European Commission

JRC TECHNICAL REPORT

Artificial Intelligence – impact on total factor productivity, e-commerce & fintech

Bassetti, T.

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2020

EUR 30428 EN

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EU Science Hub
https://ec.europa.eu/jrc

JRC122268

EUR 30428 EN

PDF	ISBN 978-92-76-24693-0	ISSN 1831-9424	doi: 10.2760/333292
Print	ISBN 978-92-76-24694-7	ISSN 1018-5593	doi:10.2760/448034

Luxembourg: Publications Office of the European Union, 2020

How to cite this report: Bassetti, T., Borbon Galvez, Y., Del Sorbo, M., Pavesi, F., *Artificial Intelligence – impact on total factor productivity, e-commerce & fintech,* EUR 30428 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-24693-0, doi:10.2760/333292 , JRC122268.

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Acknowledgements

This report is a deliverable of the Horizon 2020 project "INNOVA MEASURE IV" (857088) in support of the European Commission's DG Research and Innovation. We thank the participants of the two 2020 Innova Workshops for helpful comments and suggestions. We express special thanks to DRs Frèdèrique Bone, Tommaso Ciarli, Simone Vannuccini and Prof. Maria Savona who provided in-depth comments on a previous version of the study. Also, we thank JRC-colleagues for their support to this study: Anne-Mette Jensen-Foreman and Lorena Marcaletti. And, we would like to thank Giacomo Damioli, Research Fellow and Project manager of the INNOVA IV, Joint Research Centre (JRC) COIN Competence Centre, giacomo.damioli@ec.europa.eu.

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Abstract

The idea that Artificial Intelligence will be one of the foremost sources of innovation in years to come is one that goes well beyond the field of academia.

One relevant issue in this connection is understanding the likely impact of these technologies on productivity. Indeed, the impacts of earlier introductions of disruptive technology in history – such as the industrial revolution and the mechanisation of agriculture – suggest that the automation of existing tasks can produce extraordinary increases in productivity (Acemoglu & Restrepo, 2019).

To assess the growth potential of this new wave of innovation, in this study we examine the impact of AI technologies on **total factor productivity**.

This involves analysing improvements in productivity by firms who have patented AI technologies. In particular, we exploit a novel dataset of AI patents at firm level, to analyse whether the extent with which firms develop AI technologies positively affects productivity and wages.

Also, we draw attention to two sectors that are more extensively adopting AI – **e-commerce and fintech firms**.

Keywords: Artificial Intelligence, patents, total factor productivity (TFP), wage growth, generalised method of moments (GMM), firm level data, e-commerce, fintech

Executive summary

This study aims to provide both EU and national authorities with independent scientific evidence to help tackle one of the big social challenges related to new digital technologies and the functioning of labour markets: **how AI patents will affect company productivity** (also with a focus on e-commerce and fintech firms).

It was produced by the Joint Research Centre (JRC), a research hub providing science and knowledge services to the European Commission.

Importance of AI

Artificial Intelligence (AI) is re-modelling economies, promising to support productivity, boost efficiency and decrease costs. With its key contribution – making ever more accurate predictions and well-balanced decisions – AI has the potential to enhance quality of life for vast numbers of people, through growth, social improvements and innovation (OECD, 2019).

In its Communication, the European Commission proposes a European approach that help develop AI applications in key sectors, including the digital economy.

Artificial Intelligence is attracting the attention of academia, policymakers, industry and society at large – and for good reason. According to predictions by Price Water House Coopers, these technologies could raise global GDP by 13.1 trillion euros – a full 14% – by 2030 (Verweij & Rao, 2017).

Europe's share of this – 3rd largest, behind China and North America – is predicted to be in the order of 2.7 trillion euros. Indeed, to become the global leader AI by 2030, China is investing 125 billion euros (West & Allen, 2018).

Definition of AI

The European Commission report 'Artificial Intelligence, a European perspective' (Craglia et al., 2018) contains a broad definition: AI includes '*any machine or algorithm that is capable of observing its environment, learning, and based on the knowledge and experience gained, taking intelligent action or proposing decisions*'. This can include many technologies, with machine learning techniques being the most extensively used. For the purposes of this study, we use a similar broad definition.

Box 1. 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.'

'Artificial intelligence (AI) has become an area of strategic importance and a key driver of economic development. It can bring solutions to many societal challenges from treating diseases to minimising the environmental impact of farming. However, socio-economic, legal and ethical impacts have to be carefully addressed.'

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

The study

The Commission report also highlights the need to improve our scientific understanding and develop transparent mechanisms to assess the quality and performance of AI, to ensure it serves the purpose of advancing society. Indeed, in terms of their effects on productivity, there is evidence that the adoption of digital technologies may be leading to a reduction in employment (Autor et al. 2020). If this were the case, AI may simply replace jobs without producing sufficient welfare gains.

To explore the impact of these technologies, this study analyses productivity gains that originate from firms that have patented AI technologies, to assess the growth potential of AI.

In particular, we exploit a novel data set of AI patents at firm level, to analyse whether the extent to which firms adopt AI technologies positively affects productivity and wages. We also focus on 2 sectors – e-commerce and fintech – that are more extensively adopting AI and are growing rapidly, especially in terms of revenues (Kumar & Trakru, 2019).

Stages in the study

1. We collected firm-level data, combining 2 different sources:
   – AI and non-AI patent data, from Van Roy et al. (2019)
   – accounting data, from Orbis (Bureau van Dijk).

2. We compared the average patented firm with e-commerce and fin-tech patented firms. Using a longitudinal dataset, we investigate both cross-sectional (between) and time-series (within) effects.

3. We investigated whether the impact of AI innovation on total factor productivity also affects wage growth.

Limitations

This study represents a preliminary analysis, as we consider an objective measure of AI adoption that may be too restrictive, since it does not incorporate some less easily measurable technology adoption strategies. For example, some firms may be using AI applications without actually patenting or carrying out innovation themselves. So we may be underestimating how widespread use of AI is.

While recognising these limitations, using AI patenting as a proxy for adoption nevertheless represents a valid starting point for assessing the future prospects of these technologies.

Findings

Our findings provide evidence that AI patents have an impact on both total factor productivity and wages at firm level. We find that firms who successfully obtain a greater number of AI patents tend to increase both their total factor productivity and wages.

Thus, there is evidence that a greater number of AI patents is conducive to an increase in productivity, and that AI does not necessarily contribute to labour reduction and/or labour substitution by capital. It is true that, in many cases, AI contributes to labour reduction, but this is not the case according to our findings.

In addition, we find that e-commerce and fintech firms, through granted AI patents, achieve total factor productivity gains that are closer to the technological frontier than non-e-commerce and non-fintech firms.

Indeed, the higher productivity observed in these sectors, associated with a higher fraction of granted AI patents, remains if we also consider other firms belonging to finance and telecommunication industries. Our findings provide evidence for a 'catching-up' hypothesis – i.e., firms that are currently lagging behind are also most likely to intensely adopt productivity-boosting AI technologies.

Policy implications

These could include several options, such as facilitating AI technology adoption by firms currently on the cutting edge of productivity and encouraging more competitive environments and behaviour by firms.

This would offset some of the main forces associated with technological innovation that hinder growth – such as implementation lags, (Brynjolfsson et al. 2017) and reduction in aggregate demand (realised output) due to unemployment and reduced labour participation in the economy (Gries & Naudé, 2018).

Incentivizing the licensing of AI technologies is an example of how to accelerate their spread without crowding out the innovation incentives of the firms that are catching up.

Additionally, as other scholars have pointed out, there is a strong and clear call for better data. Good quality data allows for cross-regional analysis. Certainly, a common, shared definition of AI can help produce better data (Brundage et al., 2018), with the aim of designing policies that are more informed and solidly grounded on scientific evidence.

Findings (in detail)

We show that:

- Fintech and e-commerce, sectors that are more intensely adopting AI, also display higher levels of productivity.

- AI impacts productivity beyond these specific sectors: firms that successfully obtain a greater number of AI patents tend to increase both their total factor productivity and wages.

Thus, there is evidence that a greater number of AI patents is actually conducive to an increase in productivity.

Nevertheless, we also find that on average firms that apply for and are granted AI patents are associated with lower TFP. We explore 2 possible alternative explanations:

1. A **'catching up' hypothesis** – based on the idea that firms investing in AI start off with a lower TFP compared to the average firm that patented in AI at least once since the year 2000, but successfully obtaining AI patents reduces the TFP gap.

2. A **'cost of investment' hypothesis** – implies that investing in AI involves a short-term reduction in TFP, but if the investment successfully produces AI patents, this increases TFP.

Our analysis provides evidence that the catching up hypothesis is the most likely explanation.

In terms of our main research question, this allows us to provide further insight on the central question of whether AI could represent a breakthrough technology. Our evidence shows that among the firms that patented AI technology, those that are developing and filing more AI patents are firms that were originally lagging behind the productivity leaders.

Thus, according to our analysis, AI has not yet impacted the more productive firms. What remains to be seen is whether, once this catching up effect is completed, the competitive push will lead to pervasive spillovers across sectors that will produce a significant upward shift in productivity.

1 Introduction

This study aims to assess the impact of AI patenting activities on total factor productivity (TFP) and wages.

We collected firm-level data combining two different sources:

- AI and non-AI patent data from Van Roy et al. (2020)
- accounting data from Orbis (Bureau van Dijk).

We then processed the data using 'Tools for Innovation Monitoring' (TIM), a series of analytic tools developed by the Joint Research Centre.

We compared the average firm with firms in e-commerce and fin-tech – sectors we chose because they are extensively adopting artificial intelligence and showing extraordinary growth, especially in terms of revenues.

The study contains 5 sections:

- literature review
- business descriptive statistics with AI patent activities
- the effect on TFP and average wage structure
- policy implications
- conclusions.

2 Literature review

This literature review first highlights that a very long-term trend of economic and productivity decline, put preassure on firms developing AI technologies and solutions to revert the trend, as was the case of other 'general purpose technologies' in the past. It then explores how previous investigations analysed AI innovations and their effects on productivity and wages of firms, in general, and in ecommerce and fintech in particular.

2.1 AI as a general purpose technology – effects on productivity and wages

Many scholars, analysts, consultancies and advocacy groups argue that AI might be at the helm of the current era of innovation. It is said that the capacity of AI is such that – with minimal or even no human intervention – it is possible to control natural, social and production processes, and so generate large productivity gains (Grinin, Korotayev, & Tausch, 2016).

Such statements create expectations about the capacity of AI to reduce employment vulnerability and increase productivity, employment and per capita income (Aly, 2020). Although there are fears of job displacement, the job creation and welfare gains are expected to offset these losses at industry and aggregate levels (Khatri, Pandey, & Penkar, 2020).

AI may help firms able to re-combine knowledge production (Agrawal, McHale, & Oettl, 2018), and may benefit the economy, providing human-enhancing AI innovations offset human-*replacing* AI innovations (Trajtenberg, 2018). Net positive gains in human-enhancing AI are possible because the presence of routine tasks in a job (a factor claimed to lead to automating jobs out of existence), is not the sole factor determining the possibility of overall job automation and displacement (Bissessur, Arabikhan, & Bednar, 2020).

AI can be classed as general purpose technologies because:

1) it has **many application areas** – computing, health, manufacturing, transportation, smart cities and grids, nanotechnology, agriculture, financial services, marketing and ecommerce, waste management, education, cybersecurity, telecommunications, etc.;

2) it requires large stocks of tangible, intangible, and complementary **capital** (Brynjolfsson, Rock, & Syverson, 2017) and a **substantial amount of time** to correctly identify, produce and put together knowledge and resources (Brynjolfsson et al., 2017);

3) the **coordination of multiple elements** during the innovation processes within and across firms is what might enable AI to lead to productivity gains (Bresnahan & Trajtenberg, 1995). This means that if AI as general purpose technologies is not reflected in the productivity statistics, this is because firms still need time to coordinate innovations.

Funk (2020) states that, in terms of their effects on productivity gains, AI innovations are more evolutionary and incremental in nature than revolutionary and disruptive. He bases his statements on observing various AI applications:

- **sales and marketing** – applying AI is a zero-sum game, as it shifts customers from one competitor to other, without significantly increasing demand;

- **human-resource management** – AI modestly increases productivity, but not as much as process automation;

- **generative designs**– AI is not developed or diffused enough in terms of number and size of firms to have noticeable productivity impacts;

- **computing hardware and software** – a noticeable machine learning productivity is still years away (Funk, 2020).

Brynjolfsson et al. (2017) emphasise the presence of a modern productivity paradox characterised by declining TFP, even after the spread of AI, that can be explained by false hopes, implementation lags, redistribution of wealth through creative destruction (i.e. only few firms reap the benefits of AI), and inaccurate measurement, e.g. intangible assets already captured in firms' market values, but not measured by analysts.

This is a problem, because reduced productivity slows market growth and reduces the attractiveness of financing future rounds of improvements, in turn further reducing productivity, and so on (Thompson & Spanuth, 2018).

At micro (industry) and macro (economy-wide) level, the timespan for seeing AI productivity growth remains unclear. Valenduc (2018) expects the productivity effects of AI, like previous general purpose technologies, to be measured in decades rather than in years. Moreover, Storm (2019) does not expect AI to show larger productivity effects than previous general purpose technologies, because markets and the economy in general are less favourable now than before (Storm, 2019). For instance, in the US, there was a decline in FTP growth from 0.49 to 0.41 from the 1970s to the 2010s (Fernald, 2016).

Furthermore, Schmelzing (2020) predicts continued long-term decline in growth and productivity, where innovations (such as AI) are just palliatives, which explains why scholars propose saving humanity from a related Malthusian destiny by introducing social safety nets (Korinek & Stiglitz, 2017).

The next sections discuss the possible effects of innovations and patenting on the productivity of the firm, and whether AI patenting, and AI in the e-commerce and fintech firms that implement it, are expected to exhibit higher productivity than the average innovative firm.

2.2 Innovation and productivity

Despite the long-term decline in productivity and growth, there are firms, and even whole industries that have seen productivity growth after they implemented innovations. For instance, Turkish banks after the 1980s introduced innovations that induced efficiencies and saw substantial TFP growth (Isik & Kabir Hassan, 2003). Similarly, Eastern European banks' TFP grew during the global financial crisis (2007-8) catching-up with the declining TFP of their Western European counterparts, who showed lagging efficiency and technological regression (Degl'Innocenti, Kourtzidis, Sevic, & Tzeremes, 2017).

Malaysia's non-banking financial sector implemented innovations leading to substantial TFP growth, although this was more evident in large financial institutions (Sufian, 2008; Sufian & Habibullah, 2009). During trade liberalisation in Bangladesh, its manufacturing sector experienced TFP growth from 1993 to 1998, with export-oriented firms performing better than import-oriented ones (Hassan, Isik, & Mamun, 2010). It was shown that productivity (sales) increased in India's pharmaceutical industry thanks to firms' R&D and patenting activities (Pannu, Kumar, & Farooquie, 2010).

At **country** level, there are indications that high-tech innovation has a very low effect on TFP, and high-tech entrepreneurship has a U-shape relationship with TFP (El Ghak, Gdairia, & Abassi, 2020). The hypothesis put forward by the authors is that innovation based on digital (ICT) technologies is not as useful as innovations from previous technological revolutions, because it does not induce profound changes in production and consumption at the same time. However, after the bottom inflection point, increased entrepreneurship improves TFP (El Ghak et al., 2020). Similar findings are presented in a meta-analysis of the ICT productivity paradox (Polák, 2017), in which ICT is shown to have very little effect on productivity. The same study shows that previous studies trying to debunk the ICT productivity paradox tend to have strong research biases (Polák, 2017).

At **firm** level, an analysis by Huergo & Moreno (2011) shows that company growth and productivity have been associated with innovation outputs more than innovation inputs. Their model assessed TFP depending on technological outputs (innovations), and outputs depending on technological inputs (R&D), i.e. a Crepon Duguet Mairesse model. With panel data from the Spanish Community Innovation Survey, they show how, for innovation to have a long-term effect on TFP, R&D investment needs to be persistent over time.

The innovation and productivity relationship in a study of Dutch and French manufacturing companies showed that, to varying degrees between countries, innovations have lasting effects on labour productivity. In this case however, there was no need for persistent innovation (Raymond, Mairesse, Mohnen, & Palm, 2015).

An analysis of Italian firms observed from 1996 to 2005, using a general method of moments (GMM) with regional and sectoral controls, shows that complexity and innovation carried through local interactions lead to strong TFP growth (Antonelli & Scellato, 2013). Another company-level analysis, with a fully modified ordinary least squares (FMOLS) model, showed that embodied, disembodied, and R&D intensities have positive impacts on the TFP of Indian manufacturing firms (Satpathy, Chatterjee, & Mahakud, 2017).

In sum, innovations have shown various degrees of effects on productivity, both low and high, and the relationship might not always be linear. Therefore, the next section focuses on a particular type of innovation –

patents. These are innovation outputs, which are claimed to be a specific measure of innovation, related to knowledge – both codified knowledge (patents) and the stock of knowledge (patents stock).

2.3 Patenting and productivity

Patents are not a perfect measure of innovation, because applications focus on differentiating the patent from pre-existing knowledge, rather than future market potential (*Leydesdorff, Rotolo, & de Nooy, 2013*). However, venture capitalists and risk capital investors make their decisions to invest in patenting based on expected future profitability (Santos & Qin, 2019). Nevertheless, it needs to be acknowledged that filing patents does not require working prototypes, nor even the intention of making them (*Brennen, Howard, & Nielsen, 2018*).

Having said that, an analysis of Pakistan's patenting activities using the multivariate generalized autoregressive conditionally heteroskedastic–Baba, Engle, Kraft and Kroner (GARCH–BEKK) model, showed that innovations set out in filed patents have a long-term positive effect on TFP, as long as there is also an expansion of skilled labour employed in the country (*Mumtaz & Smith, 2017*).

Also at company level, using patent data and R&D intensities from US Census microdata, Acemoglu et al. (2018) showed not only that patenting and R&D improve productivity in the firm, but also, by freeing up skilled labour and specialised resources from firms that exit the market and probably reallocating them to 'high type incumbents', it generates broader industrial and economic gains.

At industry level, Giovanis & Ozdamar (2015), using general method of moments (GMM), showed how the technological relevance of US companies' patents have positive effects on TFP, both during economic recessions and periods of economic growth. However, the effect is stronger during recessions, and the effect and significance are actually very low during growth periods.

As regards economic recession, interestingly, in the post-war period the Japanese Patenting System allowed firms to file multiple patents in very narrow areas of applications, to help firms experiencing economic difficulties to catch up through incremental innovation. The Japanese Patenting System achieved this objective, with substantial impacts on TFP (*Maskus & McDaniel, 1999*).

The Schumpeterian view of innovation during recessions – or 'creative destruction' phases – is that for companies to be competitive, they need to free up and reallocate resources to the most efficient and productive areas of the firm.

However, an analysis of US manufacturing firms that file patents showed that this is not the case: neither resources nor market power were necessary for patenting to lead to increased TFP for US manufacturing firms, rather just competitive behaviour.

This is because firms with greater resources (indicating that they have monopoly power, or are in sectors with high market concentration) do not have the same level of incentives (measured by the differential between current and expected future profits) to innovate and patent for growth. Firms in more competitive markets have higher incentives (*Correa & Ornaghi, 2014*).

Patents are acknowledged as a reliable measure of innovation, and they have been shown to have a relationship with productivity. Christiansen (2008) shows that both R&D investment (inputs) and patents (outputs) show similar effects on labour productivity for manufacturing industries in OECD countries. Romero & Britto (2015) discovered similar results by measuring the effects on TFP; addressing unobserved effects, measurement errors, and endogeneity with a System GMM model (Romero & Britto, 2015).

Patents are widely used as measure of innovation, or as outputs of R&D activities (Patel & Pavitt, 1987). And patents granted reflect the firm's capacity to generate change and improve an area of technology, even though it can be unclear, at the time the patent is granted, whether it will in fact be useful for the firm (Robertson & Patel, 2007).

2.4 AI patenting, productivity and wages

The effects of AI patents on productivity can vary over time and according to the area of patent application. A study of AI patenting in China from 2002 to 2016 focused on finding productivity effects in the early stages of AI patenting that improved the quality and speed of pattern recognition. It then moved on to examine improvements in real time monitoring and virtual reality, and, later AI patents focused on Internet of Things, image identification and cloud systems (Huang, Miao, Zhang, Yu, & Wang, 2017).

Thus, one cannot expect AI to have same effects on company performance in all areas of application. Moreover, although China is a large producer of AI patents, the US, Japan, and Korea are close competitors; and the lead is with the US – not in terms of number of patents but in terms of value they generate (Yang & Yu, 2019).

The biggest AI classes in the USPTO from 2008 to 2018 were: electric digital data processing; automatic data recognition and handling; digital information transmission; data processing for commercial, financial, forecasting and other purposes, among others (Abadi & Pecht, 2020).

Whether AI patents may have value for the firm might not be important when a study is looking at AI patents effects on labour productivity. However, it is relevant when productivity is measured with TFP, as this measure is based on the "real value" that the firm adds.

A study by Benassi et al. (2020) shows that AI patents have significant effects on TFP. The study analysed firm-level data (global ORBIS-IP firms database from 2009 to 2014) with OLS and fixed effects regressions, focusing on 4th industrial revolution (4IR) patents (e.g. artificial intelligence, cloud computing, networked sensors, 5G networks, 3D systems, smart manufacturing, etc.). It showed positive effects on TFP.

A similar analysis of 4IR patents and performance extracted from Orbis-IP, and analysed with a SYS GMM, showed that firms located in OECD countries patenting in 4IR areas (including AI) tend to increase their wages (Li, Shi, & Fu, 2020), which according to the authors is due to rent sharing effects derived from the benefits of patent exploitation, as discussed in other research (Kline, Petkova, Williams, & Zidar, 2019).

In fact, the gains from patenting may even start before patent applications, and can continue after, at all levels of the firms, i.e. for inventors, co-workers, blue and white-collars, and shareholders; at least as shown by evidence of Finnish firms applying for patents to the European Patent Office (Aghion, Akcigit, Hyytinen, & Toivanen, 2018).

The theory that resources are reallocated to 'high type incumbents', as discussed in the previous section, is reinforced in a study at industry level, in which Autor & Salomons (2018) looked at the EU KLEMS data for 1970 to 2007, and concluded AI patenting had positive effects on TFP.

And while the industries concerned experienced short-term resource and employment losses, the study proved, using the World Input-Output Database (WIOD), that industries with TFP growth reallocate employment and resources throughout input-output linkages, stimulate aggregate demand, and spread general TFP gains to associated industries.

The study also showed that weak input-output linkages, or those that contribute little to value added, will not spread effects (either positive or negative) to the rest of the economy, but rather will tend to remain within the industry that experiences the direct effect.

At country level, an analysis from 1990 to 2014 showed that AI patenting contributed to TFP: by 8% in OECD countries, by 11% in the EU, and by 34% in the US (Venturini, 2019).

In sum, the literature suggests that AI patenting may drive labour productivity, and that 4IR patents may drive wage growth. What remains to examine is whether AI patenting leads to TFP and wage improvements at firm level. Our hypothesis that is does.

2.5 AI in fintech and e-commerce

The two industries poised to invest highly in AI in the future are banking and retail (i.e. e-commerce) (Mou, 2019).

For instance, Soni et al. (2020) show that of a sample of global AI start-ups in 2017 and 2018, commerce applications increased from 1% of the total start-ups in 2017 to 5% of the total in 2018; whilst fintech and insurance increased from 4% to 5% in the same period.

This might explain why intelligent finance and intelligent e-commerce (the application of AI technologies in finance and e-commerce) are growing rapidly, with e-commerce expected to be worth USD 4.8 trillion in 2021 (Jiao, 2018). Fintech means technological instruments developed to meet users' financial needs and demands, with the most popular development being automated or assisted management of investments by means of AI (Belanche, Casaló, & Flavián, 2019).

Patenting activity in intelligent finance grew substantially from 2011, topped by China and the US, but with the US leading in terms of R&D capacity (HE, DU, & QIAO, 2020). Patenting in e-commerce is led by the US and China – Amazon and Alibaba, respectively. For these 2 giants, alongside AI use in directed e-commerce advertising, the most important patenting activity is associated with computational systems extracting big data information to predict business behaviour (Trappey, Trappey, Wang, & Hsieh, 2018).

Whether AI patenting in fintech and e-commerce increase firms' TFP is an analysis still missing in the literature. This is the main contributing focus of this report.

3 Empirical section

3.1 A look at firms with AI patenting activities[1]

This section examines – in the 2010-16 period – 8,820 firms that had made at least one AI patent application since 2000.

The aim is to sketch the distribution of firms, patenting activities and total factor productivity by country and sector – to see whether the countries with highest AI patenting activities are also those with the highest total factor productivity, and/or vice versa.

The comparisons rely on data availability (for any country not represented, this is because of missing data).

We collected firm-level data from two different sources:

- AI and non-AI patent data from Van Roy et al. (2020)
- accounting data from Orbis (Bureau van Dijk).

Van Roy et al. (2020) classify patent data using the PATSTAT database from the European Patent Office, containing data from over 90 patent authorities, concerning the main patenting countries. The patent documents are divided into different groups (with a necessary condition for forming a group being that at least one of them is in English). The data was processed using Tools for Innovation Monitoring (TIM), a series of analytic tools developed by the JRC.

To identify AI and non-AI technologies, Van Roy et al. (2020) adopt a keyword-based search. More specifically, to qualify as an AI patent, a document must have some specific terms in the title, abstract, or project (e.g., EC, 2018; Del Prato et al., 2018). The list of these terms is based on previous scientific literature and can be found in Van Roy et al. (2020).

As mentioned above, accounting data come from Orbis. This dataset collects information on more than 375 million companies and organizations across the globe. However, since patent data refers only to firms who made at least one AI patent application in the period 2000–16 (Van Roy et al., 2020), and a large number of observations have missing values in accounting data, the sample used in this section consists of 8,820 observations.

In this section, we compare firm-level data by country and sector, and in particular we draw attention to e-commerce and financial services firms.

To identify e-commerce activities, we follow the definition suggested by the Voorburg Group[2] which includes members of several National Statistics Offices, such as Canada, Mexico, Chile, Italy and the US. The Voorburg definition takes into account the definition by the OECD in its Guide to Measuring the Information Society (Beth et al., 2018).

To identify the firms providing e-commerce services, we use the NACE classification[3], NACE 4-digit 4791 6311 6312; to identify the firms with financial technologies, we use NACE 2-digit 64 65 66.

The countries included are as follows: the EU with 27 Member States, the US, South Korea, China, Japan and the Rest of the World[4].

[1] Our sample includes firms with at least one AI patent since 2000

[2] The Voorburg Group includes: Mary Beth Garneau et al (Statistics Canada), Erika Barrera (Central Bank of Chile), John Murphy and Andrew Baer (US Census Bureau), Ramon Bravo (INEGI Mexico), Cristina Cecconi, Roberta Cacciaglia, Fabiana Cecconi (Istat, Italy).

[3] 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). And, 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

[4] 28 countries, covering the 5 continents: United Arab Emirates (the), Argentina, Australia, Brazil, Belarus, Canada, Switzerland, Chile, Hong Kong, Israel, India, Iceland, Cayman Islands, Liechtenstein, Moldova, Mexico, Malaysia, Norway, New Zealand, Qatar, Serbia, Russia, Saudi Arabia, Singapore, Thailand, Turkey, Ukraine, Vietnam.

The total factor productivity is built on 3 variables: value-added, working capital per employee, and number of employees.

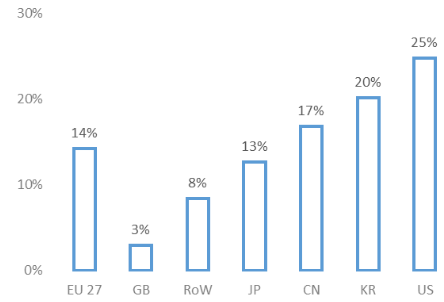
Since both the value-added and the working capital are expressed in nominal terms, we use the Consumer Price Index (2010=100) from the World Bank as a deflator.[5]

The situation is illustrated by 3 groups of charts below:

- distribution and share of firms with patenting activities, by country and sector;
- distribution of AI patent stock (applications and granted patents);
- total factor productivity averages.

3.1.1 Distribution and share of firms with AI patenting activities

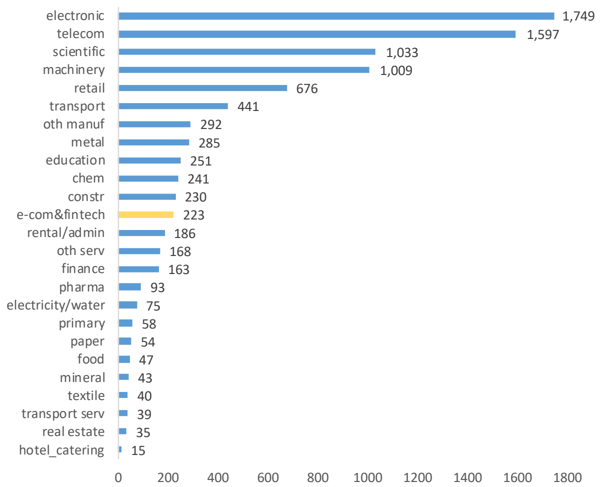
Figure 1. Share of firms by country



Sources: created by the authors and including both patent and financial data, from Van Roy et al. (2020). This database is a combination of the patents extracted from Orbis Patents and Bureau Van Dijk's Orbis database, using the EC TIM text-mining tool.

Figure 2. Distribution of firms by sector

E-commerce and financial technologies account for 223 firms, approximately 2.5% of the total.

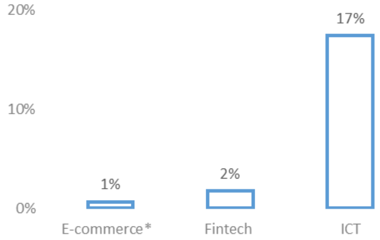


Sources: created by the authors and including both patent and financial data, from Van Roy et al. (2020). This database is a combination of the patents extracted from Orbis Patents and Bureau Van Dijk's Orbis database, using the EC TIM text-mining tool.

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. E-commerce is not a sector per se, since it covers a wide range of activities.

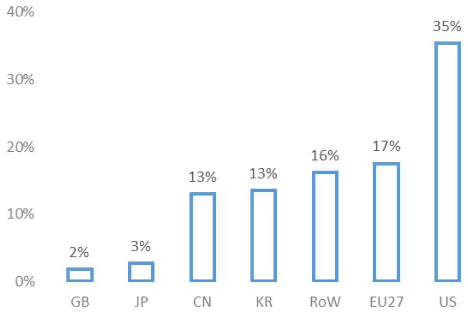
[5] We used the CPI to deflate the working capital, as in McGouldrick (1968).

Figure 3. Share of firms by e-commerce, fintech and ICT



Firms	Number
E-commerce*	60
Fintech	163
ICT	1,597
Total	9,186

Figure 4. Share of e-commerce & fintech firms, by country



Sources: created by the authors and including both patent and financial data, from Van Roy et al. (2020). This database is a combination of the patents extracted from Orbis Patents and Bureau Van Dijk's Orbis database, using the EC TIM text-mining tool.

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. E-commerce is not a sector per se, since it covers a wide range of activities.

3.1.2 Distribution of AI patent stocks: applications and granted patents

Figure 5 shows that the highest number of AI patent applications and stocks of granted patents from 2010 to 2016 were held by Korea, China, Japan and the US.

All countries saw increasing trends in their stock of applications, especially in 2016 (except the EU in 2010). As regards patents grant, stocks were on an increasing trend in the US and China, decreasing in Japan, Korea, the EU.

In 2016, rates of successful application were 37% in the US, 32% in the EU, 24% in South Korea, 23% in Japan, 18% in Korea and 15% in the rest of the world.

Overall, the stock of granted patents for AI represents about 1% of all granted patents.

Figure 5. AI patent stocks, by country (applications and granted patents)

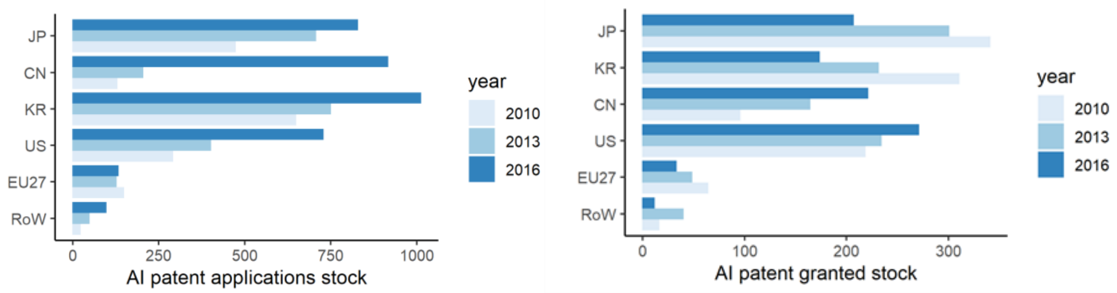
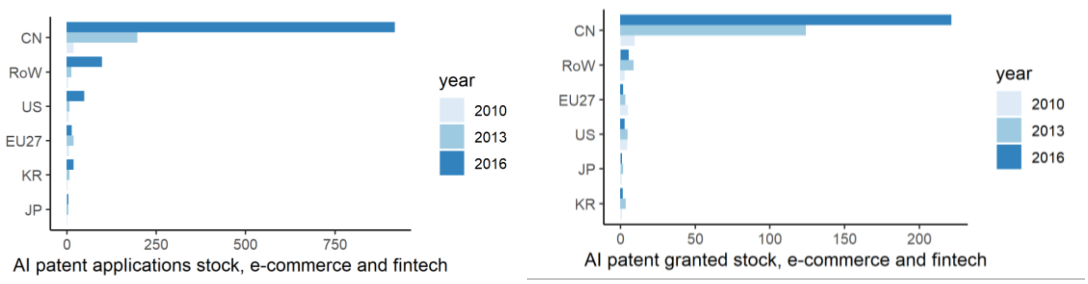


Figure 6. AI patent stocks (applications and granted patents) by country – e-commerce and fintech



Sources: created by the authors and including both patent and financial data, from Van Roy et al. (2020). This database is a combination of the patents extracted from Orbis Patents and Bureau Van Dijk's Orbis database, using the EC TIM text-mining tool.

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. E-commerce is not a sector per se, since it covers a wide range of activities.

3.1.3 Total factor productivity (TFP), firm level comparisons by country

Figure 7 shows the trend in total factor productivity by country from 2010 to 2016.

The EU saw the highest TFP averages between 2010 and 2016, followed by the Rest of the World. Overall, each region shows ups and downs, with falling productivity in 2016 (except Japan, with its rising pattern since 2012).

Firms providing e-commerce and fintech services have higher TFP in the EU and Korea (with Korea in particular starting a steep rise in 2015).

E-commerce and fintech firms with the highest TFP are in the EU and Korea (followed by the US and the Rest of the World).

Figure 8 shows the average TFP gap – the difference between the average TFP of all sectors and the average of TFP of e-commerce and fintech firms.

The gap widened remarkably in Korea and the Rest of the world between 2010 and 2016.

The **left side** of the chart shows the **negative** TFP gap – average TFP of e-commerce and fintech firms is higher than the average of other sectors.

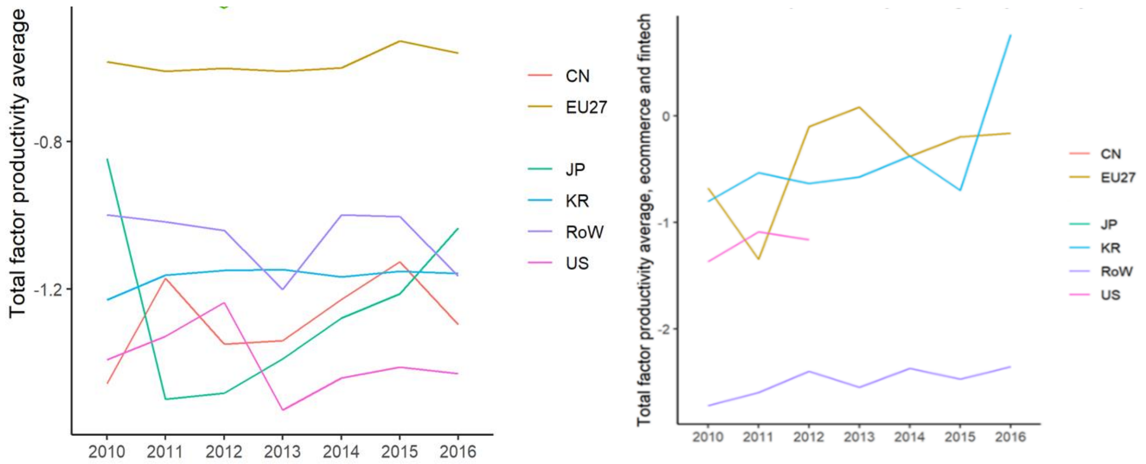
The **right side** of the chart shows the **positive** TFP gap – where average TFP in all sectors is higher than e-commerce and fintech firms.

Firms running e-commerce and fintech businesses on average record a greater productivity in Korea, the EU and the US (only in 2016), compared to the RoW.

This section has shown that, according to our sample of firms:

- the highest stocks of **granted AI patents** in 2010-16 were (in descending order) in Japan, Korea and China, followed by the US, EU27 and the Rest of the World.
- the top 3 in **AI patent applications** were Japan, China and Korea.
- in **total factor productivity**, the top 10 countries are the EU27, Rest of the World and Korea, followed by China, Japan and US.
- firms providing **e-commerce and fintech** services have higher TFP than other sectors in Korea, the EU and the US. The Rest of the world shows the opposite trend – firms in other sectors have higher TFP.

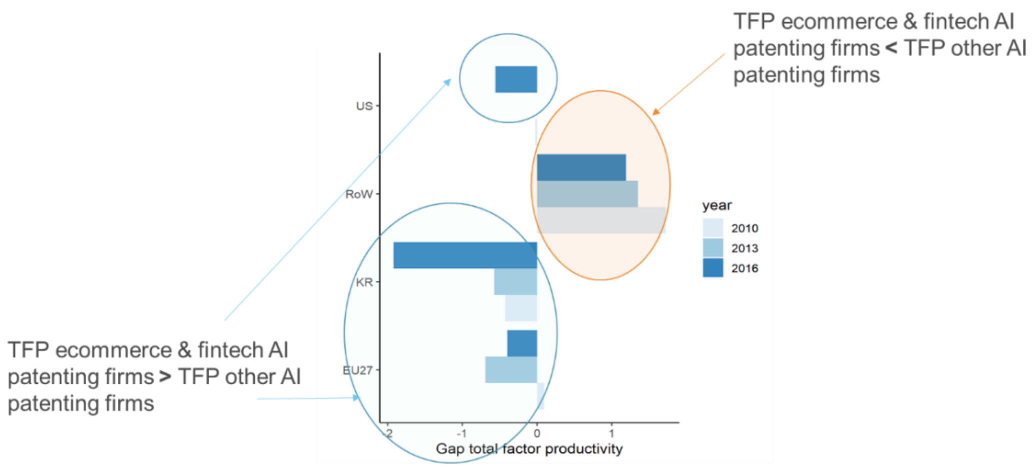
Figure 7. TFP, all sectors, and TFP for e-commerce and financial firms, 2010-2016[6]



Sources: created by the authors and including both patent and financial data, from Van Roy et al. (2020). This database is a combination of the patents extracted from Orbis Patents and Bureau Van Dijk's Orbis database, using the EC TIM text-mining tool.

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. E-commerce is not a sector per se, since it covers a wide range of activities. China and Japan data are missing.

Figure 8. Total factor productivity – average gap



Sources: created by the authors and including both patent and financial data, from Van Roy et al. (2020). This database is a combination of the patents extracted from Orbis Patents and Bureau Van Dijk's Orbis database, using the EC TIM text-mining tool.

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. E-commerce is not a sector per se, since it covers a wide range of activities. China and Japan data are missing.

The next empirical section focuses on AI patenting and its effect on TFP and wages.

[6] Data missing for China and Japan, and partially missing for the US.

3.2 AI patenting – effect on TFP and average wage structure

3.2.1 Data

We used the data described in the patenting activity section 3.1. In the present section the final sample consists of 6,617 observations[7], ending with an unbalanced panel of 1,738 companies observed over the period 2010-2016.

To limit information loss, we only use those accounting variables that are relevant for the production function and necessary to calculate a measure of TFP:

- value-added
- working capital per employee
- number of employees.

Since both value-added and working capital are expressed in nominal terms, we use the Consumer Price Index (2010=100) from the World Bank as a deflator.

Table 1 shows the main descriptive statistics. Notice that the real value-added (RVA), the stock of capital (K), and the input of labour have been log-transformed. All have a right-skewed distribution, with means greater than medians.

Moreover, as expected, the average number of patent applications is always higher than the number of granted patents. On average, our firms make 0.587 AI applications per year, but only 0.192 earn a grant. The average stock of granted AI patents is 1.187 per firm, whereas non-AI patents are much more frequent.

Table 1. Descriptive statistics (N=6,617)

Variable	Mean	Std. Dev.	Min	1st qrt.	Median	3rd qrt.	Max
Ln(RVA)	5.171	2.979	-6.571	2.882	4.800	7.288	13.418
Ln(L)	5.735	2.629	0.000	3.784	5.323	7.502	14.648
Ln(K)	4.762	2.916	-6.914	2.728	4.533	6.832	12.481
AI patent app.	0.587	5.266	0	0	0	0	241
AI patent granted	0.192	1.624	0	0	0	0	61
AI patent granted stock	1.187	8.557	0	0	0	0.614	278
Non-AI patent app.	57.961	337.112	0	0	2	13	5869
Non-AI patent granted	31.453	201.141	0	0	1	7	4108
Non-AI patent granted stock	203.368	1186.462	0	2	8	54.543	25,906

Notes: This table shows the main descriptive statistics for the variables used in analysis.

[7] Whilst in section 3.1 we use 8,820 observations, the use of lower number of observations of this second empirical section is due to the GMM analysis: firstly, because we use only those observations that simultaneously have no missing values in the determinants and in the covariates; secondly, because the GMM approach is based on lagged variables, and the observations at the beginning of the period are lost.

3.2.2 Methodology

This study examines the relationship between patents (applications and granted patents) in AI innovation and firms' TFP.[8]

Using a longitudinal dataset (and terminology from Bell et al. (2018)), we investigate both **cross-sectional (between)** and **time-series (within)** effects:

- '**between'** effect – this will tell us how time-invariant characteristics (such as sectoral differences or average degree of innovation) affect TFP.

- '**within'** effect – by contrast, this will allow us to understand whether investing in AI innovation is rewarding for a firm, controlling for time-invariant heterogeneity.

The departure point for both analyses is the following Cobb-Douglas production function:

$$Y_{it} = qA(X_{it})K_{it}^{\alpha}L_{it}^{\beta}\varepsilon_{it}, \qquad (1)$$

Where:

- Y_{it} is the real value added of firm *i* at time *t*
- q is a constant parameter
- $A(X_{it})$ represents the ex-ante unknown TFP measure
- X_{it} is a vector of TFP determinants
- K_{it} is the capital stock
- L_{it} is the labour input
- ε_{it} is the error term.

Estimating the 'between effects'

This part of the analysis is based on a 2-step procedure:

- **step 1** – deriving a reliable measure of TFP. To do so, we follow a consolidated procedure that is described in Appendix B.

- **step 2** – having obtained this measure of TFP, we use a Correlated Random Effect (CRE) estimator to separate cross-sectional and longitudinal components from the data.[9]

Mundlak (1978) shows that adding individual means for the independent variables represents an effective way to relax the assumption in the random-effects estimator that the observed variables are uncorrelated with the unobserved variables (see also Wooldridge, 2010; Greene, 2011).

The main advantage of this approach with respect to a standard fixed effect estimator is the possibility to estimate the impact of time-invariant characteristics such as sectoral differences by controlling for unobserved heterogeneity.

Formally, we estimate the following transformed Mundlak's model:

$$\ln(A_{it}) = \gamma_0 + \gamma_{1w}(X_{it} - \bar{X}_i) + \gamma_{1B}\bar{X}_i + \gamma_2 Z_i + (\varsigma_i + \upsilon_{it}), \qquad (2)$$

[8] Although AI innovation does not necessarily imply that firms are adopting the innovation, the sectoral composition of our sample indicates that many firms are producing innovation internally rather than selling it. Indeed, only a small fraction of our sample refers to sectors typically involved in ICT development.

[9] The empirical findings presented here are based on Wooldridge's (2009) methodology; however, results do not qualitatively change with the other two measures.

where:

- γ_{1w} is the within effect
- γ_{1B} is the between effect
- Z_i is a set of time-invariant characteristics
- $\varsigma_i + \upsilon_{it}$ is a composite error term.

Whereas the interpretation of the within estimator, γ_{1w}, is rather straightforward, since it indicates the marginal impact of a unit increase in the independent variable on TFP, the interpretation of the between effect, γ_{1B}, is slightly more difficult.

The between coefficient answers the following question: what is the effect of changing the level of $\bar{X}_i$, without keeping the level of X_{it} constant?

In terms of patents, the between effect can also be interpreted as the benefit (cost) of experiencing a unitary increase in the average number of patents, keeping the current absolute deviation constant. Indeed, for any given $X_{it} - \bar{X}_i$, an increase in $\bar{X}_i$ implies that we are moving the firm to a higher innovation pattern.

The between effect also represents the bias we would observe in a pooled-OLS regression that does not consider the firm's average AI performance. If the estimated coefficients of the individual means are statistically significant, then unobserved heterogeneity is likely correlated with observed variables, and the Mundlak correction is appropriate.

Estimating the within effect

Although Equation (2) already contains a full set of within effects, because of time-varying endogeneity, these coefficients can continue to be biased. Time-varying endogeneity may be related to the fact that more profitable firms have more resources to invest in innovation (reverse causality), or more in general it can arise from the omission of important time-varying controls.

Therefore, we use a system GMM estimator to address this issue and properly evaluate the within effects. This approach is appropriate when simultaneity or reverse causality problems can bias the estimates and there are no valid instrumental variables.

To be consistent with the existing literature on firm-level TFP computation (e.g., Olley and Pakes, 1996; Levinshon and Petrin, 2003; Wooldridge, 2009), we log-linearize Equation (1) and estimate the following model:

$$ln(Y_{it}) = ln(A_{it}) + \alpha_t ln(K_{it}) + \beta_t ln(L_{it}) + u_{it}, \qquad (3)$$

where $ln(A_{it}) = \gamma_{1w} X_{it}$. Now, the coefficient γ_{1w} represents the causal impact of a unitary increase in X_{it} on $ln(Y_{it})$. In particular, we are interested in the impact of AI patenting on firms' TFP.

We conclude the analysis by investigating whether the impact of AI innovation on TFP also affects wage growth. More specifically, we re-estimate Equation (3), replacing the TFP measure with wage growth and adding the past level of wages, to account for the fact that firms already paying higher wages may exhibit lower growth rates of wages.

3.2.3 Results

Productivity and AI innovation in e-commerce and fintech sectors

We start the analysis testing whether e-commerce and fintech differ from other sectors in terms of productivity and innovation. Using a simple t-test, Table 2 shows that, on average, firms belonging to the e-commerce or fintech sector exhibit higher productivity levels (independently of the TFP measure we consider) and higher AI innovation.

In this respect, e-commerce and fintech firms are twice as innovative as other firms. By contrast, e-commerce and fintech firms own a lower stock of non-AI patents than other firms. This descriptive evidence reveals that specific service sectors may drive AI innovation.

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.

AI innovation and TFP: sectoral differences

Table 3 provides the OLS and CRE estimates obtained from Equation (2). Columns 1-3 report the coefficients of pooled-OLS regressions, when we consider patent applications, granted patents, and the granted stock of patents, respectively.

According to our estimates, if we do not control for any source of endogeneity, we would conclude that there is a negative relationship between AI innovation and TFP. However, Columns 4-6 show that this negative correlation is due to time-invariant heterogeneity associated with firms' average innovative performance. This means that we cannot interpret OLS coefficients in terms of causal impact of AI innovation on TFP.

Indeed, when we consider the average number of AI granted patents and the average stock of AI patents, the between effect of AI patents is negative and statistically significant. We can formulate two alternative hypotheses explaining this result:

- the first hypothesis goes from AI patents to TFP and refers to the possibility that keeping high levels of AI innovation is costly and these costs are reflected in a lower productivity (cost hypothesis).

- the second hypothesis goes from TFP to AI innovation and is related to the possibility that less productive firms invest in AI innovation to catch up with more productive companies (catching-up hypothesis).

In line with the t-test results, Table 3 also shows a positive coefficient of the average number of granted AI patents in the e-commerce and fintech sectors. Indeed, the higher productivity observed in these sectors is associated with a higher fraction of granted AI patents. These results remain consistent if, together with e-commerce and fintech firms, we consider other firms belonging to the finance and telecommunication industries.

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*

	(1)	(2)	(3)	(4)	(5)	(6)
				(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.
Columns 3 and 6 employ the number of granted patents stock.
IMR stands 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%.

To test the catching-up hypothesis, we included in Equation (2) the firm's initial value for TFP. This strategy is common in economic growth literature, to test the absolute convergence hypothesis (see, e.g., Islam, 1995).

Table 4 shows that, once we control for the initial TFP level, the between effect of AI on TFP disappears. This evidence supports the catching-up hypothesis; that is, less productive firms invest more in AI technologies to recover from their initial productivity gap.

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
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%.

Does investing in AI innovation pay?

Table 5 shows the GMM estimates obtained from Equation (3). Now, the main effect is represented by the within coefficient of AI innovation. Indeed, this coefficient captures the TFP gain of investing in new AI technologies.

According to Column 2, returns to AI granted patents are positive and statistically significant (0.032, $p<5\%$). This means that patents are effectively assigned to more productive innovations. In contrast, both patent applications and the stock of patents do not boost current productivity.

Our results are also in line with the input elasticities found when applying traditional production function models (see Appendix A). However, given the Hansen test p-values, our coefficients seem to be less biased.[10]

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

[10] In Annex A, we may notice that with a Wooldridge (2009) estimator, we must reject the null hypothesis of instruments' exogeneity, whereas, as suggested by the Hansen test, in Table 5, we cannot reject it.

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 obtained from Equation (3).
Columns 1-3 consider as main explanatory variables the number of patent applications, granted patents, and patent stock, respectively.
IMR stands 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%.

Does AI innovation boost wages?

The last question we tackle is whether TFP gains from AI innovation are associated with higher wage growth.

Therefore, we apply the GMM specification adopted in Table 5 also to wage growth. As before, a GMM approach allows us to take into account firm and sector-level heterogeneity, providing general results.

Table 6 clearly illustrates that an additional AI patent increases wages by 1.5 percentage points (Column 2). This means that part of the productivity gain from AI innovation is reflected in higher wage growth rates. Moreover, a smaller increase in wage growth is also observed in firms characterised by a higher number of AI applications and a higher stock of AI patents, despite the lack of a significant impact of these two variables on TFP.

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 obtained from 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 stands 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%.

4 Concluding remarks

Our analysis on the impact of AI innovation on total factor productivity (TFP), with a particular focus on e-commerce and fintech, can be summarized as follows.

We first observe a **general decline in the TFP of AI-patenting firms in the EU and US**, while the rest of the world is catching up (Figure 11).

This result is consistent with the literature showing a generally low, or declining productivity in the world, more specifically in OECD countries and advanced economies (Aghion, Bergeaud, Boppart, Klenow, & Li, 2019; Brynjolfsson, Rock, & Syverson, 2017; Fernald, 2016; Gordon, 2015; Storm, 2019). But as Schmelzing (2020) would say, this is not so surprising.

What is also not very surprising for some scholars (HE, DU, & QIAO, 2020; Trappey, Trappey, Wang, & Hsieh, 2018), is the fact that **e-commerce & fintech AI patenting firms are better off in terms of TFP** than non-e-commerce & fintech AI patenting firms (table 2).

Firms with the highest TFP are those with highest average AI patents granted (table 3). Our results show that the act of filing an AI patent has no effect on TFP – significant effects on productivity are only observable when an AI patent is actually awarded.

Our analysis (table 4), shows **strong evidence of a catching-up hypothesis** – that is, compared to their counterparts in other sectors, e-commerce and fintech firms were successful in achieving innovation, and, through granted AI patents, bringing their TFP closer to the levels shown by firms on the technological cutting edge.

Indeed, the higher productivity observed in these sectors, associated with a higher share of granted AI patents, remains consistent, if – together with e-commerce and fintech firms – we also consider other firms in the finance and telecommunication sectors.

It is interesting to see how granted patents can lead to catching up:

- during periods of **economic downturn**, such as the case of the Japanese Patenting System, which facilitated the awarding of patents, with the goal of protecting firms and incentivising them to strive for continuous innovation and so catch up to the TFP frontier, which they were able to achieve (Maskus & McDaniel, 1999)

- in **competitive environments**, such as discussed by Correa & Ornaghi (2014).

Regardless of the industrial sector of the firm, every AI patent granted contributes to higher TFP by 3.2% (table 5). Comparing these results with Benassi et al. (2020)'s 4IR patents applications, which documented an effect on TFP of approximately 1.5%, it can be said that this is in line with our results; given the fact that our analysis is more narrowly focused on AI patents and does not include the extended realm of 4th industrial revolution patents.

Moreover, our results are not too distant from the analysis of patents granted and filed in the triad (EPO, JPO and USPTO), whose GMM registered a within effect of 3.8% higher TFP in US industries during economic recessions (Giovanis & Ozdamar, 2015).

Finally, our results indicate that **AI innovation boosts wages** (table 6). In fact, we find that TFP gains from AI innovations are associated with higher wages. More specifically, an additional AI patent granted increases a firm's wages by 1.5%, implying that part of the productivity gains that originate from AI innovation are reflected in positive wage growth.

5 Policy implications and future outlook

Our analysis provides evidence that the most reasonable of the two likely explanations proposed is the catching-up hypothesis – that is, firms lagging behind are the ones that more intensely adopt productivity-improving AI technologies.

One policy implication could be to design policies to facilitate adoption of AI technology by firms currently on the productivity frontier (who in theory otherwise have less incentive to do this) and promote more competitive environments and competition by firms.

The idea being to offset some of the main forces associated with technological innovation that hinder growth, such as implementation lags (Brynjolfsson et al. 2017) and reduced aggregate demand (realised output) due to unemployment and reduced labour participation (Gries & Naudé, 2018).

This could be done for instance, by incentivising the licensing of AI technologies, to accelerate their spread without crowding out the innovation incentives of the firms that are catching up.

The most important aspect of any policy intervention on AI innovation is to encourage sustained innovation, since suspending AI innovation activities has been shown to drive TFP down in the long term. Hence the need to sustain it on a continuous basis, as suggested by Huergo & Moreno (2011).

Furthermore, as other scholars have pointed out, there is a strong and clear call for better data, both at firm and country level, which can also enable better cross-regional analysis. Certainly, a commonly shared definition of AI would contribute to good-quality data (Brundage et al., 2018) that could be used to design policies which are more informed and solidly grounded on scientific evidence.

Future areas for investigation could include whether an increase in wages is accompanied by an increase in employment; mapping gender differences in management composition, exploring whether there is a relationship between AI & gender & education, and finally, exploring use cases of AI patenting firms in e-commerce and fintech.

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List of abbreviations and definitions

AI	Artificial Intelligence
E-commerce	Electronic Commerce
EPO	European Patent Office
EU27	The 27 Member States of the European Union
Fintech	Financial technology
FMOLS	Fully Modified Ordinary Least Squares
GMM	Generalized Method of Moments
GPT	General purpose technologies
JPO	Japan Patent Office
JRC	Joint Research Centre
K	Capital
L	Labour
Ln	Natural logarithm
OECD	Organisation for Economic Co-operation and Development
Orbis	Firm level database by Bureau van Dijk
RoW	Rest of the World
SPRU	Science Policy and Research Unit
TIM	Tools for Innovation Monitoring
TFP	Total Factor Productivity
US	United States
USPTO	United States Patent and Trademark Office
W	wages

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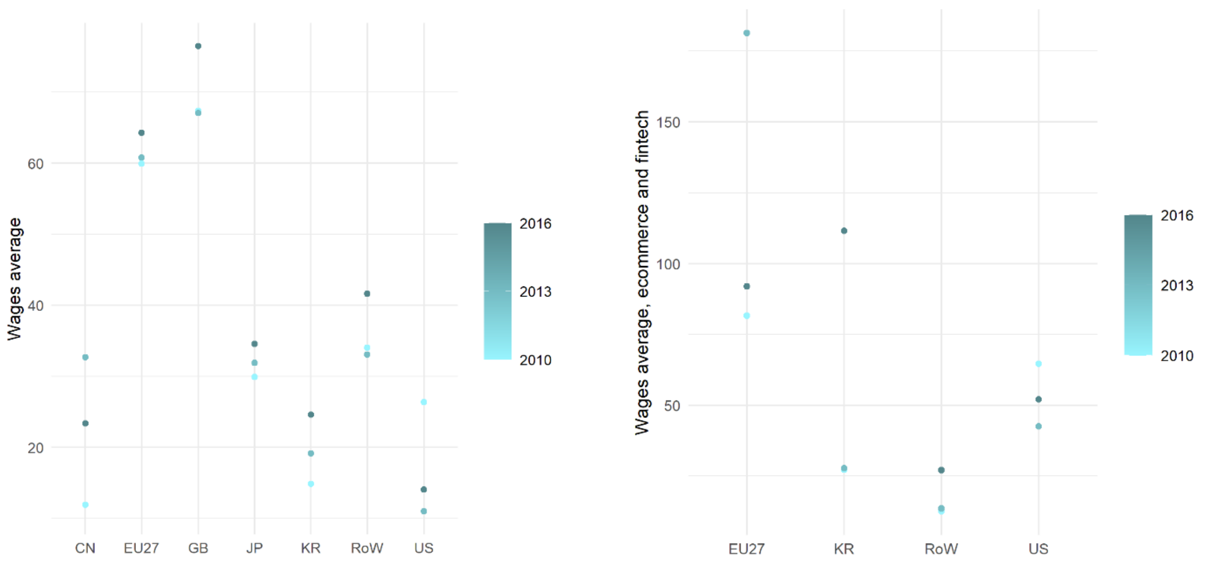
Annexes

Annex 1. Average wages and real GDP

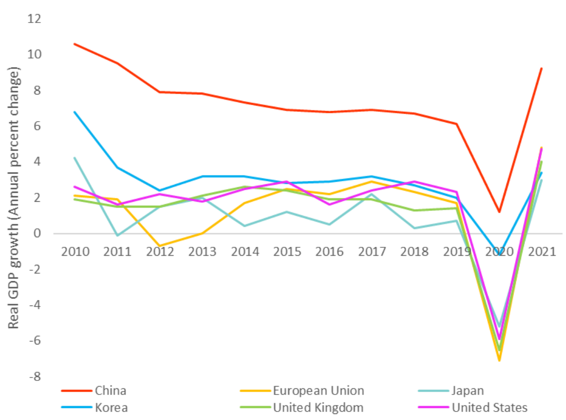
Figure 9. Average wages by country, 2010-16



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

Notes: deflated wages are in thousands of euros; TFP is in natural logarithm

Figure 10. Real GDP annual growth, 2010-21



Source(s): World Economic Outlook _(April, 2020)

Annex 2. Extracting TFP measure

This appendix describes the three econometric techniques used to extract A_{it} from Equation (1). All of them start from a log-linearization of (1):

$$ln(Y_{it}) = ln(\mathrm{q}) + ln(A_{it}) + \alpha ln(K_{it}) + \beta ln(L_{it}) + u_{it}, \qquad \text{(A1)}$$

where u_{it} is the log-transformation of the error term.

The first technique used to extract A_{it} from (A1) is the one proposed in Olley and Pakes (1996).

This method relies on the following assumptions:

a) investments, I_{it}, depend on both capital stock, $ln(K_{it})$, and technical efficiency, $ln(A_{it})$;

b) investments are strictly monotone in technical efficiency;

c) technical efficiency is an unobservable scalar;

d) the capital stock and investments are decided at time *t-1*; the labour input is decided once the shock is observed.

These assumptions ensure the invertibility of investments in technical efficiency and lead to the partially identified model:

$$ln(Y_{it}) = ln(\mathrm{q}) + \varphi(\mathrm{I}_{it}, K_{it}) + \beta \ln(L_{it}) + e_{it}.$$

This model can be estimated by using a non-parametric approach. In the first stage, we take advantage of the Markovian nature of productivity. We can exploit assumption (d) as a moment condition to estimate the production function parameters. Subsequently, we can estimate the following residual equation:

$$ln(Y_{it}) - \beta \ln(L_{it}) = ln(\mathrm{q}) + \mathrm{g}(\ln(\mathrm{A}_{it-1}), \chi_{it}) + e_{it}$$

where g(.) is typically left unspecified and approximated by a n-th order polynomial and χ_{it} is an indicator function for the attrition in the market.

The second technique used to extract A_{it} from (A1) is the one proposed in Levinshon and Petrin (2003). This technique is similar to the one proposed by Olley and Pakes. However, Levinshon and Petrin aimed to overcome the empirical issue of zeros in the investment data. Therefore, they proposed instead to use intermediate inputs, M_{it}, as a proxy variable for investments, under the following assumptions:

a) once the technical efficiency shock is observed, firms immediately adjust the level of inputs according to demand function $M_{it} = M(\mathrm{A}_{it}, \mathrm{K}_{it})$;

b) M_{it} is strictly monotone in A_{it} ;

c) A_{it} is scalar unobservable in $M_{it} = M(.)$;

d) the capital stock is decided at time *t-1*, the labour input is decided once the shock is observed.

The rest of the process follows the Olley and Pakes' procedure.

Finally, we use the method proposed in Wooldridge (2009). This is a more efficient approach for implementing the two methodologies mentioned above. In particular, Wooldridge suggests using a system GMM method to jointly estimate the two stages. In this way, input elasticities do not suffer from the collinearity issues identified in previous methods.

Wooldridge's methodology is based on the following, less stringent assumptions:

a) productivity is an unknown function of unobserved state and flow variables;

b) productivity's dynamics follow a first-order Markov chain process;

c) productivity is an unknown function of lagged productivity.

Table A1 reports the estimates of the Cobb-Douglas production function obtained with the techniques described above. Estimated elasticities are rather constant across the three methods and in line with traditional, aggregate estimates of factor elasticities (see, e.g., Barro, 1991).

Notice that the Wald test on returns to scale rejects the hypothesis of constant returns to scale for the LP and WRDG estimates. However, on the basis of the Hansen over-identification test conducted for WRDG estimates, we cannot rule out that our estimates suffer from time-varying endogeneity. This evidence justifies the use of the augmented GMM model provided in Table 5.

Table 7. TFP derivation

	OP	LP	WRDG
	(1)	(2)	(3)
Ln(L)	0.794***	0.870***	0.765***
	(0.014)	(0.088)	(0.023)
Ln(K)	0.270***	0.253***	0.285***
	(0.086)	(0.052)	(0.023)
IMR	-0.112***	-0.095***	-0.210***
	(0.025)	(0.027)	(0.029)
N	3532	3532	2355
Wald (p-value)	0.31	0.30	0.000
Hansen (p-value)			0.000

Notes: This table shows the derivation of three different TFP measures:
Column 1 considers the methodology proposed in Olley and Pakes (1996).
Column 2 is the methodology proposed in Levinshon and Petrin (2003).
Column 3 is Wooldridge's (2009) estimator.
Robust standard errors are in parentheses. Significance: *p<10%, **p<5%, ***p<1%.

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doi:10.2760/333292

ISBN 978-92-76-24693-0