Constant	0.477***	0.499***	0.345***	0.366***
	(0.068)	(0.070)	(0.087)	(0.082)
Time, industry and country dummies	included	included	included	included
Observations	40059	40059	35487	35487
Number of firms	7374	7374	6467	6467
Wald test	2850000***	2820000***	684045.76***	669632.64***
AR(1)	-19.11***	-19.18***	-17.21***	-17.25***
AR(2)	1.37	1.34	1.51	1.58
Hansen test	237.19***	413.01***	339.28***	337.66***

CONCLUSIONS AND POLICY IMPLICATIONS

Our findings confirm the possible **labor-friendly nature of innovation** at the firm level, in line with prior empirical research.

However, our sectoral estimates show that this positive employment impact is statistically significant **only in high- and medium-tech manufacturing** sectors, while irrelevant in low-tech manufacturing and services. Therefore, patented innovations fully display their labor-friendly nature in the new and emerging sectors, characterized by higher technological opportunities, by higher demand elasticity and by a likely dominance of product innovation.

These outcomes prove that the aim of the **EU2020 strategy** - that is to develop an European economy based on knowledge and innovation - points in the right direction also in terms of job creation. Moreover - since our impact variable takes into account the **quality of the introduced innovation** - for policy makers it is also reassuring to know that the demand for labor may further increase as the quality of innovation increases.

However, the positive and significant employment impact of innovation **is not equally detectable across the different sectors**. This is something that should be taken into account by a European innovation policy which considers employment as one of its specific targets.

CAVEATS

It is important to keep in mind that this study has only tested the labor-friendly nature of patented innovation, while **neglecting the possible labor-saving impact of non-patented process innovation.** This means that embodied technological change and process innovation with their possible adverse impact on employment are probably underestimated in this work.

Our citation-weighted patent indicator may be a more sophisticated measure of innovation than sheer patent counts, but it should be noted that **patents are imperfect indicators of innovation**, particularly for firms in the service sectors.

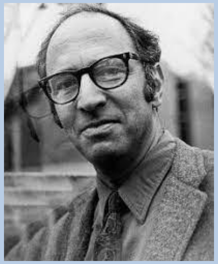
This study has been conducted on **a sample of medium-large IPR-intensive firms**; therefore, generalizing our results to more aggregate levels is not straight-forward and must take into consideration possible biases in our data coverage.

AI AS A NEW PARADIGM

AIMS AND STRUCTURE

- First research question: **are we facing a new technological paradigm or a deepening of the ICT trajectory?**
  - Definitions of TP and TT and comparisons
  - Evidences (preliminary)
  - Preliminary conclusions

- Second research question: **which are the impacts of AI onto the labor market?**
  - Previous evidence
  - Evidences (published)
  - Conclusions and policy implications



DEFINITIONS

A technological revolution (for example ICT) redefines the **technological paradigm**:
"A vision (or model or pattern) that identifies and solves a selected set of problems, using a selected set of scientific principles and technological materials".
The new paradigm (the new "state of the art") asserts itself following the interaction between science-technology, markets and institutions.

EXAMPLES:
1780-1840: First industrial revolution: mechanization and factory system
1840-1890: Second industrial revolution: steam power and railways
1890-1930: Managerial capitalism: electricity, steel, Taylorism
1930-1980: Fordism: mass production and new income distribution
1980-2020: Digital era: ICT technologies, PC, internet, smart phone

*"The **technological trajectory** is the normal technological path of problem solving. This path has strong characteristics of cumulativeness and irreversibility*."
Cumulativeness and«path-dependence»
Irreversibility: there is no return of techniques (in contrast to standard theories)

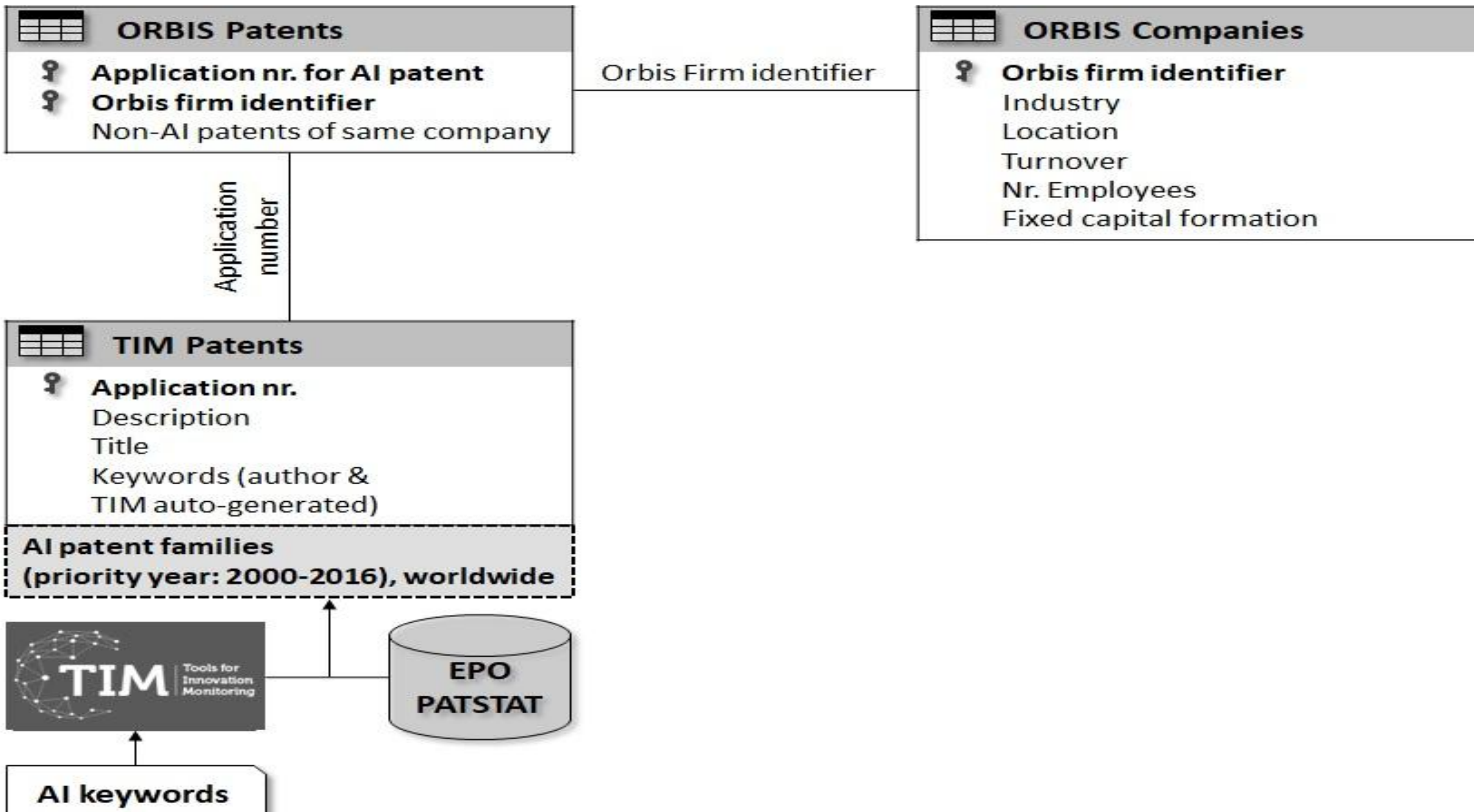
AI is rooted/nested/embedded within digital ICT technologies, but it is also revolutionary and pervasive: **is AI a new technological paradigm or a kind of deep trajectory?**

COMPARISONS

	NEW PARADIGM	TRAJECTORY
TECHNOLOGICAL CHANGE	RADICAL CONSTELLATIONS OF NEW KEY TECHNOLOGIES ENABLING OTHER TECHNOLOGIES	INCREMENTAL INNOVATION
INNOVATION	PRODUCT>PROCESS	PROCESS>PRODUCT
SECTORAL STRUCTURE	PERVASIVENESS (GPT) CREATIVE DESTRUCTION	KEY SECTORS DOMINATING
MARKET STRUCTURE	COMPETITIVE/ ENTREPRENEURIAL (SM1)	CONCENTRATED/ROUTINIZED (SM2)
FIRMS'AGE AND SIZE	START-UPS, YOUNG FIRMS, HGFs, SMEs	LARGE AND ESTABLISHED COMPANIES
INVESTMENTS	EXTENSIVE AND ADDITIONAL	INTENSIVE (SCRAPPING)
PRODUCTIVITY	FIRST: SOLOW'S PARADOX AND PRODUCTIVITY SLOWDOWN; THEN: PRODUCTIVITY BOOM	MODERATELY INCREASING
DEMAND AND GROWTH	INCREASING WITH DIFFUSION	GRADUALLY SATURATING
INSTITUTIONS	MISMATCH	MATCH
EMPLOYMENT IMPACT	LABOR-FRIENDLY	LABOR-SAVING

DATA SOURCES

1. Identify AI patent families worldwide using a keyword-based (AI-aided) approach
2. Link patents to corporate balance sheet data (ORBIS)
3. Collect patents in non-AI technologies for selected firms



DATA: List of keywords related to Artificial Intelligence

Artificial intelligence	Evolutionary Computation	Probabilistic modeling
Artificial intelligent	Face recognition	Random Forest
Artificial reality	Facial recognition	Reinforcement learning
Augmented realities	Gesture recognition	**Robot***
Augmented reality	Holographic display	Self driv*
Automatic classification	Humanoid robot	Sentiment analysis
Automatic control	Internet of things	Smart glasses
Autonomous car	Knowledge Representation	Speech Recognition
Autonomous vehicle	Machine intelligence	Statistical Learning
Bayesian modelling	Machine learn	Supervised learning
Big data	Machine to machine	Transfer Learning
Computational neuroscience	Mixed reality	Unmanned Aerial Vehicle
Computer Vision	Natural Language Processing	Unmanned aircraft system
Data mining	Neural Network	Unsupervised learning
Data science	Neuro-Linguistic Programming	Virtual reality
Decision tree	Object detection	Voice recognition
Deep learn	Predictive modelling	

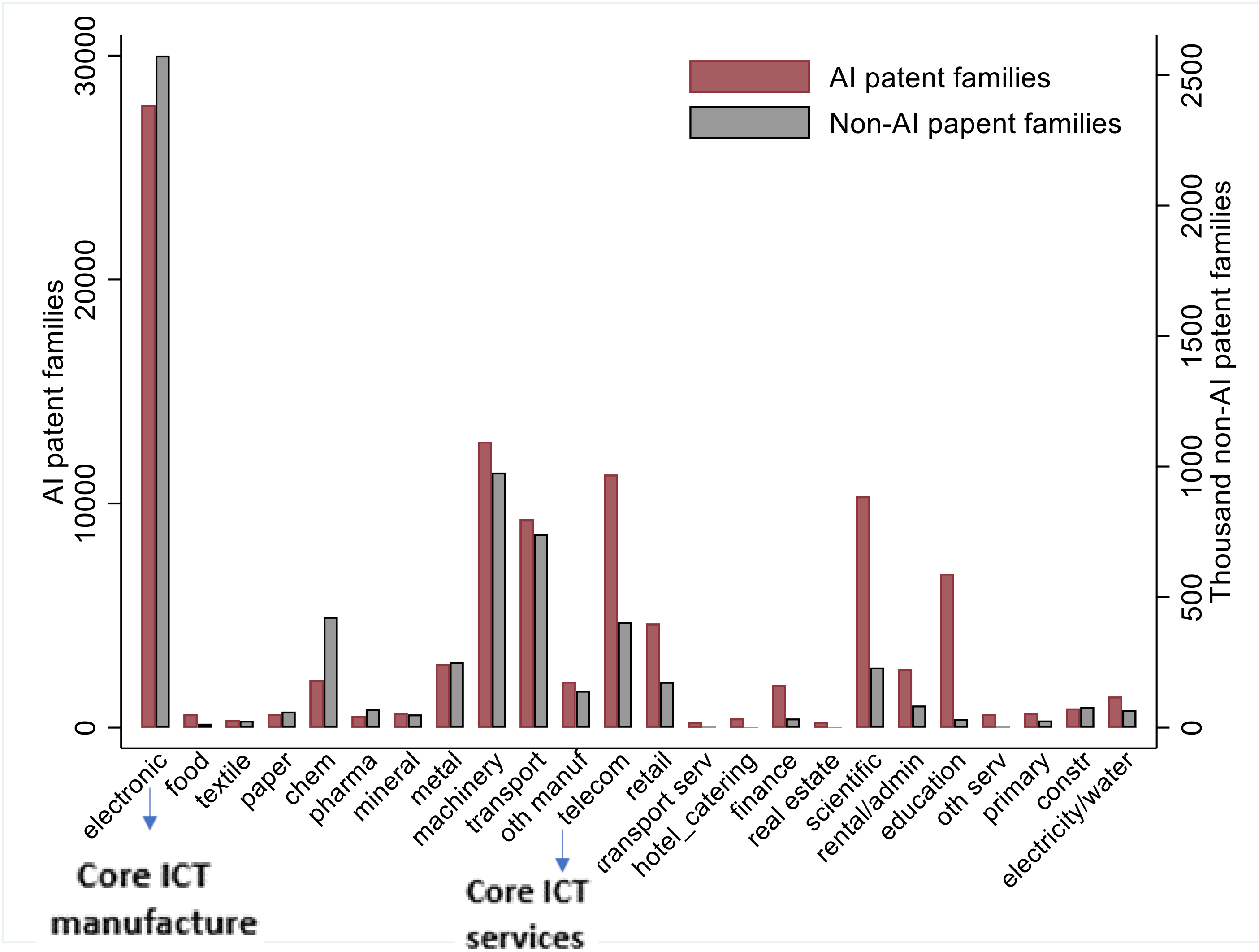
EXPONENTIAL GROWTH OF A STILL LIMITED TREND

Patenting activities of AI patenters, 2000-2016

Period	Companies with 1+AI patent families		AI patent families		AI patent families per patenting company	Non-AI patent families		Ratio AI/non-AI patent families
	Number	Yearly % change	Number	Yearly % change		Number	Yearly % change	
2000	**804**		**2,372**		**3.0**	**343,771**		**0.007**
2001	879	9.3	2,715	14.5	3.1	352,847	2.6	0.008
2002	871	-0.9	2,704	-0.4	3.1	347,394	-1.5	0.008
2003	901	3.4	2,777	2.7	3.1	349,223	0.5	0.008
2004	922	2.3	2,848	2.6	3.1	370,073	6.0	0.008
2005	1,056	14.5	3,220	13.1	3.0	382,250	3.3	0.008
2006	1,214	15.0	3,603	11.9	3.0	372,544	-2.5	0.010
2007	1,352	11.4	3,866	7.3	2.9	375,901	0.9	0.010
2008	1,625	20.2	4,515	16.8	2.8	385,425	2.5	0.012
2009	1,912	17.7	4,803	6.4	2.5	359,245	-6.8	0.013
2010	2,131	11.5	5,595	16.5	2.6	373,957	4.1	0.015
2011	2,560	20.1	6,668	19.2	2.6	390,467	4.4	0.017
2012	3,245	26.8	8,301	24.5	2.6	419,099	7.3	0.020
2013	3,535	8.9	9,038	8.9	2.6	420,946	0.4	0.021
2014	3,660	3.5	10,122	12.0	2.8	411,022	-2.4	0.025
2015	5,279	44.2	14,242	40.7	2.7	425,432	3.5	0.033
2016	**5,531**	4.8	**14,205**	-0.3	**2.6**	**402,193**	-5.5	**0.035**
Total 2000-2016	**23,915**		**101,594**		**4.2**	**6,481,789**		**0.016**
% change between 2000-2005 and 2011-2016	**338.2**		**276.1**		**-24.6**	**15.1**		**226.9**

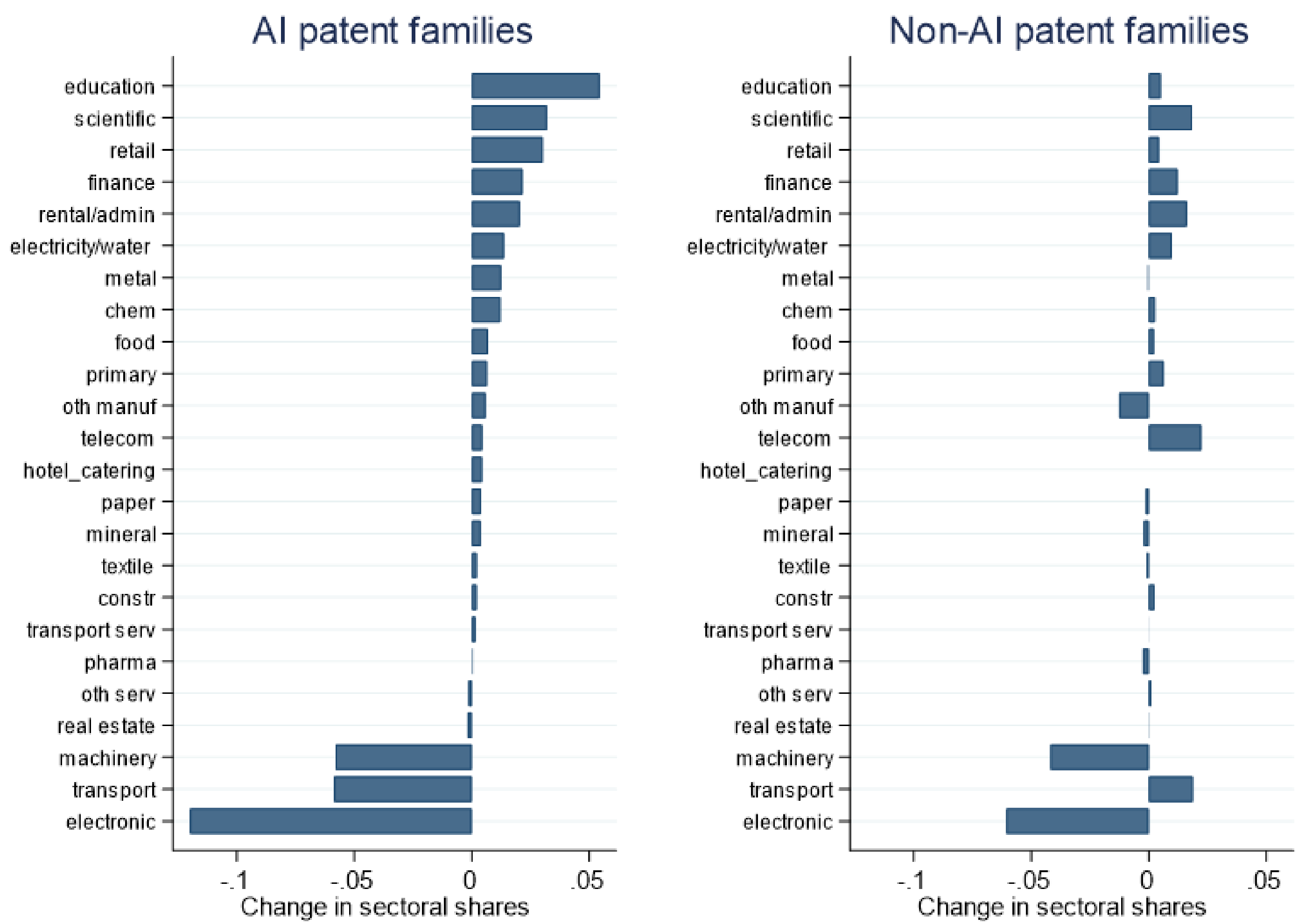
Notes: yearly non-AI patent families, as well as the resulting total 2000-2016 and % change between 2000-2005 and 2011-2016, include non-AI patent families of all 23,915 companies making 1+ AI patent in the period, independently on a company making or not AI patent families in the considered year.

Distribution of patent families filed by AI patenters, by industries

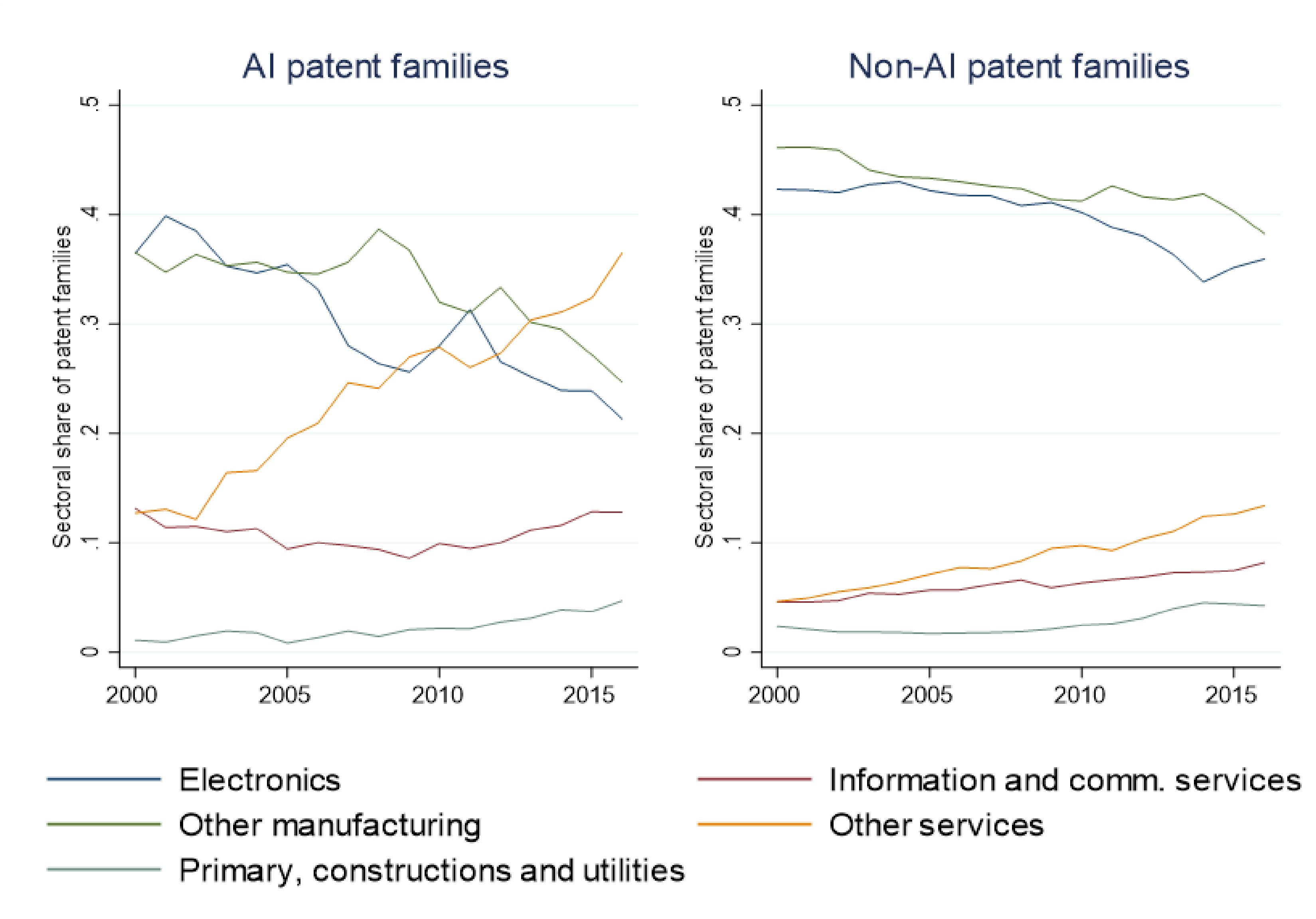


- **Core ICT manufacturing:** Manufacture of computer, electronic and optical products + Manufacture of electrical equipment
- **Core ICT services:** Publishing, audiovisual and broadcasting activities + Telecommunications + IT and other information services

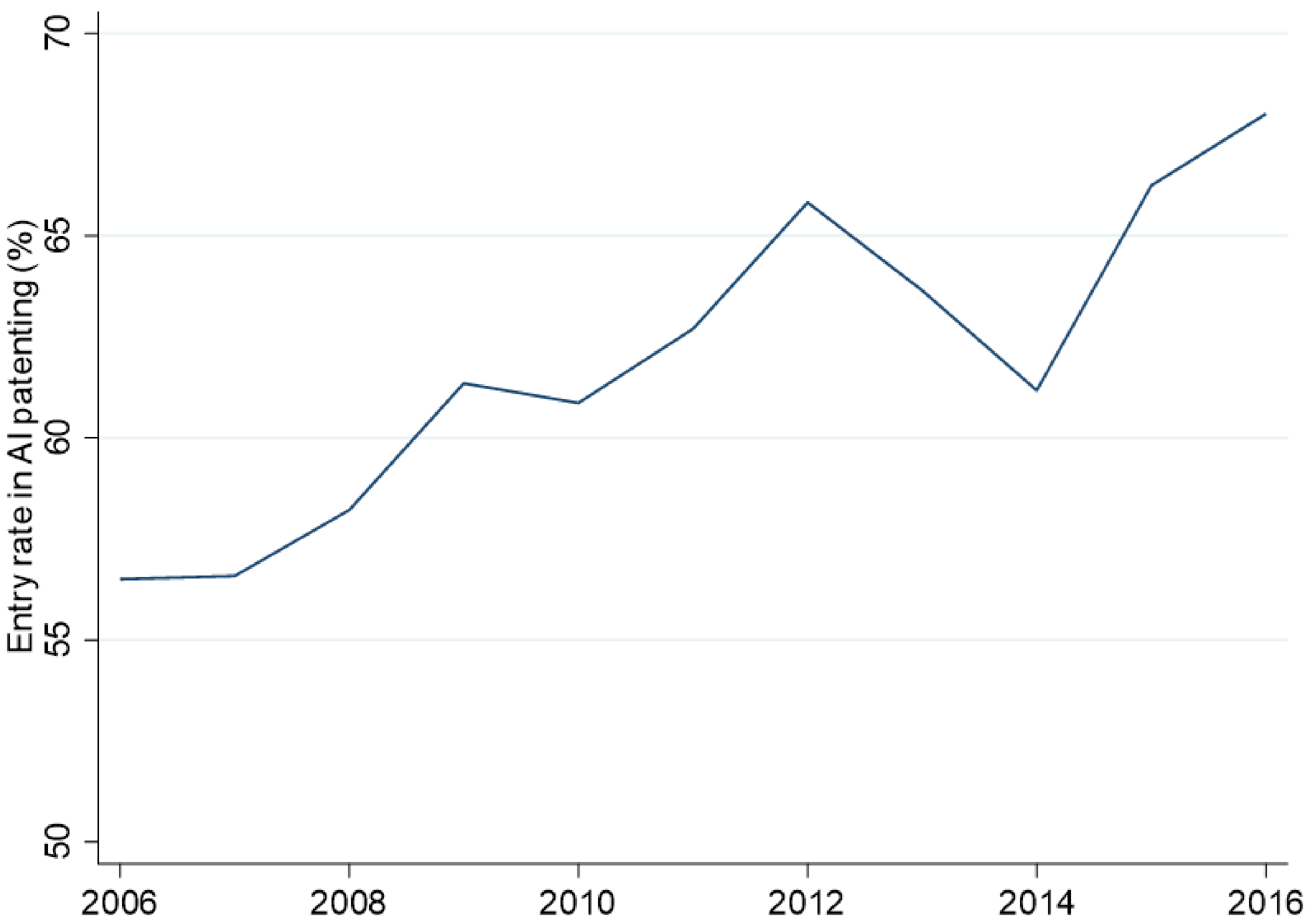
Change in industry shares of patent families of AI patenters between 2000-2005 and 2011-2016



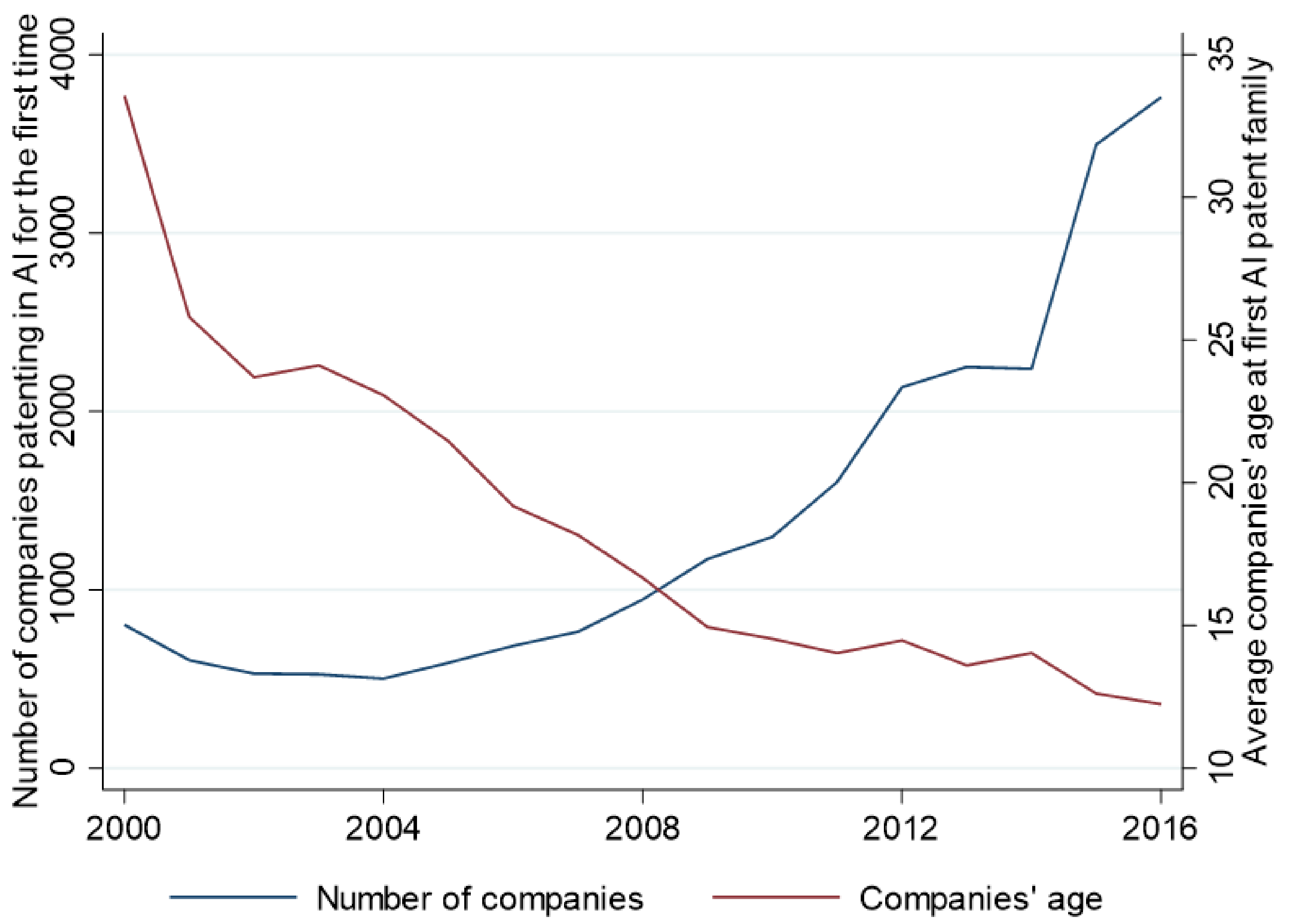
Trends of patent families filed by AI patenters, by industry group



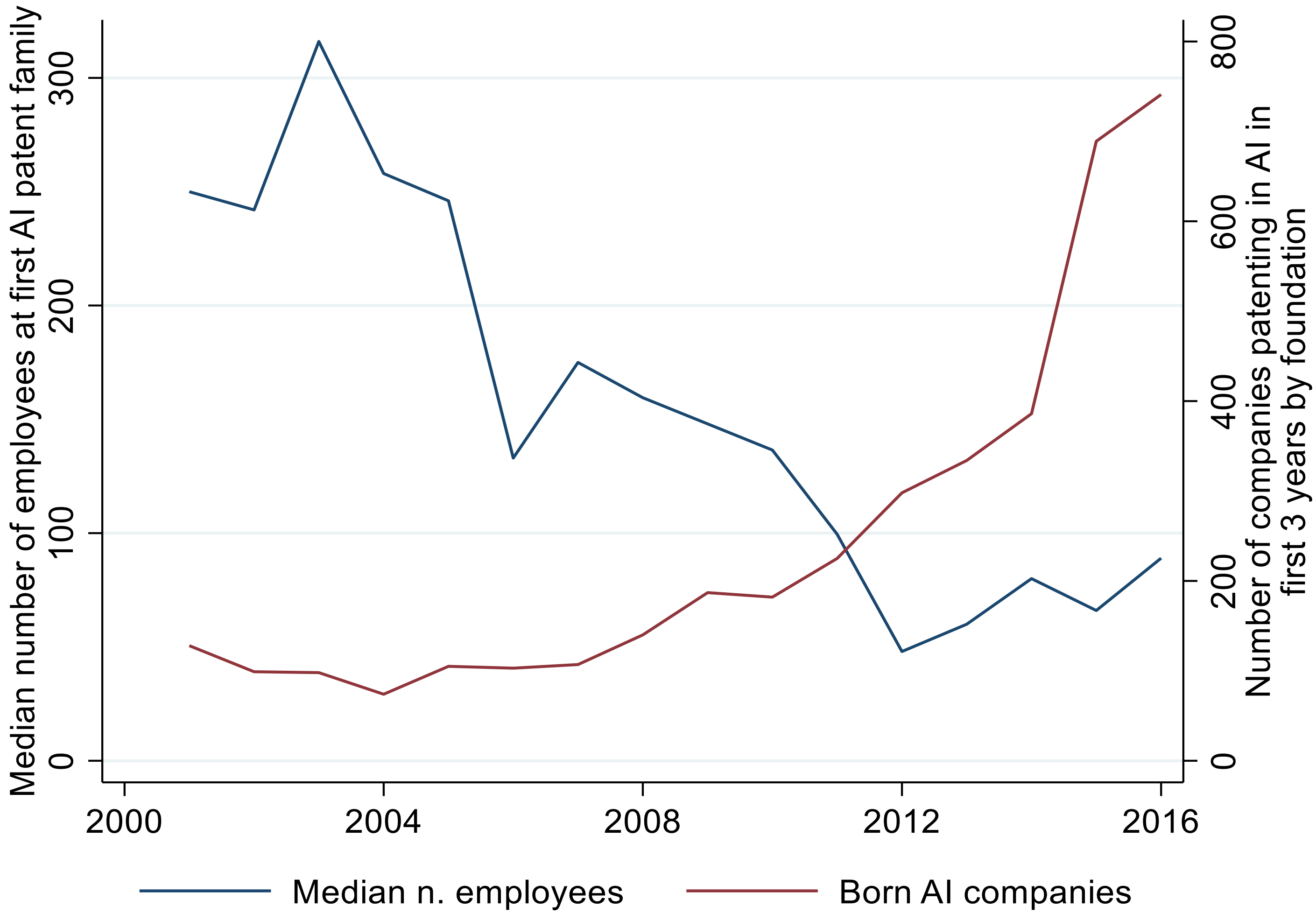
Innovative entry rates (percentage of companies patenting in AI for the first time over all companies patenting in AI)



Number and age of new innovative entries

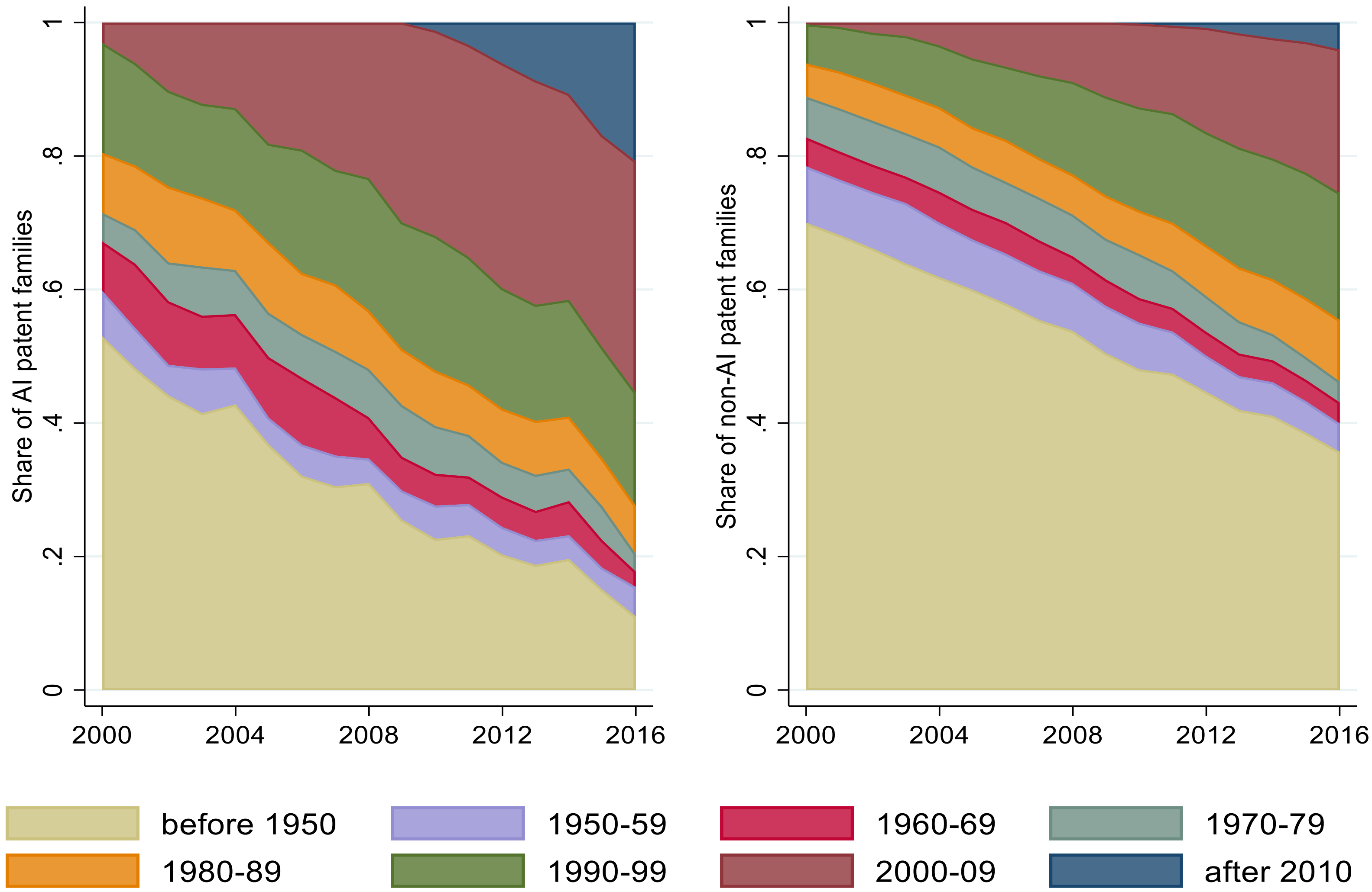


Size of AI patenters at year of first AI patent family and number of ‘born AI patenters’

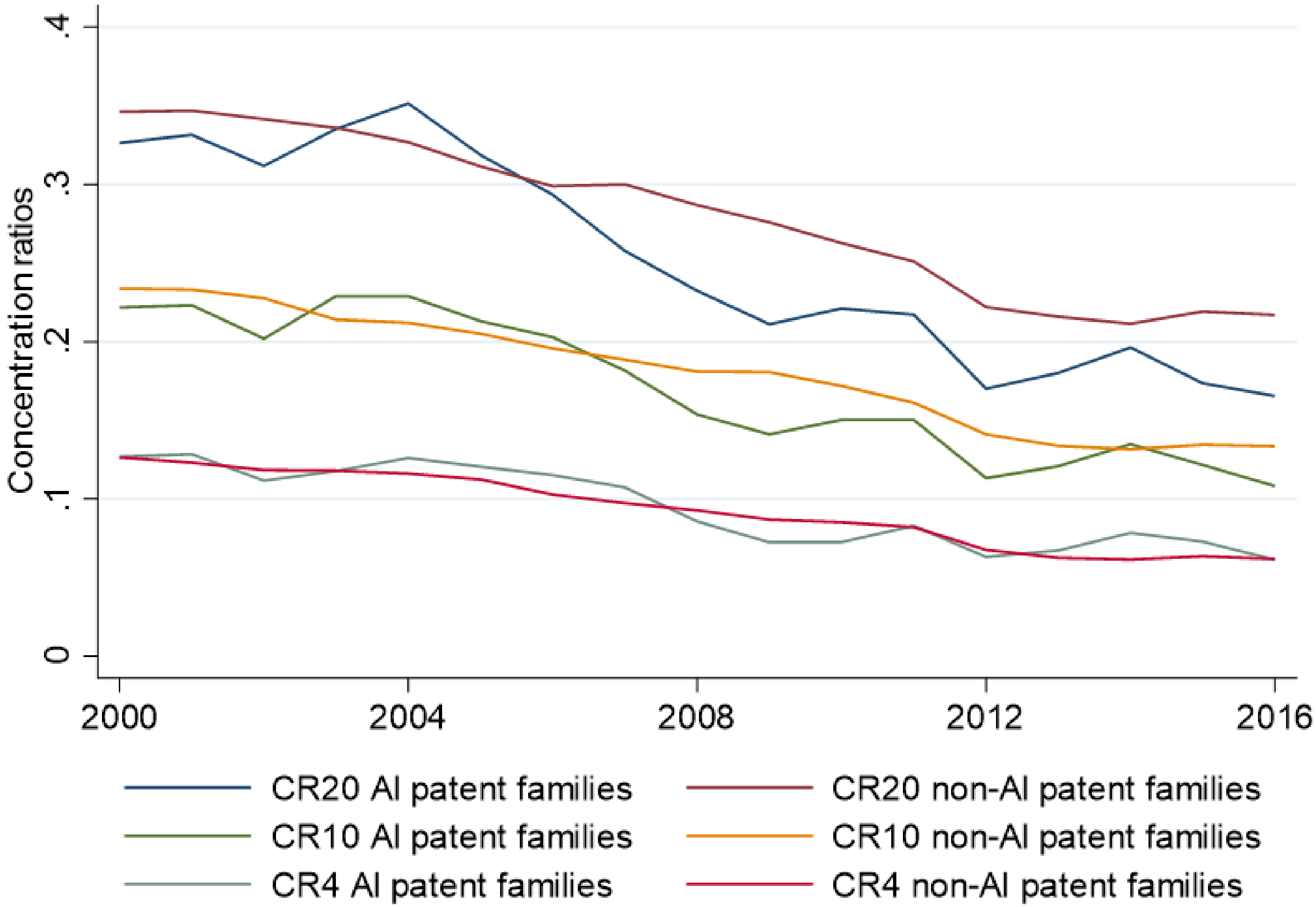


Notes: employment at first year of AI patenting is valid for 29% of companies, imputed using the closer valid value in time for 30%, and missing for remaining 41% companies.

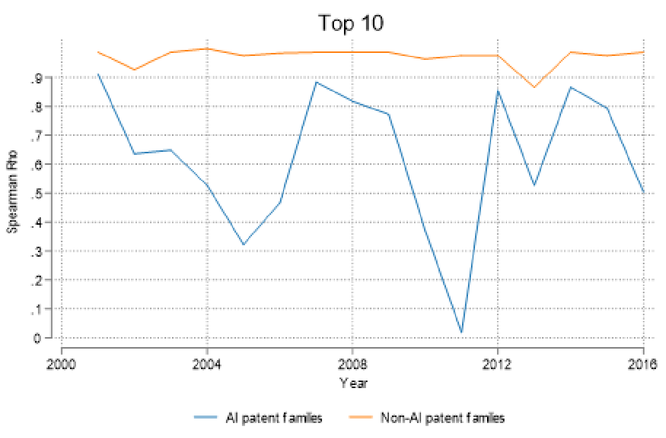
Share of AI and non-AI patent families by year of foundation or consolidation of applying company

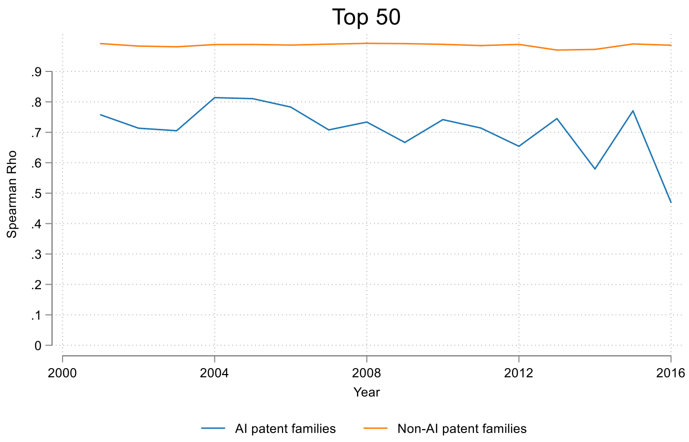


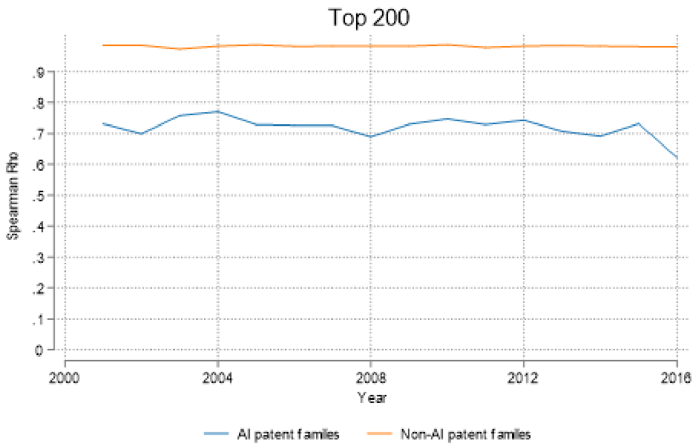
Innovative concentration ratios

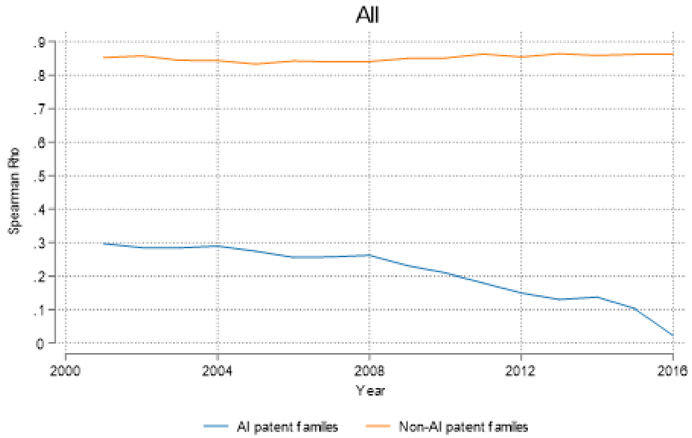


Stability of rankings









AI AS ENABLING TECHNOLOGY:

Change in non-AI patents in the 3 years following the first AI patent

	All companies	Company distribution of the number of non-AI pat. families in 3 years prior to first AI patent family			
		Bottom 75 percentiles	Between 75th and 90th percentiles	Between 90th and 99th percentiles	Top 1st
Number of companies	10,624	7,914	1,636	967	107
Per-company percentage change in non-AI pat. families in 3 years after first AI pat. family with respect to prior 3 years	**19.2**	**0.5**	**23.0**	**133.5**	**311.5**
Per-company non-AI pat. families in 3 years prior to first AI pat. family	24.4	0.0	7.0	138.0	1070
Total absolute change in non-AI pat. families in 3 years after first AI pat. family compared to prior 3 years	**203,799**	3,714	37,635	129,115	33,335
% of total absolute change	100.0	**1.8**	**18.5**	**63.4**	**16.4**

These figures imply an average **78.5%** (= 19.2/24.4) increase of non-AI patenting in the first three years after the first patenting in AI, with respect to the prior three ones. This compares with an average 3-years increase in the same period (2003-2013) equal to **5.9%** in our sample (see table above).

Top-20 companies with the largest number of AI patent families in the period 2000-2005
Comparison with their rankings in other periods

Rank 2000-2005	Company name	Country	Rank 2006-2010	Rank 2011-2016	Rank 2000-2016
1	SAMSUNG ELECTRONICS CO.,LTD.	KR	1	3	1
2	PANASONIC HOLDINGS CORPORATION	JP	9	21	9
3	HONDA MOTOR CO., LTD.	JP	3	29	6
4	INTERNATIONAL BUSINESS MACHINES CORP	US	11	4	3
5	LG ELECTRONICS INC.	KR	7	5	4
6	YASKAWA ELECTRIC CORPORATION	JP	4.5	13	12
7	CANON INCORPORATED	JP	10	7	11
8	TOYOTA MOTOR CORPORATION	JP	2	17	7
9	TOSHIBA CORPORATION	JP	14	34	15
10	MICROSOFT CORPORATION	US	6	6	8
11	DENSO CORPORATION	JP	22	32	18
12	MITSUBISHI ELECTRIC CORPORATION	JP	21	45	19
13	NEC CORPORATION	JP	20	54	22
14	NISSAN MOTOR CO., LTD.	JP	29	86.5	30
15	NIPPON TELEGRAPH AND TELEPHONE CORPORATION	JP	24	42.5	21
16	SIEMENS AG	DE	23	91	29
17	FANUC CORPORATION	JP	26	16	16
18	SHARP CORPORATION	JP	39.5	33	24
19.5	KONINKLIJKE PHILIPS N.V.	NL	98.5	103.5	53
19.5	MITSUBISHI HEAVY INDUSTRIES LTD	JP	137	228	62

Top-20 companies with the largest number of AI patent families in the period 2011-2016
Comparison with their rankings in other periods

Rank 2011-2016	Company name	Country	Rank 2000-2005	Rank 2006-2010	Rank 2000-2016
1	SEIKO EPSON CORPORATION	JP	27	8	2
2	STATE GRID CORPORATION OF CHINA NETWORK OPERATION BRANCH	CN		894	5
3	SAMSUNG ELECTRONICS CO.,LTD.	KR	1	1	1
4	INTERNATIONAL BUSINESS MACHINES CORP	US	4	11	3
5	LG ELECTRONICS INC.	KR	5	7	4
6	MICROSOFT CORPORATION	US	10	6	8
7	CANON INCORPORATED	JP	7	10	11
8	ELECTRONICS AND TELECOMMUNICATIONS RESEARCH INSTITUTE	KR	24	4.5	10
9	SHENYANG INSTITUTE OF AUTOMATION, CHINESE ACADEMY OF SCIENCES	CN	57	16	13
10	SHANGHAI JIAOTONG UNIVERSITY	CN	53.5	17	14
11	SOUTHEAST UNIVERSITY	CN	370	54.5	26
12	INTEL CORP	US	38	123	23
13	YASKAWA ELECTRIC CORPORATION	JP	6	4.5	12
14	SOUTH CHINA UNIVERSITY OF TECHNOLOGY	CN	314.5	94	28
15	BEIJING INSTITUTE OF TECHNOLOGY	CN	237.5	38	25
16	FANUC CORPORATION	JP	17	26	16
17	TOYOTA MOTOR CORPORATION	JP	8	2	7
18	HYUNDAI MOTOR COMPANY	KR	21	25	17
19.5	QUALCOMM INC	US	79.5	94	36
19.5	ZTE CORPORATION	CN	210	19	27

PRELIMINARY CONCLUSIONS

- Artificial intelligence starts as a **technological trajectory** well rooted in the ICT paradigm and deeply linked to ICT industries.
- Over time AI shows both an **acceleration** in diffusion and a qualitative **change** in nature.
- AI is increasingly **detaching from core ICT** manufacturing industries and from ICT services.
- AI is becoming **more pervasive**, more intersectoral, more internationalized, and more distributed among companies.
- AI patenters are increasingly **new comers and younger companies**.
- AI innovation activity is becoming **less concentrated** and market leadership is dramatically evolving.
- On the whole, AI appears to increasingly approach the characteristics of a **new technological paradigm**.