The impact of Artificial Intelligence on the performance of (e-commerce and fintech) firms

JRC Innova measure IV-WP 2.2

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** speaker(s)*

Outline

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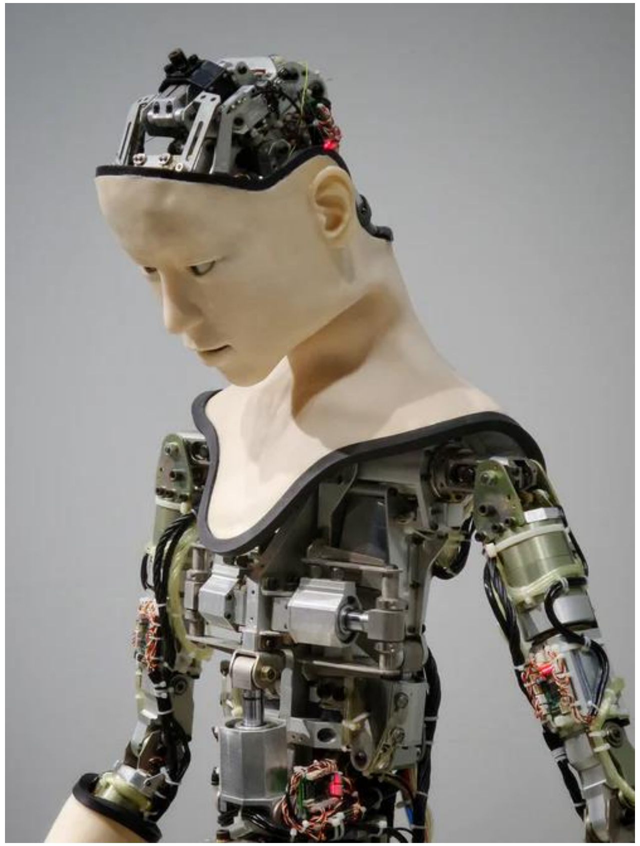

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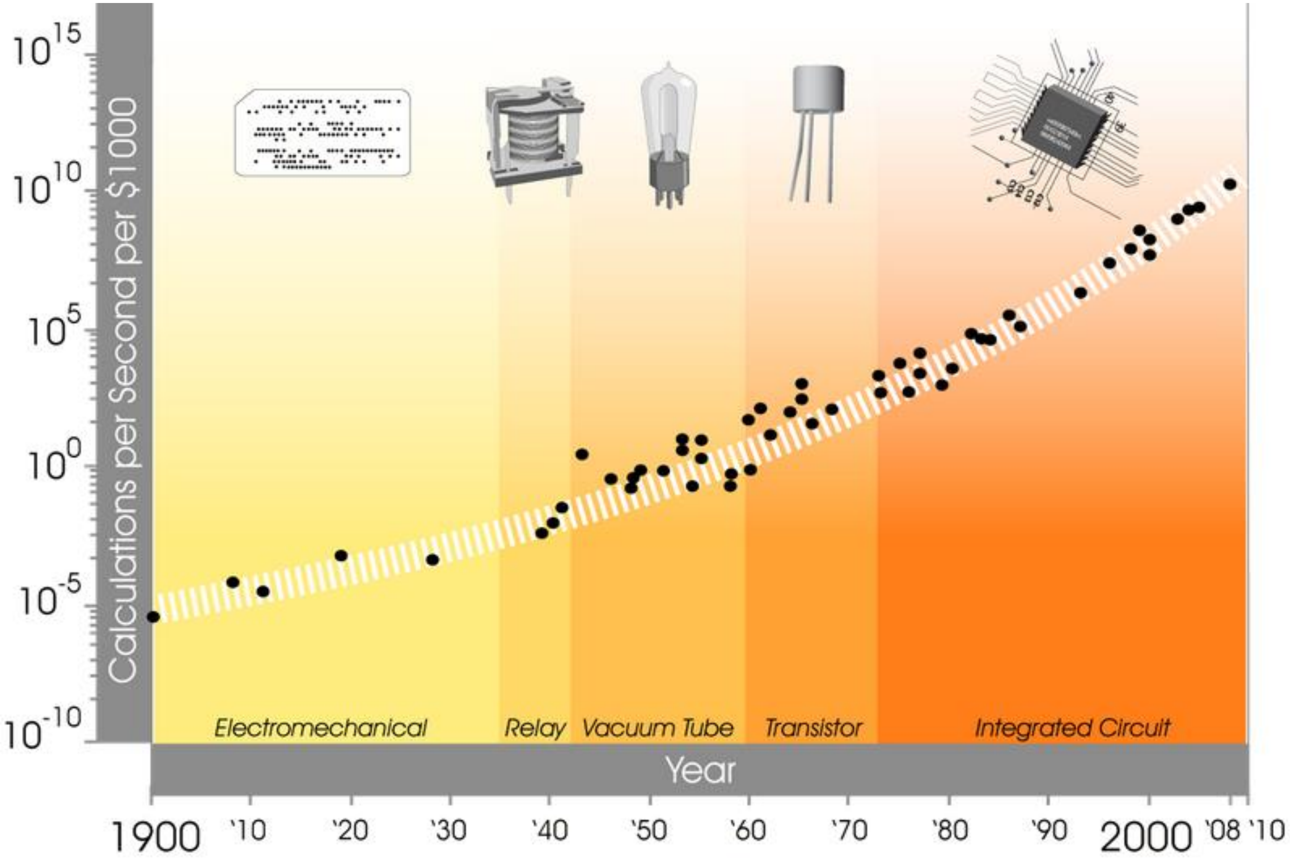
Motivation

Technological progress and social change



The IBM Model 350 disk file with a storage space of 5MB from 1956 and a Micro SD Card

The Computer power that consumers could purchase for a price of $1000 (854 euros). It is intuitive to see how technological progress counted as a driver of social change.
Source: Increasing productivity quality for a decreasing price, Our World in Data, 2020, https://ourworldindata.org/technological-progress

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Motivation: shaping Europe’s digital future

‘The European Commission puts forward a European approach to Artificial Intelligence and Robotics. It deals with technological, ethical, legal and socio-economic aspects to boost EU's research and industrial capacity and to put AI at the service of European citizens and economy….’

‘AI can bring solutions to many societal challenges from treating diseases to minimizing the environmental impact of farming. However, socio-economic, legal and ethical impacts have to be carefully addressed.’

Source: https://ec.europa.eu/digital-single-market/en/artificial-intelligence

Motivation: Supra Secular Stagnation

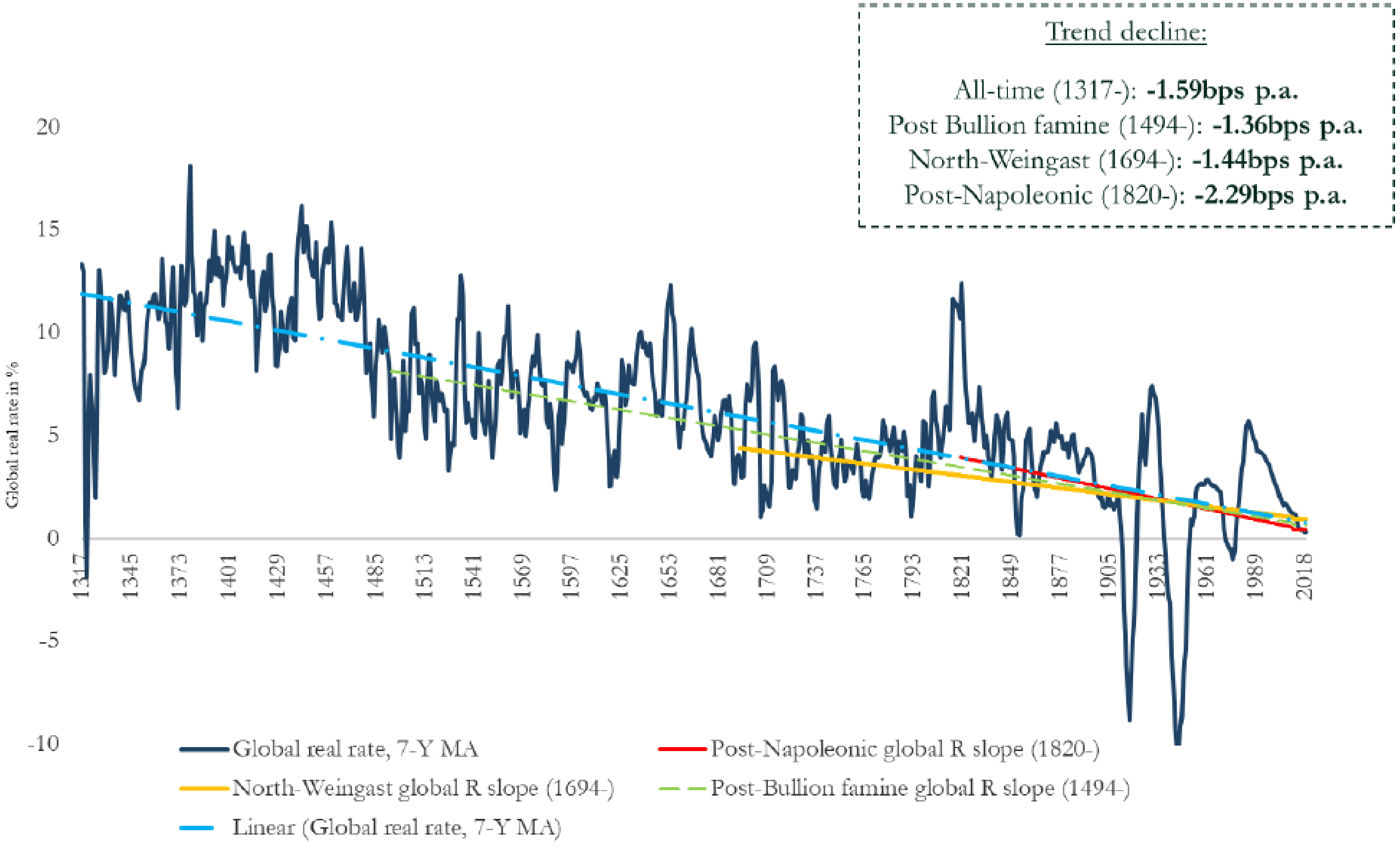
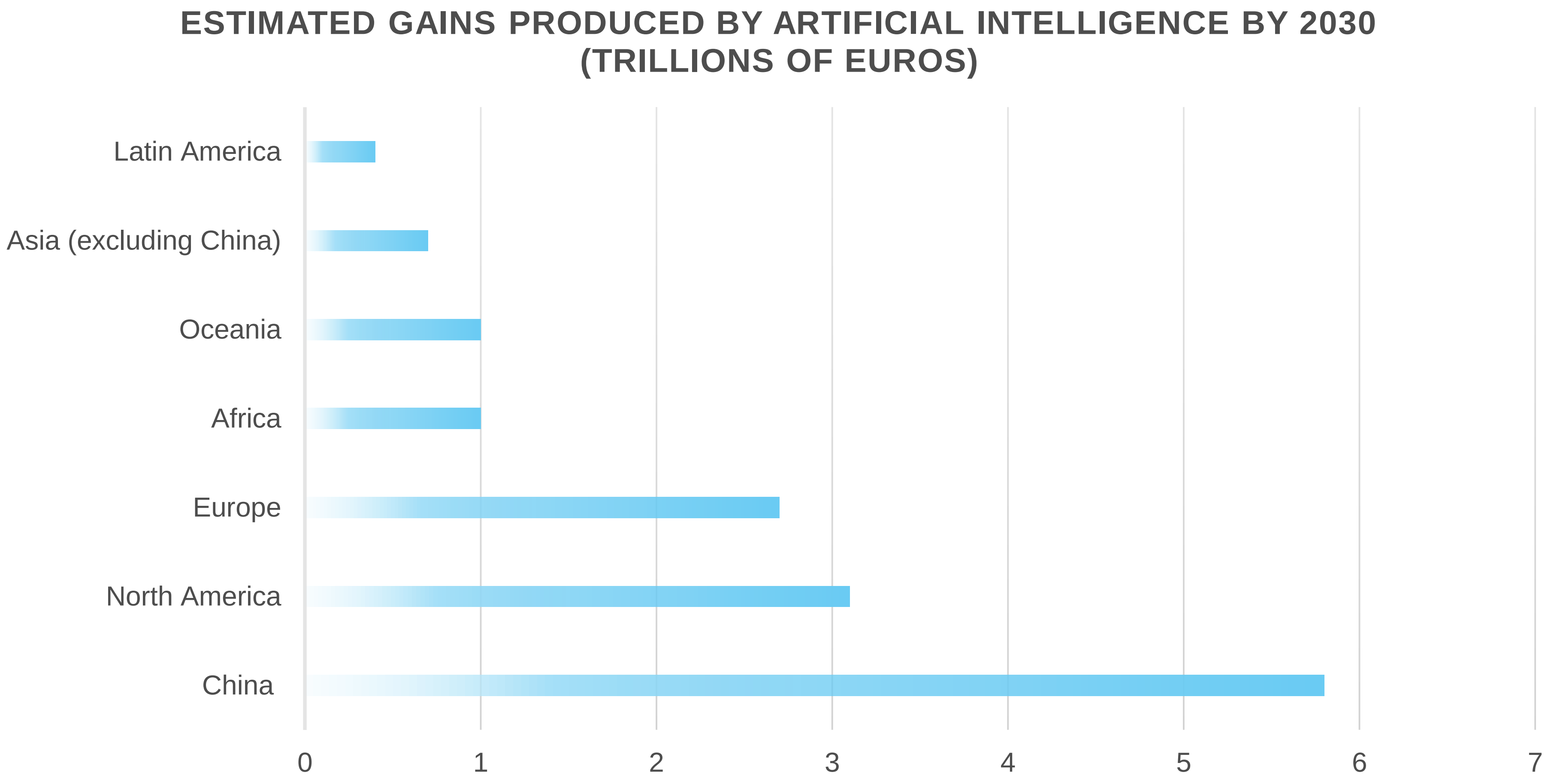


Figure IV: Headline global real rate, GDP-weighted, and trend declines, 1317-2018.

Source: Schmelzing (2020, p.16)

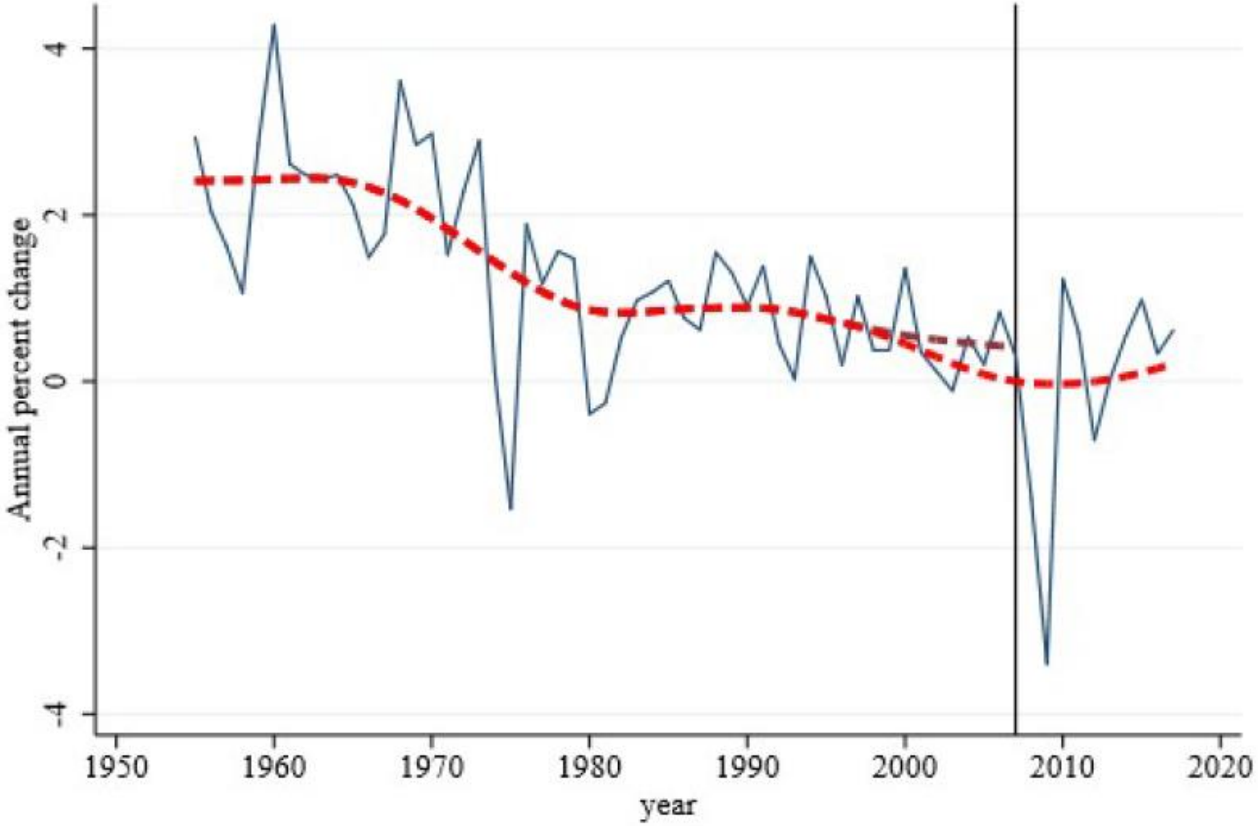
After the long depression advanced economies experienced declining productivity and growth; and this trend is still at play

Motivation: AI and potential GDP growth



Source: Elaborated by the authors, data Price Water House Coopers, (West & Allen, 2018).

Motivation: Sluggish Productivity in Europe



Source: Source is PWT 9.1 (Feenstra, Inklaar, and Timmer, 2015).
Note: The solid line is European TFP growth, defined as a Törnquist index of TFP growth for 15 countries that were members of the European Union before 2004. Country TFP is variable RTPNA, and weights are nominal PPP-adjusted GDP, variable CGDPO. Countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and the United Kingdom. The red dashed line is biweight trend with bandwidth of 12 years. The maroon dashed line that diverges from the red line after the late 1990s, and ends in 2007, is the estimated trend using data through 2007 only.

(Fernard & Inklaar, 2020)

Is AI able to upturn this trend?

Background

What do we know from previous technological disruptions?

- Past disruptive innovations such as mechanization of agriculture, suggest that the automation of existing tasks produced extraordinary increases in productivity.

- However, it took electricity since the 1890s and computers since the 1970s more than 30 years to be seen on the productivity statistics

- Some scholars have suggested that unlike these past “revolutions”, AI may introduce automation (*Narrow AI*) without significantly affecting productivity (Acemoglu & Restrepo, 2019)

Key previous studies
Is the Solow (1987) paradox back?

- TFP growth has declined steadily from 1.5 to 1.0 per cent per year over the past 50 years (Crafts and Mills, 2017).
- This creates a future paradox between a potential highly automated world and likely economic slowdown, much as the Solow (1987) Paradox:
  - Robert Solow said in 1987 that the computer age was everywhere except for the productivity statistics.
- The Solow Paradox cleared up in the 1990s when a few sectors -technology, retail, and wholesale - led an acceleration of US productivity growth (Krishnan, Mischke, & Remes, 2018).

Aim

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Aim

Study the impact of AI innovation on total factor productivity drawing special attention to e-commerce and financial firms:

to analyze improvements in productivity that originate from firms that have developed AI technologies, in order to assess the growth potential of this new wave of innovation

Why patents, why TFP?

- Given worldwide data limitations, the INNOVA team built a dataset of highly innovative companies, patenting in AI, and compared whether e-commerce and fintech companies were behaving any different than other highly innovative companies in terms of their TFP
- Patents to measure innovation and it is suitable to measure technological shocks (Christiansen, 2008)
- Total factor productivity to measure productivity, TFP relates an index of output to a composite index of all inputs. TFP growth is commonly associated with innovation and technological change (Murray and Sharpe, 2016).

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Findings

Findings

Causal relationship of AI patents on TFP and wages:

- Firms that **successfully obtain a greater number of AI patents** tend to **increase** both their **total factor productivity and wages**

- A **greater number of AI patents** contribute to an **increase in productivity**

- Evidence supporting the catching-up hypothesis: low productive firms invest more in AI technologies to recover from the initial productivity gap

Findings

- **e-commerce and fintech firms** through granted AI patents **achieve better TFP convergence** to the **technological frontier** compared to non-e-commerce and fintech firms
- **Results are consistent** if, together with e-commerce and fintech firms, we consider other **firms** belonging to **finance and telecommunication industries**

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Results

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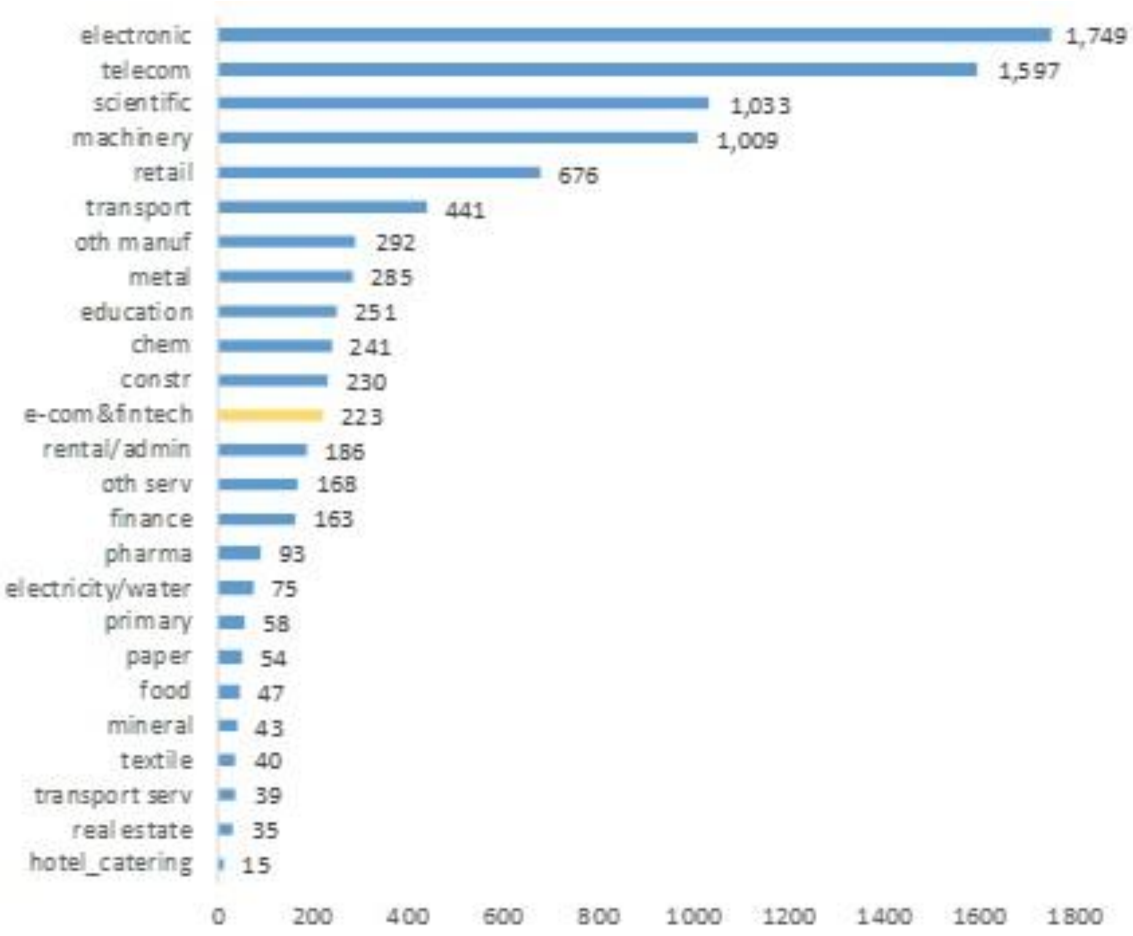
Firms distribution by sector



E-commerce NACE 4-digit

- Retail trade 4791: Commerce de detail: Retail trade is defined in the International Standard Industrial Classification (ISIC) as the re-sale (sale without transformation) of new and used goods to the general public, for personal or household consumption or utilization
- Data processing, hosting, and related services 6311;
- Internet publishing and broadcasting, and web search portals, 6312 (Beth et al., 2018)

Fintech NACE 2-digit

- Financial service activities, except insurance and pension funding, 64
- Insurance, reinsurance and pension funding, except compulsory social security, 65
- Activities auxiliary to financial services and insurance activities, 66

Source(s): both patent and financial data by Van Roy et al. (2020). The database combines patents extracted from the EC TIM text-mining tool with Orbis Patents and Bureau Van Dijk's Orbis database.

Notes: Total number of firms 8,820; e-commerce includes firms belonging to 4-digit NACE 4791 6311 6312; fintech includes firms belonging to 2-digit NACE 64 65 66

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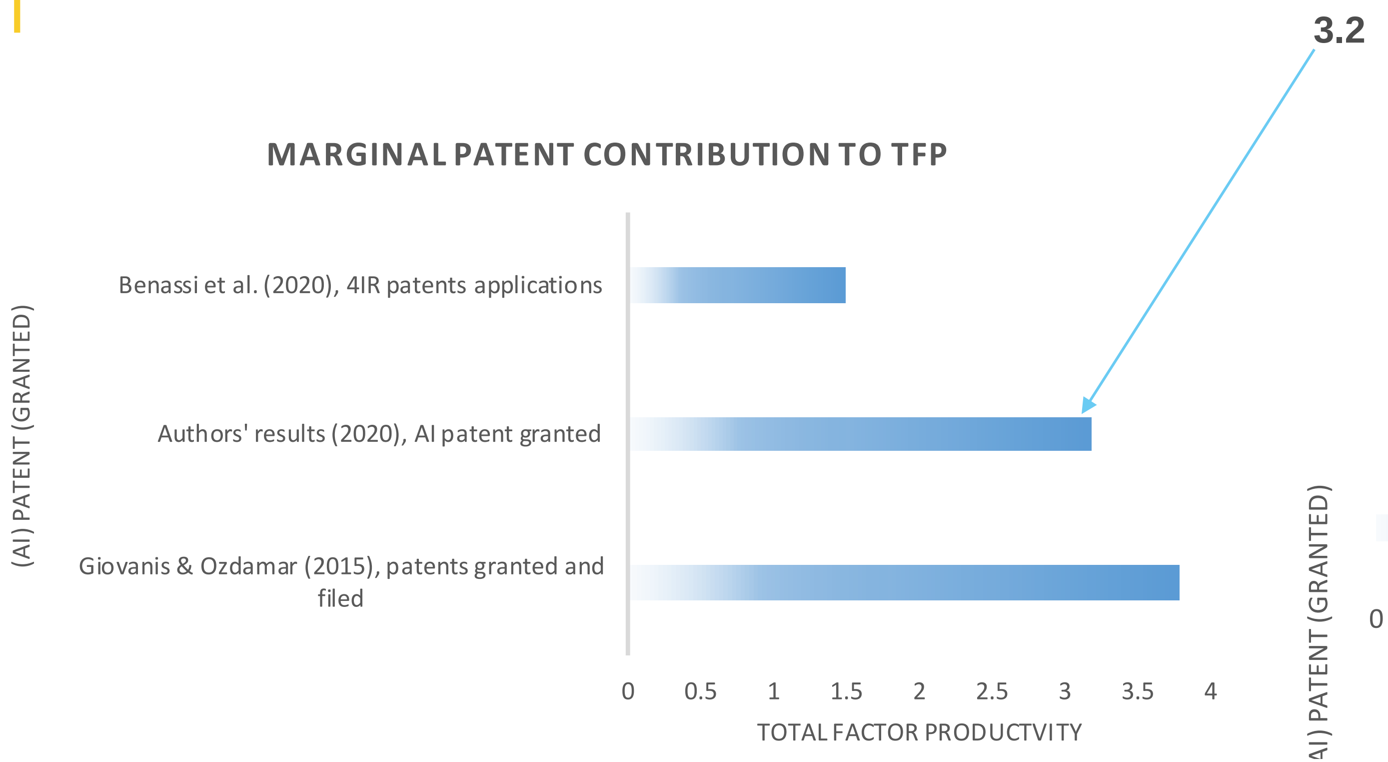
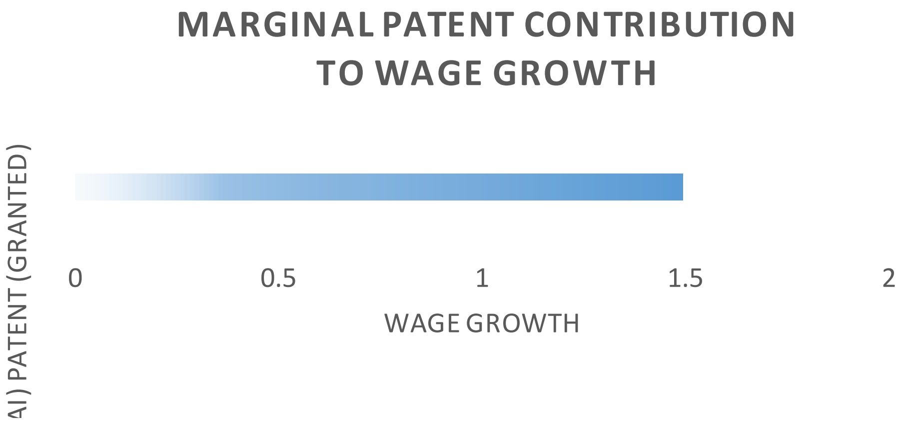
Results

- **AI patent applications** have **no effect on TFP**
- **AI granted patents** have **positive effects on TFP**
  - Firms with the highest TFP are those with highest average AI granted patents
- **AI patenting ecommerce and fintech** companies have **higher positive effects on TFP** than **non-ecommerce & fintech companies**

It is necessary to get the AI patents granted to show a significant effect; filing AI patents has no effect on TFP

Results





TFP gains coming from AI innovations are associated with higher wage growth rate

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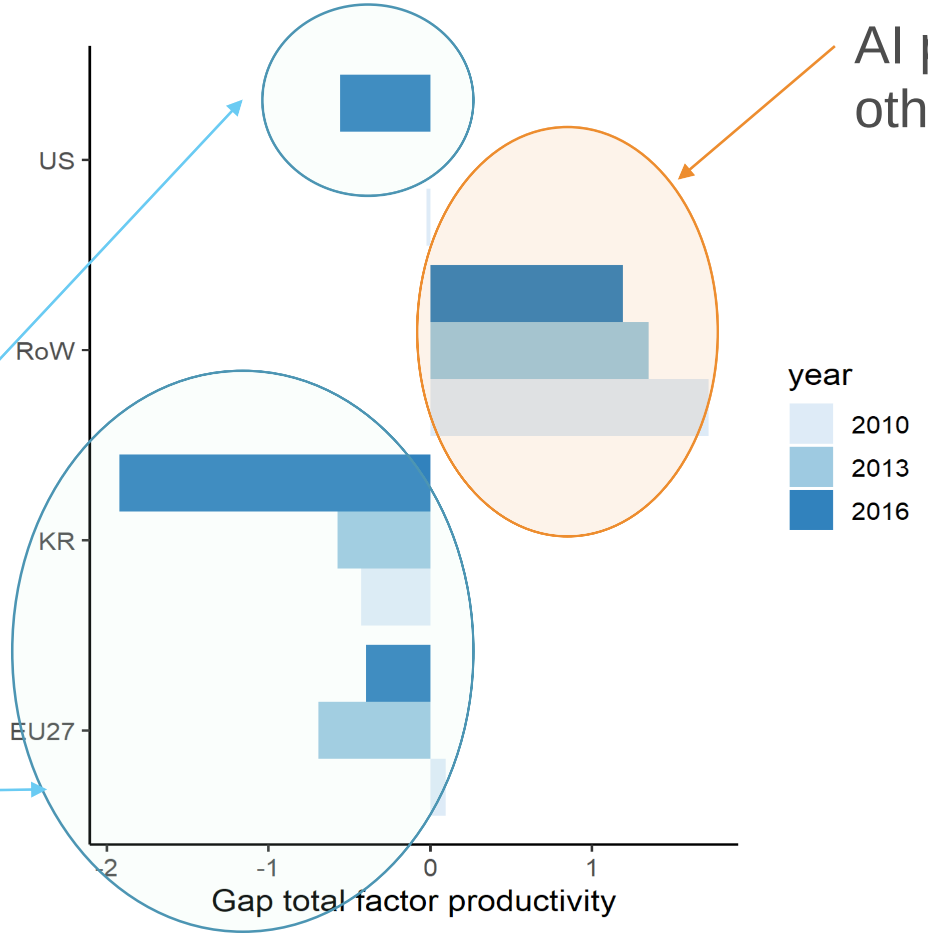
Results

TFP ecommerce & fintech AI patenting firms **<** TFP other AI patenting firms



TFP ecommerce & fintech AI patenting firms **>** TFP other AI patenting firms

Source(s): elaborated by the authors. Both patent and financial data by Van Roy et al. (2020). This database is a combination of the patents extracted from the EC TIM text-mining tool with Orbis Patents and Bureau Van Dijk's Orbis database.

Notes: TFP gap is the average TFP of all sectors minus the average of TFP of e-commerce and fintech firms. Total number of firms 8,820; e-commerce includes firms belonging to 4-digit NACE 4791 6311 6312; fintech includes firms belonging to 2-digit NACE 64 65 66. China, Great Britain and Japan data are missing

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Policy implications and future outlook

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Policy implications

Catching-up hypothesis, lagging firms are most likely to, more intensely, take advantage from AI technologies improving productivity

- **Exploiting patents, e.g., incentivizing the licensing of AI patents** to facilitate diffusion without crowding out the innovation incentives of the firms that are catching up

Policy implications

- **More and better data at firm** and country levels need to be developed and made publicly available
- **Development of an internationally shared framework for the measurement of AI**, to support the development of good and reliable data (Brundage et al., 2018). Thus far AI is an evolving blurred concept.

Future outlook

- Investigating whether an increase of wages is accompanied by an increase of employment.
- Mapping gender differences in management composition and explore if there is a relationship between AI & gender & education
- Exploring use cases of AI patenting firms in ecommerce and fintech

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Thank you

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Appendix

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Methodology

I. Sectoral Differences

- We use different approaches to extract a measure of TFP from the RVA
- Then, we use a Correlated Random Effects model to separate between and within effects of AI patents on TFP
- This allows us to investigate cross-sectional differences (i.e., differences among heterogeneous firms and sectors).

II. Firm-Specific Effects

- We use a Generalized Method of Moments (GMM) estimator to address endogeneity issues related to simultaneity problems between firm’s productivity and its investment decisions.
- In this way, we can identify the causal impact of AI patents on TFP for a generic firm, since we control for firm heterogeneity.

Results (June presentation)

Differences among sectors

	Others	E-commerce & Fintech	P-value
TFP (OP)	-0.902	-0.598	0.002
TFP (LP)	-0.822	-0.522	0.002
TFP (WR)	-0.450	-0.143	0.002
AI patent app.	0.468	1.037	0.000
AI patent granted	0.161	0.269	0.003
Patent app.	28.220	25.881	0.331
Patent granted	15.980	14.566	0.321
AI patent granted stock	0.978	1.049	0.352
Patent granted stock	100.427	44.579	0.002

TFP derivation

Ln (RVA)			
	Olley-Pakes (1996)	Levinsohn-Petrin (2003)	Wooldridge (2009)
	(1)	(2)	(3)
Ln (L)	0.794***	0.818***	0.765***
	(0.014)	(0.000)	(0.023)
Ln (K)	0.270***	0.294***	0.285***
	(0.086)	(0.000)	(0.023)
IMR	-0.112***	-0.088***	-0.210***
	(0.025)	(0.000)	(0.029)
Observations	3532	3532	2355
Wald p-value (CRS)	0.310	0.000	0.000
Hansen p-value			0.000

Results

Table 2. T-test for e-commerce & fintech sectors

	Non e-commerce & fintech	E-commerce & fintech	p-value
TFP	-0.451	-0.123	0.001
AI patent app.	0.673	1.156	0.000
AI patent granted	0.231	0.300	0.084
Patent app.	40.534	28.865	0.042
Patent granted	22.953	16.246	0.040
AI patent granted stock	1.404	1.170	0.160
Patent granted stock	144.250	49.719	0.000

Notes: T-test results contrasting e-commerce & fintech sectors against other sectors in terms of productivity and patents.

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Results

Table 3. AI innovation and TFP (OLS and CRE models)

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			CRE	
Patents	Applications	Granted	Granted stock	Applications	Granted	Granted stock
AI patent (w)	-0.005**	-0.028***	-0.008***	0.002	-0.001	-0.001
	(0.002)	(0.008)	(0.002)	(0.002)	(0.008)	(0.005)
Patent (w)	-0.000	0.000	0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI patent (b)				-0.009	-0.054**	-0.012**
				(0.007)	(0.024)	(0.005)
Patent (b)				0.000	0.000	0.000*
				(0.000)	(0.000)	(0.000)
Fintech & e-com	0.333**	0.332**	0.333**	0.862***	0.858***	0.859***
	(0.163)	(0.162)	(0.162)	(0.194)	(0.194)	(0.194)
IMR (w)	-0.482***	-0.465***	-0.425***	0.014	0.010	0.010
	(0.167)	(0.160)	(0.165)	(0.152)	(0.152)	(0.152)
IMR (b)				-0.389	-0.371	-0.330
				(0.256)	(0.254)	(0.255)
Intercept	-0.154	-0.164*	-0.189*	-0.263	-0.273*	-0.299*
	(0.103)	(0.099)	(0.102)	(0.161)	(0.159)	(0.160)
N	6617	6617	6617	6617	6617	6617
RMSE	0.841	0.841	0.841	0.441	0.441	0.441
R^2	0.004	0.005	0.006	0.004	0.005	0.005
R^2 (w)				0.000	0.000	0.000
R^2 (b)				0.015	0.017	0.017

Notes: This table shows the OLS and CRE coefficients of Equation (2). Columns 1 and 4 consider the number of patent applications as main explanatory variables. Columns 2 and 5 replace these variables with the number of granted patents, whereas Columns 3 and 6 employ the number of granted patents stock. IMR stays for Inverse Mills Ratio and serves to control for sample selection problems. Robust standard errors are in parentheses. Significance: *p<10%, **p<5%, ***p<1%.

Results –catching up hypothesis

Table 4. AI innovation and TFP (OLS and CRE models with initial TFP)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS			CRE		
Patents	Applications	Granted	Granted stock	Applications	Granted	Granted stock
AI patent (w)	0.000	-0.002	0.000	0.002	0.004	0.000
	(0.001)	(0.004)	(0.001)	(0.002)	(0.008)	(0.005)
Patent (w)	-0.000**	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AI patent (b)				-0.000	-0.004	0.000
				(0.003)	(0.011)	(0.003)
Patent (b)				-0.000	-0.000	-0.000
				(0.000)	(0.000)	(0.000)
Fintech & e-com	0.006	0.006	0.006	0.023	0.024	0.024
	(0.075)	(0.075)	(0.075)	(0.140)	(0.140)	(0.140)
IMR (w)	-0.252**	-0.238**	-0.242**	0.098	0.102	0.098
	(0.107)	(0.100)	(0.106)	(0.157)	(0.157)	(0.156)
IMR (b)				-0.327**	-0.309*	-0.312*
				(0.163)	(0.159)	(0.162)
Initial TFP	0.788***	0.788***	0.788***	0.795***	0.795***	0.796***
	(0.023)	(0.023)	(0.023)	(0.016)	(0.016)	(0.016)
Intercept	0.053	0.045	0.047	0.098	0.086	0.089
	(0.063)	(0.059)	(0.063)	(0.100)	(0.098)	(0.100)
N	4207	4207	4207	4207	4207	4207
RMSE	0.494	0.494	0.494	0.392	0.392	0.392
R^2	0.590	0.590	0.590	0.590	0.590	0.590
R^2 (w)				0.000	0.000	0.000
R^2 (b)				0.765	0.765	0.765

Notes: This table shows the OLS and CRE coefficients of Equation (2). Columns 1 and 4 consider the number of patent applications as main explanatory variables. Columns 2 and 5 replace these variables with the number of granted patents, whereas Columns 3 and 6 employ the number of granted patents stock. IMR stays for Inverse Mills Ratio and serves to control for sample selection problems. Robust standard errors are in parentheses. Significance: *p<10%, **p<5%, ***p<1%.

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Results, AI patent granted

Table 5. AI innovation and TFP (GMM)

	(1)	(2)	(3)
Patents	Applications	Granted	Granted stock
Ln(L)	0.704***	0.874***	0.749***
	(0.107)	(0.105)	(0.106)
Ln(K)	0.453***	0.249*	0.457***
	(0.135)	(0.135)	(0.141)
AI patent	-0.000	0.032**	0.007
	(0.004)	(0.015)	(0.008)
Patent	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
IMR	0.345	1.091	1.056
	(0.860)	(0.922)	(0.907)
Intercept	-1.223	-1.694**	-1.930**
	(0.765)	(0.777)	(0.806)
N.	6617	6617	6617
N. of firms	1738	1738	1738
AR(1) p-value	0.000	0.002	0.000
AR(2) p-value	0.993	0.857	0.967
Hansen (p-value)	0.431	0.144	0.140

Notes: This table shows the GMM estimates of Equation (3). Columns 1-3 consider as main explanatory variables the number of patent applications, granted patents, and patent stock, respectively. IMR stays for Inverse Mills Ratio and serves to control for sample selection problems. Robust standard errors are in parentheses. Significance: *p<10%, **p<5%, ***p<1%.

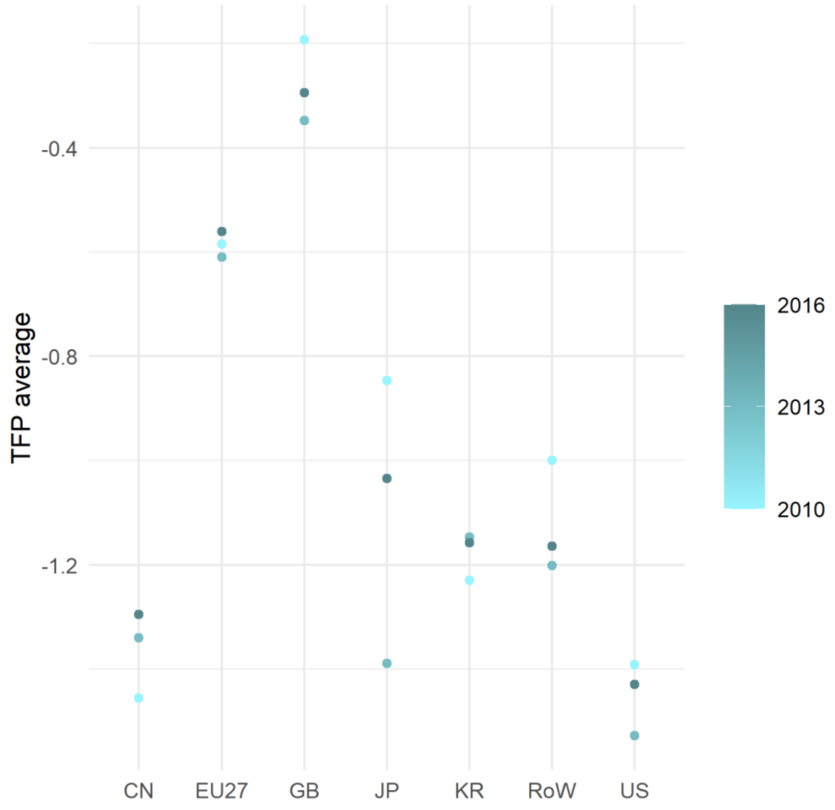
Results, wages

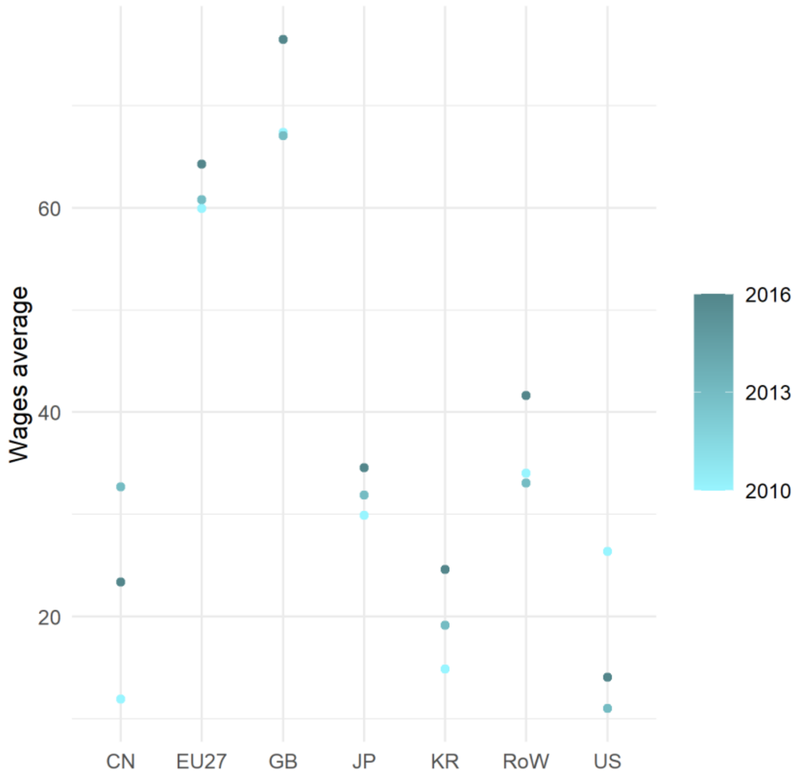
Table 6. AI innovation and wage growth (GMM)

	(1)	(2)	(3)
Patents	Applications	Granted	Granted stock
L. Ln(w)	-0.995***	-0.972***	-1.059***
	(0.082)	(0.064)	(0.067)
Ln(L)	-1.204***	-1.121***	-1.191***
	(0.122)	(0.139)	(0.156)
Ln(K)	0.099	0.016	0.073
	(0.070)	(0.042)	(0.081)
AI patent	0.002**	0.015***	0.003*
	(0.001)	(0.005)	(0.002)
Patent	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
IMR	0.230	0.452*	0.505
	(0.588)	(0.247)	(0.381)
N	4683	4683	4683
N. of firms	1323	1323	1323
AR(1) p-value	0.014	0.003	0.039
AR(2) p-value	0.694	0.856	0.261
Hansen (p-value)	0.322	0.762	0.314

Notes: This table shows the GMM estimates of Equation (3) when the dependent variable is the log of wage. Columns 1-3 consider as main explanatory variables the number of patent applications, granted patents, and patent stock, respectively. IMR stays for Inverse Mills Ratio and serves to control for sample selection problems. Robust standard errors are in parentheses. Significance: *p<10%, **p<5%, ***p<1%.

Wages and TFP (means), AI patenting firms





Source(s): both patent and financial data by Van Roy et al. (2020). This database is a combination of the patents extracted from the EC TIM text-mining tool with Orbis Patents and Bureau Van Dijk's Orbis database
Notes: wages are in thousand of euros; TFP is in natural logarithm

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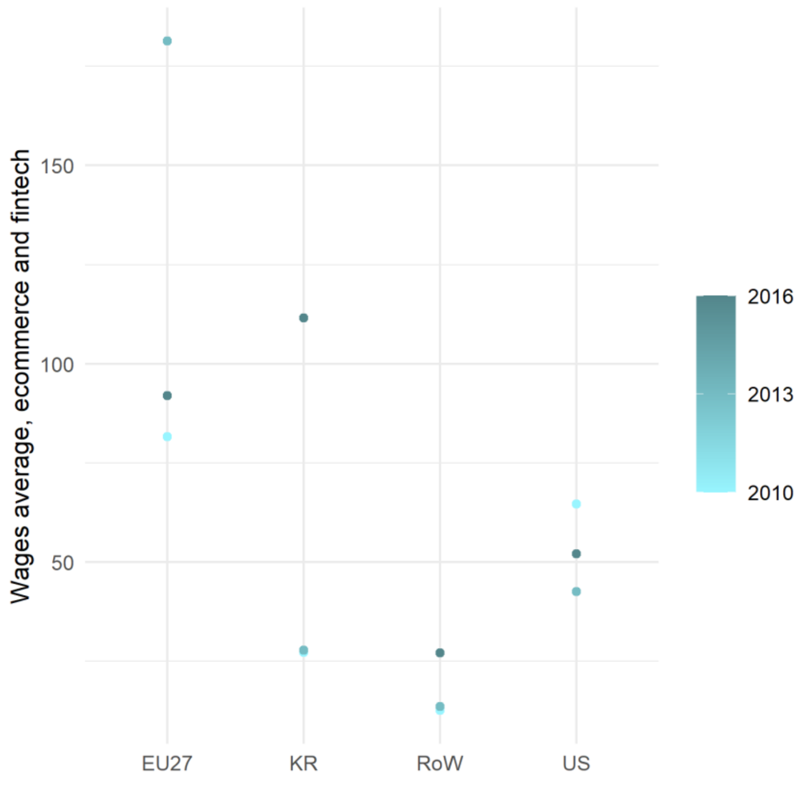
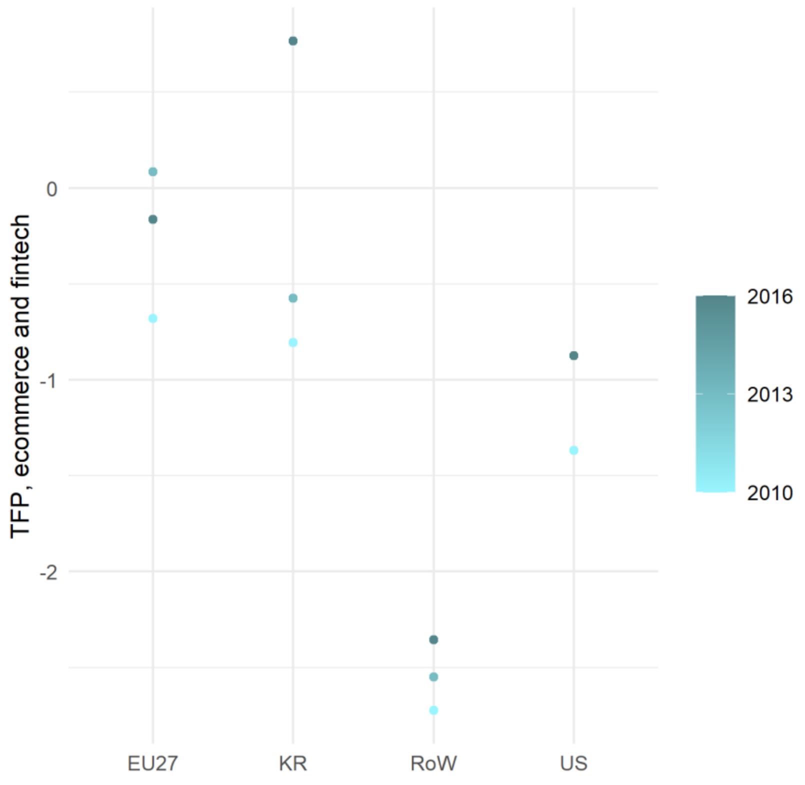
Wages and TFP (means), AI patenting firms - ecommerce and fintech





Source(s): both patent and financial data by Van Roy et al. (2020). This database is a combination of the patents extracted from the EC TIM text-mining tool with Orbis Patents and Bureau Van Dijk's Orbis database
Notes: wages are in thousand of euros; TFP is in natural logarithm

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