Intelligent technologies and productivity spillovers: Evidence from the Fourth Industrial Revolution

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Abstract

The possible take-off of a Fourth Industrial Revolution (4IR) is at the core of a vibrant academic debate. An increasingly larger number of studies investigate the effects of the latest generation of new technologies, namely artificial intelligence (AI), flexible automation, additive manufacturing, big data, etc., — hereinafter defined as *intelligent technologies*. Thus far, a great deal of attention has been paid to the effects associated with the adoption of such transformative technologies, whilst the impact associated with their production, and in particular with the development of related technological knowledge, has remained almost unexplored. Using patent data at country level for a sample of industrialized economies between 1990 and 2014, this paper seeks to quantify the productivity spillovers associated with intelligent technologies. We show that the elasticity of aggregate productivity to the stock of knowledge related to intelligent technologies is statistically significant and economically important, ranging between 0.02 and 0.06. Since these innovations have increased by a factor of 3 from the early 1990s, knowledge related to intelligent technologies accounts for 8% of observed productivity change. We also document that the time pattern of productivity spillovers associated with intelligent technology patents may conform to a *productivity J-curve*, corroborating the view that such innovations could behave as General Purpose Technologies (GPTs).

Keywords: Intelligent technologies; Productivity Spillovers; General Purpose Technologies

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1 Introduction

Academics and policymakers dispute around the advent of the Fourth Industrial Revolution (hereinafter 4IR) and the astonishing productive transformations associated with the introduction of the latest generation of new technologies, called *intelligent (or smart) technologies* (Brynjolfsson and McAfee, 2014).

Intelligent technologies are considered path-breaking innovations, with important effects on various dimensions of economic activity. Being equipped with extremely huge computing capabilities, these technologies are able to adapt rapidly to the changing productive environment by acquiring and elaborating massive information in real time. These data are collected online and through connected sensors, are distributed by cloud-computing, and analyzed by artificial intelligence (AI) machines endowed with human-like cognitive abilities. Analytics of digitized information gathered through web contacts, app feedbacks, social networks, enables real-time product customization, broadening the range of product characteristics that firms are able to offer (OECD, 2015).

The new modes of production are based on highly automated machines, three dimensional (3D) systems of design and additive manufacturing and, as a consequence, are more flexible, lean and integrated than in the past (Schwab, 2016). Intelligent technologies are pervasive and have a broad use as they are adopted in different areas of the economy (manufacturing, health, defense, finance, etc.). Furthermore, these technologies are argued to fuel technological dynamics, co-invention and innovation complementarities between producers and users, potentially behaving as the greatest inventions of the past known as General Purpose Technologies, GPTs (Trajtenberg, 2018). The transformations induced by the new technologies are disruptive and may yield breakthrough effects on productivity, employment, and market competition (Cockburn et al., 2018, Brynjolfsson et al., 2018).

The increasing capacity of AI, robots, etc., to perform tasks with capabilities similar to humans – especially routinized manual jobs or cognitive tasks in the domains of voice recognition, visual image recognition, translations – explains why the literature has primarily focused on the occupational effects associated with the adoption of intelligent technologies (Brynjolfsson and Mitchell, 2017). On theoretical ground, several works have sought to design the impact of robotization on the labor market (measured in terms of occupation, wages, income inequality, etc.), identifying several alternative mechanisms of transmission (Berg et al., 2018, Zhang, 2019). Acemoglu and Restrepo (2018a) show that robotisation has several opposing effects. As a first-order effect, automation leads to replacing humans in existing production tasks (displacement effect). However, this is counter-balanced by the expansion of nonroutinised tasks that is favored by automation-driven cost savings or the increased productivity of these jobs (productivity effect). The overall impact of robotisation is negative when the mismatch between the skills required by the new technologies and those offered by the workforce is large, or when the adoption of highly automated machines is so fast to persistently hinder the labor market clearing. Prettner (2019) quantifies numerically that 14% of the observed decline in aggregate income accruing to labor input would be explained by the rising investment in robots.[1]

Evidence on the labor market effects of robotisation, however, is still unclear, and is often limited to few countries. Acemoglu and Restrepo (2020) find that, in the US, one more robot adopted (per thousand workers) has reduced the employment ratio by 0.18-0.34 percentage points (and wages by 0.25-0.50 percentage points). According to Aghion et al. (2018), however, there is little correlation between changes in the intensity of robot adoption and changes in the labor shares on income. Using industry-by-country data, Graetz and Michaels (2018) show that robotisation does not alter the labor demand as a whole, but promotes worker reallocation towards high-skilled positions and away from low-skilled jobs. Kromann et al. (2019) find that automation commands higher wages and, in some cases, even higher employment levels. Arntz et al. (2017) reconsider the risk of occupation loss associated with automation, accounting for task heterogeneity within occupations. They estimate that, in the US, the share of jobs at risk is 9%, and not 38% as estimated in earlier works.[2]

Another finding of the theoretical literature is that advances in AI and robotisation would exponentially increase the rate of economic growth (Aghion et al., 2018). Nordhaus (2020) identifies a set of conditions that would be conducive to a steady-state growth with "singularity", i.e. an equilibrium path with ever-accelerating GDP growth in which, as a result of the explosive computing power, machines would have the same intelligence of humans and would eventually replace workers.

Optimism is high concerning the potentialities of the latest wave of new technologies to speed up the rate of economic expansion. AI is estimated to accelerate the annual rate of GDP growth between 1.2 and

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[1] Prettner and Strulik (2019) develop a model predicting that automation raises the rate economic growth via human capital accumulation, but in the meantime leads income and wealth inequality to widen and the labor share to shrink. DeCanio (2016) simulates the labor market effects of automation applying a flexible production function framework to US industry data. The author finds that the wage bill would decrease even for moderate-to-low substitutability between robots and labor. Since robotization is found to spread income inequality, it is now debated whether, from a social welfare perspective, it is optimal taxing robot adoption (Zhang, 2019, Guerreiro et al., 2017). Other debated issues are how automation relates to demographic change (Abeliansky and Prettner, 2017, Acemoglu and Restrepo, 2018b), re-shoring (Krenz et al., 2018) and the gender wage gap (Ge and Zhou, 2020).

[2] A fewer number of studies have looked at the drivers of automation. Among them, Fan et al. (2020) study the effects of the minimum wage laws on Chinese firms' adoption of robots, finding a significant impact only for the very recent years. See Raj and Seamans (2018) for an early overview of the literature on the occupational effects of robotisation.

4%, and the rate of labor productivity growth by 2%, *above* their long-run trends (Purdy and Daugherty, 2016, Bughin et al., 2018). Notwithstanding, only a handful of works have quantified econometrically the productivity effects associated with the adoption of intelligent technologies (mainly robots). Graetz and Michaels (2018) document that the increased robot usage has contributed to raise labor productivity by 0.4-0.8 percentage points annually since 1997 in OECD industries. This effect is channeled by an increase in production efficiency and a fall in output prices. In magnitude, the impact of robots would not differ much from the growth contribution of steam engine during the First Industrial Revolution, as estimated by Crafts (2004). Kromann et al. (2019) illustrate that a one-standard deviation increase in the intensity of robot usage is associated with a 5 percentage increase in industry-level productivity. PWC (2018) finds that a 1% increase in AI, roughly approximated by cumulative investments in software, databases, computer hardware and machinery, is associated with a higher rate of labor productivity growth in Europe (0.20% per year), America (0.50%) and China (0.90%). Kromann and Sørensen (2020) study the effect of automation on output performance of Danish companies, finding a positive effect between 0.02 and 0.07%. Edquist et al. (2019) provide early-bird evidence on the productivity effect of Internet-of-Things (IoT) at country level for the period 2010-17: a 1% increase in the adoption of IoT (cellular connections per inhabitant) is found to spur the rate of TFP growth by 0.023%.

A common feature of all these studies is to focus on the adoption of intelligent technologies, i.e., they look at the productivity effects channelled by firms' investment in these technologies, such as the installation of industrial robots. However, little is known about the impact associated with the production of intelligent technologies and the development of related technological knowledge. This issue is of primary importance for understanding the nature of the latest generation of new technologies and the breadth of their effects, for at least two reasons. First, albeit knowledge related to intelligent technologies is created in specific segments of the economy, the capacity of a country to produce these technologies is likely to yield aggregate productivity effects as important as those produced by the investment channel. This issue is extensively discussed by prior research on Information and Communication Technologies, ICT (Stiroh, 2002, Inklaar et al., 2005, Venturini, 2015). Second, knowing which countries specialize on developing intelligent technologies is of fundamental importance to gain insights on which economy will take the lead in a technological area crucial for the future (global) growth prospects and the functioning of modern democracies.

A pilot study conducted by the European Patent Office (EPO, 2017) illustrates that technological fields featuring the 4IR are a very active area of innovation, with almost 50,000 patent applications at the EPO as of 2017 (see below). Global trends in specific areas of intelligent technologies, such as AI, are described by WIPO (2019) and Fujii and Managi (2018). Nonetheless, research on economic effects of innovations related to intelligent technologies is hitherto scarce and confined to few countries. Mann and Puttmann (2018) study the link between automation-related innovation (patents) and employment in the US local labor market, finding a positive and quantitatively important association. Dechezlepretre et al. (2019) document that firms' incentives to automation innovation increase with the wages of low-skilled workers. Another line of research has looked at the usage of big data as a means to innovate. Niebel et al. (2018) find that, in Germany, companies exploiting big data bring more new products to the market and have a larger share of turnover associated with these products.[3]

Another challenging issue is the role that intelligent technologies, in particular AI, may play for the development of research and innovation. Tracking advances in the fields of artificial intelligence with patent data, Cockburn et al. (2018) document that deep learning is the most prolific innovative area of AI, well above symbolic systems and robotics. This finding is pathbreaking for the future of research, both within and outside the fields of AI. Deep learning indeed creates highly reliable prediction methods based on neural networks, favoring the development of highly automated (AI-driven) methods of conducting R&D. In other words, deep learning would not be a standard innovation, nor a typical GPT, but rather an invention of a new way of innovating (*GPT of innovation*).[4]

The present paper contributes to this increasingly influential literature providing first genuine evidence at the country level on productivity spillovers generated by knowledge created in the field of intelligent technologies. Our aim is to answer, in a simple and intuitive way, two challenging questions: First, does knowledge related to intelligent technologies yield significant productivity gains? Second, do intelligent technologies behave as the breakthrough inventions of the past, namely as GPTs? As shown in various respects, GPTs such as the steam engine, the factory system, the electricity, and semiconductors, produced sizable productivity gains but only with a long lag after arrival (David, 1990, Jovanovic and

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[3] Relatedly, using big data methods to analyze web information on product lunches, Nathan and Rosso (2019) document that, in the UK, high-tech SMEs are substantially more launch-active than low-tech firms.

[4] AI applications in innovation and research activities are rapidly widening. For instance, in the pharmaceutical sector, AI is used to predict treatment results, design drug and process data, and dedicated machine learning platforms are extensively offered to drug producers (see https://emerj.com/ai-sector-overviews/artificial-intelligence-for-pharmacies-an-overview-of-innovations; accessed October 15, 2019). An overview on the effects of AI for R&D in the chemical sectors can be found in Ulbrich et al. (2015). In the US, the National Aeronautics and Space Agency (NASA) exploits AI to implement several projects, such as to find intelligent life beyond the Earth through the FDL (Federal Development Lab) research accelerator, teamed up with Google Cloud (see https://cloud.google.com/nasa-fdl/).

Rousseau, 2005). Their introduction was often associated with low factor returns and falling productivity, as the new technology forced a change in production modes, factory organisation, and human capital investment. Furthermore, GPTs opened new technological trajectories in downstream industries and favored co-invention between producers and users of the new technology (Bresnahan and Trajtenberg, 1995, Bresnahan, 2001). Since complementary investments required to implement GPTs are intangible in nature, and hence hard to measure, productivity growth declined in the early stages of the diffusion of the new technology, but then surged when measurable output was generated by hidden complementary capital. This would explain why productivity usually follows a J shaped pattern with the advent of a GPT (*productivity J-curve*, Brynjolfsson et al., 2020).

To answer these two questions, we first develop a simple theoretical growth framework explaining how intelligent technology knowledge may affect aggregate productivity and then assess econometrically this prediction using patent data for a sample of industrialized countries from 1990 to 2014. First, we find that significant spillovers are yielded by this knowledge as the elasticity of productivity to the stock of patents in the fields of the 4IR ranges between 0.02 and 0.06. As innovations in this technological area have increased by a factor of 3 in the last quarter of century, knowledge featuring the 4IR would account for 8% of observed productivity growth. The estimated productivity effects are robust to using alternative patent indicators (EPO patent applications vs triadic patent families) and various measurement issues, such as for instance to how technological knowledge is approximated (stock vs flow) and to the assumed rate of knowledge obsolescence (fast vs slow). Not secondarily, these effects are distinct from productivity gains yielded by other sources of knowledge spillovers (patents in other technological fields, human capital, etc.), by the *adoption* of a kind of intelligent technologies such as industrial robots, and other unobservable factors (exogenous technology shocks, foreign knowledge, etc.) that create inter-dependence across countries (Eberhardt et al., 2013). Since intelligent technologies have been expanding rapidly, with disruptive effects on follow-up innovation/production, we also allow the impact of this variable to be heterogeneous across countries and over time. By tracing the time (year-by-year) pattern of productivity effects, we are able to show how the impact of intelligent technologies has changed over time with their take-off and the significant increase in innovation counts. Our empirical model therefore allows to capture the effect of intelligent technologies over their (up-to-now) observed life cycle (gestation and take-off). A focused description of the patenting surge in the fields of AI in the US and Europe can be found in Cockburn et al. (2018), Webb et al. (2018) and Igna and Venturini (2020). From this perspective our evidence represents an important contribution to the debate on technological and social transformations related to the Fourth Industrial Revolution (Jager et al., 2016, OECD, 2018, Autor and Salomons, 2018).

Second, we find that the time pattern of knowledge spillovers generated by intelligent technologies conforms to a productivity J-curve. The productivity effects of intelligent technologies appear to have been low and decreasing at the very beginning of their diffusion. Then, these effects have risen and become positive, stabilizing in terms of value after few years. Although this evidence is, admittedly, purely indicative, it is quite suggestive about the role that intelligent technologies may play as next generation of GPTs, and possibly about their ability to reverse the trend in "secular" stagnation (Gordon, 2015). Our findings would corroborate the view that, along with the mismatch between measured investment and measured output of the new GPT, the productivity J-curve may also be due to the spread (and absorption) of knowledge embodied in intelligent technologies in industries far from their sector of origin. In other words, the observed productivity pattern would be a reflection of technological dynamism, co-invention and innovational complementarities induced by the diffusion of such pathbreaking technologies in downstream sectors (Brynjolfsson et al., 2018). This would be the second contribution of our paper to the literature.

The structure of the work is the following. Section 2 develops the theoretical (structural) framework used to guide the empirical analysis and then describes the econometric model adopted. Section 3 presents data and shows descriptive statistics. Section 4 presents estimates, whilst Section 5 discusses our results quantitatively. Finally, Section 6 concludes the paper.

2 Analytical framework

2.1 Theoretical setting

We develop a baseline setting of R&D-based growth , with exogenous factor allocation, explaining how the steady-state (long-run) equilibrium level of aggregate productivity may depend on knowledge related to intelligent technologies. Following Jones (2005) we assume that, in our knowledge-based economy, there is no physical capital and final output (GDP) depends on low-educated labor, L_t, and the level of productivity, Z_t (t denotes time):

$$Y_t = Z_t L_t \tag{1}$$

Productivity levels reflect the state of overall technology, $\bar{A}$, sourced by knowledge (ideas) accumulated in the area of intelligent technologies, A_I and in the area of traditional technologies, A_T ($f = I$ or T):

$$Z_t = \bar{A}_t^{\mu} = (\prod_f A_t^{\eta_f})^{\mu}, \tag{2}$$

where μ and η_f are exogenous (time-invariant) parameters, with $\mu > 0$, $\eta_f \in (0, 1)$ and $\eta_I + \eta_T = 1$. In final production, knowledge is a non-rival input, labor is rival. μ measures productivity spillovers yielded the overall knowledge stock and characterizes the extent of departure from constant returns to scale associated with the use of the rival input. η_I identifies the proportion of productivity spillovers induced by intelligent technologies, relatively to those yielded by traditional technologies, η_T.

There are two kinds of workers in this economy, low educated/skilled (L_t) and highly educated/skilled (H_t). As shown above, the former are employed in the manufacturing sector to produce final goods, the latter in the knowledge sector to produce intelligent or traditional technologies, $H_t = H_{It} + H_{Tt}$. Assuming full employment, the total number of workers is equal to the working-age population and this grows at the exogenous rate n over time, $N_t = N_0 e^{n \cdot t}$. The labor market equilibrium implies $N_t = L_t + H_{It} + H_{Tt}$. Assuming exogenous labor allocation between sectors,[5] we define s_{Ht} as the share of highly educated employees on total workforce ($s_{Ht} = H_t/N_t$), and s_{ft} as the proportion of highly educated workers employed in each technology sector f ($s_{ft} = H_f/H_t$).

We model ideas creation with the knowledge production function devised by Ha and Howitt (2007) and assume that, in each technology sector, the state of technology (knowledge) evolves according to the following dynamic law:

$$\dot{A}_{ft} = \lambda_f (\frac{H_{ft}}{Q_{ft}})^{\sigma_f} A_{ft}^{\phi_f}. \tag{3}$$

$\dot{A}_f$ is new technological knowledge (new patents), A_f is the stock of existing knowledge (patent stock), and H_f is the number of highly educated workers (researchers) employed to create new technologies (knowledge). λ_f is an exogenous parameter of research productivity, $\sigma_f (> 0)$ identifies returns to R&D investment, whereas ϕ_f captures inter-temporal (within-sector) spillovers, reflecting whether existing knowledge stock crowds in ($\phi_f > 0$) or crowds out ($\phi_f < 0$) the opportunities to develop new technologies. Q_f measures the degree of product proliferation and rationalizes the idea that, as population expands,

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[5] This condition implies abstracting from the agent's choice of optimizing time allocation between education or production, and that of highly educated workers (researchers) of selecting in technology sectors to be employed. This assumption does not alter the main prediction of the model about the long-run relationship between productivity and intelligent technology.

more product varieties are demanded. In each technology sector, product varieties grow proportionally with population $Q_{ft} = N_t^{\beta_f}$. β_f is the exogenous parameter of proliferation/duplication, $\beta_f \in [0,1]$. With expanding product varieties ($\beta_f > 0$), R&D resources spread thinly across a larger number of product projects and hence the amount of R&D input per product line keeps constant ($\beta_f = 1$), or increases less than proportionally with respect to research resources ($\beta_f < 1$). Without product proliferation or, equivalently, with product duplication ($\beta_f = 0$), R&D input is independent of population.

In each technology sector, knowledge grows at the following rate:

$$g_{A_{ft}} = \frac{\dot{A}_{ft}}{A_{ft}} = \lambda_f \big(s_{Ht} \cdot s_{ft}\big)^{\sigma_f} \, \frac{L_{ft}^{\frac{1-\beta_f}{\sigma_f}}}{A_{ft}^{1-\phi_f}} \tag{4}$$

Equation (4) admits, at the sector level, all main mechanisms identified by Schumpeterian growth theory (and their hybrid forms) to explain economic growth: (i) first-generation fully endogenous growth ($\beta_f = 0$ and $\phi_f = 1$); (ii) semi-endogenous growth ($\beta_f = 0$ and $\phi < 1$); and (iii) second-generation fully endogenous growth ($\beta_f = 1$ and $\phi_f = 1$). The latter two families of theories have been developed after the critiques formulated Jones (1995) against the prediction of the first-generation, R&D-based endogenous growth models that, in equilibrium, economic growth would be proportional to the level of R&D (and hence to the scale of the economy).[6]

Along the steady-state growth path, all variables grow at constant, not necessarily identical, rates of growth and the shares of factor (labor) allocation are positive and time invariant. Under second-generation, fully endogenous growth (FE), the sectoral rate of knowledge growth is constant and proportional to the share of researchers on population:

$$g_{A_f}^{fe} = \tilde{\lambda}\big(s_f \cdot s_H\big)^{\sigma_f} \tag{5}$$

Under semi-endogenous growth (SE), the sectoral rate of knowledge growth is constant and proportional to the rate of population growth (or product proliferation):

$$g_{A_f}^{se} = \frac{n}{(1-\phi_f)\sigma_f}. \tag{6}$$

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[6] Schumpeterian growth theories have undergone scrutiny by an increasing number of empirical works. Examples of these studies include Madsen (2008), Ang and Madsen (2011) and Ang and Madsen (2015) for analyses based on country-level data, and Zachariadis (2003) and Venturini (2012) for analyses based on industry-level data. See Bond-Smith (2019) for a survey of this literature and its latest developments.

Along the equilibrium path, the stability of g_{A_f} ensures that TFP growth (g_Z) is constant, being g_Z a weighted average of the sectoral rates of knowledge growth, scaled on the spillover size:

$$g_Z = \mu\big(\eta g_{A_I} + (1-\eta) g_{A_T}\big). \tag{7}$$

A nice property of our setting is that the equilibrium growth rate of TFP is stable irrespective of the type of growth mechanism featuring the research sector (semi- vs fully-endogenous) and the fact that this mechanism may differ between technological fields. Our framework helps conjugate the evidence that, on aggregate, the difficulty of R&D is increasing – corroborating the view that economic growth is semi-endogenous (Bloom et al., 2020), with the evidence that technological progress is growing exponentially in certain technological fields such as AI – potentially giving rise to a growth process with singolarities (Nordhaus, 2020).

Equation (7) implies that, along the equilibrium path, the level of productivity is structurally *dependent* on the state of technological knowledge and is shaped as follows:

$$Z_t = Z_0 \cdot e^{g_z \cdot t} = \tilde{Z}_0 \big(A_I^{\eta} \cdot A_T^{1-\eta}\big)^{\mu} \tag{8}$$

with Z_0, A_{I0} and A_{T0} all positive and $\tilde{Z}_0 = Z_0/(A_{I0} \cdot A_{T0}) > 0$.

2.2 Empirical specification

We are interested to identify the long-run relationship between TFP and the stock of knowledge related to intelligent technologies. Our empirical model is the stochastic counterpart of the structural relation designed by eq. (8), expressed in logs (A_T omitted here for simplicity):

$$\ln Z_{it} = \gamma_{0i} + \gamma \ln A_{I,it-1} + \varepsilon_{it}, \tag{9}$$

where γ ($= \mu\eta$) is the long-run coefficient of interest, i denotes countries and t year points. Equation (9) is a long-run stationary (cointegration) relationship expressing how TFP *responds* to intelligent knowledge stock. As standard in the literature, the explanatory variable is one-year lagged to capture the fact that technological advances may require some time before producing significant economic effects and showing up in productivity statistics (Guellec and Van Pottelsberghe de la Potterie, 2004, p. 358).

Equation (9) can be designed as a dynamic specification and formulated as an Error Correction Mechanism (ECM). To simplify, here we express the ECM model without lag structure of the variables (Z_{it} and $A_{I,it-1}$) and discuss later the implications of considering a less parsimonious specification. Our baseline model is therefore shaped as:

$$\Delta \ln Z_{it} = \alpha_{0i} + \alpha_1 \Delta \ln A_{I,it-1} + \alpha_2 \ln Z_{it-1} + \alpha_3 \ln A_{I,it-2} + CSD_t + \epsilon_{it}, \tag{10}$$

where the operator Δ expresses the (annual) first differences of the variables. α_{0i}'s are country-specific fixed effects capturing, among others, cross-sectional differences in the propensity to innovate (and patent), in technological specialization and other unobservable characteristics that do not change over time. CSD are terms controlling for the effect of time-varying unobservable factors, such as global technology shocks, foreign knowledge, etc., that are sources of co-movements across countries, namely cross-sectional dependence (CSD). These terms will be introduced below. ϵ_{it}'s are spherical error terms.

The long-run productivity effect of knowledge related to intelligent technologies, γ, is derived as a non-linear combination of the parameters estimated from eq. (10), $\gamma = -\alpha_3/\alpha_2$. From an economic point of view, γ measures the breadth of productivity spillovers yielded by A_I. From an econometric point of view, γ is a cointegration coefficient (elasticity) identifying the structural relation between dependent and explanatory variable. Any deviation from the stochastic trend shared by Z and A_I, induced by exogenous shocks, is temporary as the economy adjusts and converges to the long-run equilibrium by filling year by year this gap. α_2 is the adjustment rate towards the (cointegration) equilibrium, capturing the proportion of the disequilibrium gap that is closed annually. A significantly negative value of α_2 is indicative of a stable (cointegration) relation between Z and A_I.

As known, cointegration estimators are asymptotically immune to measurement errors, omitted variables and reverse causality bias, that instead affect static models of regression and call for an identification strategy based on instrumental variables. In eq. (10), α_1 captures short-run co-movements between dependent and explanatory variables, that may be induced by serial correlation or worse simultaneity bias (that is, A_I responses to temporary shocks to Z). In dynamic settings of analysis like ours, the choice of the optimal number of lags, p, of the first-differenced regressor ($\Delta \ln A_{I,it-p}$, with $p = 0, .., T$) is crucial to remove short-run endogeneity bias from long-run estimates. We will address this issue in Section 4.2.

In the analysis below, we initially assume that the effect of technological knowledge is homogeneous across countries and over time. In a later step, we relax this assumption and admit that productivity spillovers may change with the technology base of each country and vary over time with the advances in intelligent technologies. Not less importantly, we also account for alternative (observable) sources of spillovers that, if omitted from the analysis, may lead to biased estimates for γ.

3 Data description

3.1 Data sources and methods

The analysis is developed using country-level data for a sample of 32 industrialized economies between 1990 and 2014.[7] The regression sample is obtained by matching five types of data. First, as main measure of intelligent technologies, we consider the number of innovations in the fields of the 4IR, based on patent applications at the European Patent Office (EPO, 2017, Annex Figure 2). Second, as an alternative indicator, we consider the number of triadic patent families related to the 4IR, extracted from the OECD Triadic Patent Families database (July 2020). Third, we take the total number of patent applications at EPO (by applicant's country of residence and application date) from OECD Directorate for Science, Technology and Industry Economic Analysis & Statistics Division, in order to derive, as difference, a measure of knowledge in technological fields not related to the 4IR (denoted above by A_T). This source is also used for the count of EPO patent applications in the area of ICT. Fourth, we use data on robot installations, extracted from the International Federation of Robotics database (IFR, 2018). Finally, we measure productivity in terms of Total Factor Productivity (TFP) and use data from the Penn Word Tables (PWT), release 9 (Feenstra et al., 2015).

We proxy knowledge related to intelligent technologies, A_I, with the cumulative number of patent applications in the technology areas of the 4IR, based on the classification developed by EPO (2017). For each country, A_I is computed with the perpetual inventory method from the annual number of patent counts (denoted by C): $A_{I,it} = C_{I,it} + (1 - \delta) \times A_{I,it-1}$, assuming a depreciation rate of 15% ($\delta = 0.15$). The initial stock of knowledge is obtained as $A_{I,0i} = C_{I,i0}/(\delta + v_{I,i})$, where v is the average rate of change in patent applications between 1990 and 2014 (Hall and Mairesse, 1995). A similar procedure is adopted for computing the knowledge stock in traditional technologies or ICT, A_T.

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[7] Country list: AUS: Australia AUT: Austria; BEL: Belgium; CAN: Canada; CHN: China; CZE: Czech Republic; DEU: Germany; DNK: Denmark; ESP: Spain; EST: Estonia; FIN: Finland; FRA: France; GBR: Great Britain; HUN: Hungary; IRL: Ireland ISL: Iceland ISR: Israel; ITA: Italy; JPN: Japan; KOR: Korea; MEX: Mexico; NLD: Netherlands; NOR: Norway; NZL: New Zealand; POL: Poland; PRT: Portugal; ROU: Romania; SGP: Singapore; SVN: Slovenia; SWE: Sweden; TUR: Turkey; USA: United States of America.

EPO (2017) classifies innovations as related to the 4IR those when combining four main characteristics: computing, connectivity, data exchange and intelligent devices. These applications can be classified along three distinct (non-mutually exclusive) dimensions: *core technology fields* (around 35% of total 4IR applications), *enabling technology fields* (50%), and technology fields in *application domains* (70%).

Core technologies are inventions concerning: (*i*) Hardware; (*ii*) Software; and (*iii*) Connectivity. These technologies are more directly related to earlier innovations patented in the fields of ICT. Examples of hardware technologies include sensors, advanced memories, processors, adaptive displays. Software technologies include, for instance, intelligent cloud storage and computing structures, adaptive databases, mobile operating systems, virtualisation. Connectivity systems collect patents concerning network protocols for massively connected devices and adaptive wireless data systems.

Enabling technologies are inventions with multiple applications the fields of (*i*) Analytics (interpretation of information such as diagnostic systems for massive data); (*ii*) User interfaces (virtual reality, information display in eyewear); (*iii*) 3-D support system (3D printers and scanners for parts manufacture, automated 3D design and simulation); (*iv*) Artificial intelligence (machine learning and neural networks-based methods); (*v*) Position determination (enhanced GPS, devices for relative and absolute positioning); (*vi*) Power supply (intelligent power handling through situation-aware charging systems and shared power transmission objectives); and (*vii*) Security (adaptive or intelligent safety systems for data or physical objects' security).

Application domains distinguish inventions in terms of their usage: (*i*) Personal (applications pertaining to the individual such as personal health monitoring devices, smart wearables, entertainment devices); (*ii*) Home (applications for the home environment such as smart homes, alarm systems, intelligent lighting and heating, consumer robotics); (*iii*) Vehicles (applications for moving vehicles such as autonomous driving, vehicle fleet navigation devices); (*iv*) Enterprise (applications for business enterprises such as intelligent retail and healthcare systems, autonomous office systems, smart offices, agriculture); (*v*) Manufacture (smart factories, intelligent robotics, energy saving); and (*vi*) Infrastructure (intelligent energy distribution networks, intelligent transport networks, intelligent lighting and heating systems).

A key characteristic of intelligent technologies is of building upon prior technological advances in the field of ICT. According to skeptics (Gordon, 2018), the former technologies would simply represent the latest generation (or follow-ups) of the latter (broader) family of innovations and would not contribute to productivity growth much differently. One may therefore wonder whether intelligent technologies have an independent productivity effect, or rather whether the impact estimated for these innovations reflects the marginal effect of knowledge accumulated in information and communication technologies. On this basis, we use the stock of ICT patents as control factor.

In the current technological age, industrial robots are one of the most diffused disruptive technologies. As discussed in Section 1, these machines have been long disseminating across firms both in manufacturing and service industries. The International Federation of Robots collects data on shipping and installation of multipurpose robots since 1993, classifying them in relation to the purpose, industry, country and year of installation. An industrial robot is defined as "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". We consider the operational stock of robots, which is built by IFR assuming for each machine an average service life of 12 years and immediate withdrawal afterwards; in each year, the operational stock is given by the sum of robots with less than thirteen years from installation. Since incentives to automation investment (*adoption effect*) might be similar to those leading to developing 4IR technologies (*production effect*) – both aim at making production more efficient, we use the stock of operational robots as control to exclude any overlap between the effect of these machines and that of intelligent technology knowledge.

Using data from a single patent office (EPO) has the advantage of reducing the bias associated with the different filing rules existing across countries, but has the drawback of creating a potential home bias for the European countries, whose (measured) patenting activity may result systematically overstated compared to the other economies. Our panel regression analysis controls for this distortion by including country-specific fixed effects and time controls. However, as long as these deterministic components are unable to fully capture cross-country differences in the patenting propensity at EPO, we minimize the risk of (residual) home bias by adopting an alternative indicator of 4IR-related technologies based on triadic patent families. A patent family is a group of patents related the same invention that the applicant extends to foreign patent offices, broadening the jurisdiction of legal protection over the original invention. Triadic patent families are classified by OECD as those applications filed in the three main world's technology markets, the European Patent Office (EPO), the United States Patent Trademark Office (USPTO), and the Japan Patent Office (JPO). OECD re-classifies patents related to the original priority application into a single record to get a unique patent family. As summary statistics below show, triadic patent families are a sub-group of EPO applications but (probably) identify higher quality innovations as the procedure of filing patent protection abroad is expensive and is usually routed only for the best innovations (Dernis and Khan, 2004, Martinez, 2010).

We measure productivity in terms of TFP. This variable is defined as number index and, hence, is benchmarked to 1 in 2011 for each country. This measure of productivity is obtained as Solow's residual, i.e. as difference between real GDP growth and factor input contributions (capital and labor). Labor input is defined as the number of workers multiplied by an index of human capital per worker, derived considering the workforce' s average years of schooling and assuming different rates of return for each educational level. Aggregate capital stock accumulates investment in different asset types, namely structures, transport equipment, machinery, and separately computers, communication equipment, and software (ICT capital). In robustness checks, we use an alternative measure of TFP expressed in relation to US levels. This measure of productivity is derived by deflating relative GDP (expressed at current year prices) with a Törnqvist quantity index of relative factor endowments.

3.2 Summary statistics

Table 1 presents some key summary statistics. The top section of the table reports figures based on EPO patent applications; the bottom section relies on triadic patent families. The annual number of EPO patent applications related to intelligent technologies has been on average 62.8 (standard deviation 145) or, equivalently, 3 patents per million worker if we express these applications as ratio to the employment of the applicant country. Between 1990 and 2014, the stock of intelligent patents has averaged around 258 (in absolute values), showing a 3-factor increase over this time interval. Patents in the fields of the 4IR represent 1.5% of total applications at EPO. This share has increased significantly in the latest years, reaching 4% of total innovations (see Figure 1). The US, Japan and Germany have the largest number of patents in the field, respectively with 500, 357 and 140 applications annually (Figure 2). If we express these figures in ratio to employment, Finland and Sweden stand out as the most innovative countries with 12 and 8 intelligent patents per million worker per year (Figure 3). Summary statistics based on triadic patent families are lower than when using EPO patent applications. Figure 1 shows a common trend between the two series of intelligent patent stock until 2000, but diverged since then on. For sake of precision, it should be stressed that data on triadic patent families are unavailable for all our regression sample (22 vs 32 countries covered by EPO patent applications' data) and include patent grants (rather than patent applications) at USPTO until 2000, making the two series of intelligent patent stock not fully comparable.

[TABLE 1 about HERE]

[FIGURE 1 about HERE]

[FIGURE 2 about HERE]

[FIGURE 3 about HERE]

Figure 4 illustrates the correlation between variation in TFP and intelligent patent stock (based on EPO patent applications) at country level, both expressed in terms of average annual rate of change of logged variables between 1990 and 2014. The coefficient yielded by a simple OLS regression on such cross-sectional data is positive and statistically significant, 0.035. This finding is clearly influenced by China. However, even when we weigh such parameter estimates with GDP per worker (in logs) to mitigate the bias associated with the large variance of the laggards, the OLS coefficient does not change much (0.032).

[FIGURE 4 about HERE]

4 Modelling estimation results

4.1 Baseline estimates

The regression analysis is developed in two parts. In the first part, we estimate productivity spillovers associated with knowledge related to intelligent technologies by addressing various measurement issues that may affect identification of these effects (Table 2). This is a non-trivial issue as the economic literature on the 4IR is at its infancy and researchers still have limited information about the characteristics of new technologies, the nature of embodied knowledge and its degree of pervasiveness. etc. In the second part, we assess the robustness of our findings to various econometric issues, using a richer dynamic specification, admitting heterogeneity across countries and over time in the effect of technological knowledge, and accounting for the impact of (un)observable confounders (Table 3).

Table 2 reports our baseline estimates for the long-run (cointegration) impact of intelligent patent stock on aggregate TFP (γ). The table also displays in brackets the p-value of significance of the estimated parameter obtained with the delta method. This first set of estimates relies on a parsimonious lag structure and does not account for serial correlation in the data. The model is estimated with a set of time dummies to capture the effect of common exogenous shocks. In so doing, we assume that such un-observable factors have identical effects across countries and are source of weak cross-sectional dependence, CSD (Pesaran, 2006). Moreover, in these regressions, heterogeneity is limited to country-specific fixed effects and γ is considered homogeneous across countries.

To exclude spurious regression problems, we have preliminarily studied the dynamic properties of our series. First, we have performed the panel unit test robust to cross-sectional dependence devised by Pesaran (2007). The null hypothesis of unit roots cannot be rejected both for (the logs of) TFP and intelligent patent stock, Z and A_I (p-value equal to 0.52 and 1.00, respectively). Second, we have run the variance ratio test developed by Westerlund (2005) to ascertain the existence of cointegration between these variables. We find that the null hypothesis of no cointegration can be rejected at the maximum level of significance (p-value < 0.01) either when we use the alternative hypothesis of cointegration in some units of the panel sample or we use the alternative hypothesis of cointegration in all panel units. All this ensures that there is a long-run stationary equilibrium (cointegration) relation between Z and A_I. In the regression table, we also report the adjustment parameter (α_2 in eq. 10) which gives insights on the existence of cointegration in the data, along with indicating the speed at which the economy returns to the long-run equilibrium.

In the baseline regression, the elasticity of productivity to the stock of intelligent patents, obtained from EPO patent applications' data, is found to amount to 0.061 and be significant at a 1% level (col. (1)). In column (2), as robustness check, we replicate the baseline regression using a measure of knowledge stock derived from triadic patent families. This estimation points to larger spillovers, maybe reflecting the higher quality content of innovations covered by this patent indicator or the slightly different composition of the regression sample (490 vs 563 obs). In column (3), we use a measure of TFP expressed in relation to US levels (US TFP = 1 every year). Along with neutralizing the differences in purchasing power, this variable allows to better capture the effect of technical change common across countries. In column (4) we exclude the US from the latter estimation to ascertain how sensitive our estimates are to the inclusion of the world's technology leader. In column (5), we replicate our baseline estimation, based on country-specific values of TFP, but exclude the US. Estimates are only slightly more conservative when using the relative measure of TFP, whilst increase in size when excluding the country with largest endowment of intelligent patents.

In the last three columns of Table 2, we assess the robustness of estimates to the nature of the variable used as a proxy for technological knowledge. In column (6), we use the number of patent counts per million worker in place of the cumulative value of intelligent patents. In this way, we mitigate the distortion potentially deriving from the assumptions made in constructing the knowledge stock. In column (7), we still consider the patent stock as a proxy for technological knowledge, but hypothesize a slower rate of obsolescence for intelligent technologies' knowledge. As lower bound value, we take the percentage used by Graetz and Michaels (2018) to depreciate the stock of installed robots at industry-by-country level. Conversely, in column (8), we assume a faster rate of depreciation in building the patent stock (40%). As Li and Hall (2020) show, this percentage well approximates the annual decay of technological knowledge in the computer and software sector, and therefore represents a valid upper bound value for our analysis, as most innovations featuring the 4IR are rooted in the field of information technology (EPO, 2017). Results in columns (6)-(8) largely confirm the stability of our baseline estimates in column 1.

[TABLE 2 about HERE]

4.2 Econometric checks

Table 3 reports our second group of estimates. For comparative aims, column (1) illustrates the results of our baseline regression shown above. As a first check (column 2), we estimate the ECM model controlling for serial correlation in the data, i.e. adding some lags of the first-difference variables (two lags). Using a richer lag structure is important to remove short-run feedbacks between dependent variable and regressors and neutralize thus simultaneity (endogeneity) bias in long-run estimates. As column (2) shows, the main pattern of our results is not altered when we allow for a two-year lag order of the variables. Estimates do not appreciably change even when we consider one or more lags (unreported). All this indicates that reverse causality is a minor concern in our regression framework, as intelligent technologies are produced by a relatively small number of (global) big tech companies whose innovation (patenting) performance is more likely to be affected by own (internal) capabilities than external (country-level) conditions (EPO, 2017, Baruffaldi et al., 2020, Igna and Venturini, 2020).

Next, we account for stronger levels of cross-sectional dependence than usually assumed with the use of time dummies, and adopt the common correlated effects (CCE) devised by Chudik and Pesaran (2015). In our data, high levels of correlation may result from the increasing market integration, the commercialisation of new technologies and the circulation of new technological ideas on a global scale (Eberhardt et al., 2013). All these factors are hard to measure and can yield strong cross-country spillovers and other co-movements, creating error dependence in our empirical model. Using CCE terms we account for all possible forms of un-observable spillovers existing across countries and get consistent estimates of productivity effects of intelligent patent stock.[8] In column (3), we estimate a pooled regression but allow the effect of CCEs to vary across countries, by interacting these terms with country-specific fixed effects. In this regression, the coefficient of intelligent patent stock is lower than in our earlier estimates, but remains highly significant. In the light of the discussion above, this may reflect the presence of unobservable factors that are correlated with our main regressor and cannot be easily captured by time dummies.

In column (4), we relax the assumption of homogeneity in the impact of intelligent patent stock and allow γ to vary for each country (γ_i). As well known, assuming parameter homogeneity may yield seriously biased estimates if this condition is not satisfied (Pesaran and Smith, 1995). For this reason, in column (4), we estimate the empirical model country by country (with CCE terms) and then compute the mean group (MG) value of long-run (country-specific) coefficients. To mitigate the effect of outliers (i.e., countries with anomalously large value of γ_i), we adopt the robust version of the mean group estimator as in Bond et al. (2010).[9] Accounting for cross-country heterogeneity, the parameter size of intelligent technology knowledge increases somewhat compared to the pooled regression with CCE (0.027 vs 0.021 of col. 3).

In columns through (5) to (8), we evaluate the sensitivity of MG-CCE estimates to the presence

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[8] CEE terms are constructed on a annual base as cross-country averages of the dependent variable and regressors.

[9] The robust version of the MG estimator is defined as $\gamma = (1/N) \sum_{i=1}^{N} \omega_i \gamma_i$, where ω is a weight proportional to the closeness of γ_i to the average fit.

of omitted variables, i.e. measurable factors potentially sourcing productivity spillovers that can be correlated with the intelligent patent stock. In column (5), we introduce the cumulative value of EPO patent applications not related to the 4IR (traditional knowledge, A_T), in order to exclude that our estimates collect spillovers associated with knowledge created in other technological areas. In column (6), we include the patent stock in ICT which, as discussed above, is the antecedent field of intelligent technologies (EPO, 2017, Edquist et al., 2019). In column (7), we consider the index of human capital, as made available in the PWT dataset, to verify whether there are more general productivity spillovers associated with educational attainments of the workforce. In column (8), we introduce the operational stock of installed robots to exclude that our estimates for γ are biased by the productivity effects of automation. The risk is potentially high as those countries investing more in robots are also particularly active in patenting in 4IR-related technological fields: in our data, the pairwise correlation between the stocks of intelligent patents and installed robots is 0.66 (significant at a 1% level).

In such robustness checks, all control variables turn out to be not significant (NS), leaving un-changed the overall pattern of results.[10] The coefficient of the intelligent patent stock loses some significance when including the ICT patent stock, a reflection of the high correlation between these variables (0.87). Note that the ICT patent stock turns out to be insignificant even in most bivariate regressions using alternative estimation methods (see Appendix Table A.2). These findings therefore suggest that the impact estimated for intelligent technologies cannot be only seen as the marginal effect of ICT knowledge, but that 4IR-related technologies would have independent productivity effects. From this perspective, our evidence conforms to the results of the firm-level analysis conducted by Igna and Venturini (2020) on the determinants of innovation (patenting) in Artificial Intelligence in Europe. These authors find that AI patentees have self-selected among the most prolific ICT innovators and that prior knowledge acquired in ICT is a necessary but *not* sufficient condition to innovate in AI. In other words, creation of AI knowledge would depend on own specific factors such as, for instance, firm's maturity and knowledge diversification in AI-related fields.

Two important points concerning parameter interpretation deserves discussion. First, the stocks of

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[10] Control variables are added one at the time in order to have sufficient degrees of freedom in estimation, as the model is run on individual country data and each specification includes CCE terms. Similar findings emerge even when we consider the stock of ICT patents or the number of robot installation expressed in per worker terms, or when we introduce a measure of trade openness defined as the import share on GDP (unreported). The adjustment speed differs across specifications in relation to how parameter heterogeneity and cross-sectional dependence are modeled. The adjustment parameter falls outside the significance region in the regression using the robot stock as control, indicating that there is no cointegration between TFP, intelligent patent stock and robot installations, taken together.

installed robots and human capital may not be significant as these factors are already included in the primary inputs (capital and labor) used to compute TFP, implying that there are no excess (or above-the-normal) returns associated with their usage as production factors. Conversely, the insignificance of the patent stocks of traditional technologies and ICT excludes the presence of pure knowledge spillovers associated with these innovations, as they do not enter the GDP production function as inputs (Guellec and Van Pottelsberghe de la Potterie, 2004). Second, our estimates allow to recover a range of values for the parameters of our theoretical framework. Given that the coefficient of intelligent patent stock is significant, whilst that of traditional knowledge is not statistically different from zero (col. 5), we can infer that $\eta = 1$ and $\mu = 0.037$.

As a last robustness check, we run the empirical model by allowing the effect of intelligent patent stock, A_I, to change both along the cross-sectional dimension (across countries) and the time dimension (across years) of the data. This is a challenging issue as these innovations have been developed prevalently in the latest decade, and their patent counts remain fairly below those of other technologies such as ICT. One may then be concerned that the econometric model used, which assumes a constant elasticity between TFP and A_I along the entire time interval, does not fit well the nature of the data but produces biased productivity estimates for A_I, due to the low innovation counts in the gestation period of the new technology and the relatively recent take-off. To accomplish this task, we estimate the ECM model with the Mean-Observation OLS (MS-OLS) estimator (Keane and Neal, 2020). This procedure decomposes the impact of the explanatory variable into three components: an unit-specific term i, a time-specific term t and a common constant ($\gamma_{it} = \gamma_i + \gamma_t + \gamma$). The MO-OLS estimate for γ is obtained by averaging along the cross-sectional and time dimension the observational OLS estimate for γ_{it}, which an estimation of the parameter on each country-year pair. As the last column of Table 3 shows, these estimates do not much differ from the benchmark results reported in column (4), broadly confirming our main inference.

Overall, our regression findings are confirmed by a broader set of sensitivity estimations using alternative estimation methods and different combinations of control variables (see Table A.2).

[TABLE 3 about HERE]

5 Derived knowledge spillovers

5.1 Magnitude of productivity effects

This section discusses quantitatively the magnitude of knowledge spillovers associated with intelligent technologies and investigates how these effects have shown up over time. Our main aim is to understand whether such technologies behave to some extent similarly to the greatest inventions of the past (GPTs). This analysis will allow to gain insights into the pathbreaking effects of the 4IR technologies and better frame our results in the literature.

To get an intuitive measure on the importance of knowledge related to intelligent technologies, we compute how much variation in TFP is explained by the stock of intelligent patents in the light of our regressions. We use estimates in column (4) of Table 3 as reference, since they are robust to various econometric issues and, not secondarily, are obtained from individual country regressions and hence facilitate a comparison in the effects of intelligent technologies between different country groupings.[11]

In Table 4, we compare results for the overall sample of 32 countries with those arising for the group of OECD economies (total sample less China and Singapore), the EU member states (19 countries, Great Britain included) and the US taken alone. For each of these aggregates, we report the cumulative change in intelligent patent stock between 1990 and 2014, the corresponding (mean-group) elasticity of TFP, and in the last column the product between these two terms, which should approximate the percentage of TFP variation explained by knowledge related to intelligent technologies.

Our estimates indicate that 4IR-related technologies have accounted for 8% of productivity change in the overall sample of countries (and OECD members).[12]

Although this finding may be influenced by the sluggish productivity dynamics observed for most countries between 1990 and 2014, which could amplify the effect estimated for fast-growing innovations, the proportion of TFP variation related to intelligent technologies is notable as they represent only 1.5% of total patents at EPO (see Table 1). The scale of this effect is comparable to that found by Edquist et al. (2019) for the Internet of Things (i.e. one type of intelligent technologies) on TFP growth of a global sample of countries. Edquist et al. (2019) quantify that the observed 30 percent increase in IoT connections per inhabitant would have contributed to TFP growth by 0.69% per year. In the time span of their analysis (2010-17), it would consist in a cumulative increase of 5%. The productivity effects

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[11] Using MO-OLS estimates (col. 9, Table 3) yields slightly lower quantitative results. We discuss this issue later.

[12] If we consider the median estimate, the explained proportion of TFP variation would be 7% (see Table A.3 in the Appendix).

estimated for intelligent technologies in our paper are of a smaller order than found for robot investment by Graetz and Michaels (2018). This gap can be explained with the differences in the channel under investigation (production effect of intelligent technologies vs adoption effect of automation), type of effects (spillover vs capital deepening), data aggregation (country- vs industry-level), specification (levels vs rates of change), and procedure of analysis (cointegration vs static IV regression).

According to our estimates, the explained percentage of TFP variation is only slightly larger for the member states of the EU (9%) whilst the predictive capacity of our model is much higher for the US (34%). Since the rate of change in intelligent patent stock is similar among all groupings, differences in explained variation of TFP come from the gap in the spillover effect: the elasticity of productivity to our measure of technological knowledge amounts to 0.128 for the US, but only to 0.028 for the EU members and 0.031 for OECD countries. Table A.3 in the Appendix details the quantitative analysis for each country.[13]

[TABLE 4 about HERE]

5.2 Time pattern of productivity effects

Although knowledge spillovers associated with intelligent technologies look quantitatively important, it does not imply that IoT, robots, AI, etc., are revolutionary as the greatest inventions of the past (Gordon, 2018). The literature on GPTs documents that Industrial Revolutions are waved by the advent of breakthrough technologies which change radically production in core industries, but also favor innovation and technological dynamics in vertically/horizontally related sectors. In brief, GPTs are not only pervasive in the use and disruptive in the effects, but also stimulate technical improvements and innovational complementarities far from their sector of origin, fueling clusters of innovations in downstream industries (Bresnahan and Trajtenberg, 1995). Through this mechanism, GPTs would endogenously drive the process of economic growth (Carlaw and Lipsey, 2006).

Another fundamental characteristic of GPTs is that their implementation requires significant adjustment costs and investments in complementary intangible assets, such as organizational change, human

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[13] Individual country estimates have to be taken with caution due to their low degrees of freedom. In Table A.3, Singapore emerges as the economy with the largest variation of TFP explained by the rise in intelligent patent stock (66%), followed by Sweden, Australia and Poland that are found to perform similarly to the US.

capital accumulation, skill upgrade, workforce training, etc. (Brynjolfsson et al., 2020).[14] As long as the investment rate in complementary assets exceeds the accumulation rate in the installed capacity of the new technology, measured inputs largely overcome forgone output. Hence, returns to investment in GPTs are low or even negative in the early phases of diffusion and turn positive and become quantitatively important after some lag, i.e. when the installed capacity of the new technology achieves its steady-state value and adjustment costs vanish. This would explain why productivity effects of GPTs follow a J shaped curve. To corroborate this view, Brynjolfsson et al. (2020) estimate mis-measured returns of the new technology with the gap between the stock market value and R&D investment of US companies. The rationale is that the market is able to fully evaluate firm investment and, hence, when the stock market value of the firm rises more than observed investment, the difference should reflect the value of intangible investments. Brynjolfsson et al. (2020) find that the stock market value of US companies predicted by R&D stock has followed a J shaped curve between 1960 and 2017. This would match the pattern of measured TFP simulated from their theoretical framework.

Below, we perform a similar analysis and study how knowledge spillovers yielded by intelligent technologies have materialised over time, seeking to understand whether this pattern conforms to the model identified by Brynjolfsson et al. (2020). Figure 5.A displays dynamics of measured TFP as simulated by these authors; in this figure, the horizontal line in orange defines the steady-state equilibrium value where unmeasured input and unmeasured output cancel out. In our setting, the year-by-year impact of intelligent patent knowledge can be derived from the MO-OLS regression. The time pattern of these effects between 1990 and 2014 is shown in Figure 5.B. For comparative aims, Figure 5.C reports the time effects of the ICT patent stock that is used in the MO-OLS as control variable (see column 7, Section C, Table A.2). In Figure 5.B. and 5.C, the horizontal line in orange identifies the long-run (cointegration) coefficient of the regressors: $\gamma = 0.020$ for the intelligent patent stock (significant at 1%), and $\gamma = -0.001$ for the ICT patent stock (not significant). Our graph illustrates that the evolution of knowledge spillovers related to intelligent technologies matches the productivity J-curve identified by Brynjolfsson et al. (2020). TFP effects of intelligent technologies were low and decreasing in the early years, but then increased rapidly in the second part of the time interval converging towards the long-run value. Notably, this pattern seems specific to intelligent technology knowledge (Figure 5.B), as productivity effects associated with advances in the field of ICT follow a different temporal path (Figure 5.C).

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[14] This issue has been earlier discussed by Brynjolfsson and Hitt (2003), Basu et al. (2004), Marsh et al. (2017) in the context of the productivity puzzle related to the ICT boom of the late 1990s.

Our results suggest that the J-shaped curve of productivity could reflect the timing with which knowledge spillovers yielded by intelligent technologies materialize, and not only the mismeasurement of input and output increases associated with the new technology.

This evidence is admittedly indicative and has two main caveats. First, our year-by-year estimates may be affected by the low counts of intelligent technologies, especially in the early half of the sample period, making the time pattern of their productivity effects itself a statistical artifact of sample composition and other measurement issues. Second, the life cycle of intelligent technologies that has been observed thus far is partial, and hence the pattern of productivity effects may still change in relation to how pecuniary and knowledge spillovers of these new technologies will propagate across industries and countries. All this suggests that further research is needed to support the view that AI, robots and other intelligent technologies act as GPTs, and to estimate the delay with which their gains show up in aggregate productivity. Nonetheless, the present paper offers some useful insights to the literature on GPTs and that investigating which technologies may be driving the Fourth Industrial Revolution. First, we show that intelligent technologies may not have only disruptive effects on occupation and jobs as found in earlier works, but could yield important productivity gains. Understanding which force prevails (employment vs productivity effects), or their impact on welfare, goes beyond the scope of the present paper, as it would require a structural model describing all mechanisms of transmission (see for instance Acemoglu and Restrepo, 2018a). Second, our graphical analysis suggests that the mismatch between measured investment and output, shaping the productivity J-curve of GPTs, may depend on the spread (and absorption) of knowledge embodied in these new technologies in industries far from their sector of origin. In other words, the observed pattern of productivity effects of intelligent technologies would reflect technological dynamism, co-invention and innovational complementarities enabled by the diffusion of this new type of GPT (Brynjolfsson et al., 2018). Third, our results cast a fairly positive light on the advent of the 4IR and on the ability of underlying technologies to speed up the growth process and reverse the trend to stagnation (Gordon, 2015). The pessimistic view has gained credit recently (see Syverson, 2017) finding some motivation in the documented decreasing returns to R&D (Segerstrom, 1998, Venturini, 2012, Bloom et al., 2020). According to our more conservative estimates, doubling the patent stock in the field of intelligent technologies would yield a 2-3 percent increase in productivity ($1\% \times 100 \times 0.020/0.027 = 2/3\%$). To get an idea on the magnitude of these effects, it is worth noting that in our sample the cumulative rate of TFP growth slowed down from 4.3 to 1.0% between the 1990s and 2000s. This makes it clear the important role that important intelligent technologies could play to reverse the downward trend in productivity growth. From this perspective, our findings lend support to the view advanced by Mokyr (2018), based on a retrospective analysis of past Industrial Revolutions, that there are no reasons to expect a persistent decline in growth perspectives. Last but not least, our work relates to those studies proving that breakthrough (patented) innovations are valid predictors of future productivity growth. Kelly et al. (2020) document that a one-percent increase in radical patents is historically associated with a 2 percent increase in aggregate productivity in the US, and that this effect shows up in around 5 years from innovation.

[FIGURE 5 about HERE]

6 Concluding remarks

The present paper has offered first-hand evidence on productivity effects enabled by the wave of technologies driving the Fourth Industrial Revolution, 4IR (so-called intelligent technologies). Using country-level data between 1990 and 2014, we have performed a long-run (cointegration) regression analysis relating aggregate productivity to the stock of knowledge in technological fields featuring the 4IR, as proxied by patent applications at the European Patent Office. We have sought to answer two simple questions. First, whether intelligent technologies source knowledge spillovers at an economy-wide level. Second, whether these new technologies behave similarly to greatest inventions of the past, GPTs.

We have found that knowledge related to intelligent technologies yields statistically significant and economically important effects on TFP. From a statistical point of view, intelligent patent stock is found to explain 8% of TFP variation in our sample of countries. From an economic point of view, estimated productivity effects are not trivial as a 1% increase in the stock of intelligent patents is found to raise TFP between 0.020 and 0.027% depending on estimates. Since the amount of these patents has grown by around 300% in the last three decades, our evidence indicates that the development and the implementation of these technologies may be an avenue to relocate productivity growth of industrialized countries on a fast track.

We have also studied the time pattern of spillover effects enabled by knowledge related to intelligent technologies, finding that it conforms to the productivity J-curve devised by Brynjolfsson et al. (2020).

This evidence is admittedly purely indicative. Nonetheless, it is challenging as it would suggest that intelligent technologies could act as GPTs, and be conducive of revolutionary productive transformations. On this basis, evidence presented in this paper calls for further research on the area of 4IR, specifically to understand which intelligent technologies are sourcing spillovers (artificial intelligence, analytics, 3D systems, IoT etc.), identify which industries are involved in knowledge sourcing and exchange (technology producers vs users) and to quantify inter-industry spillover flows.

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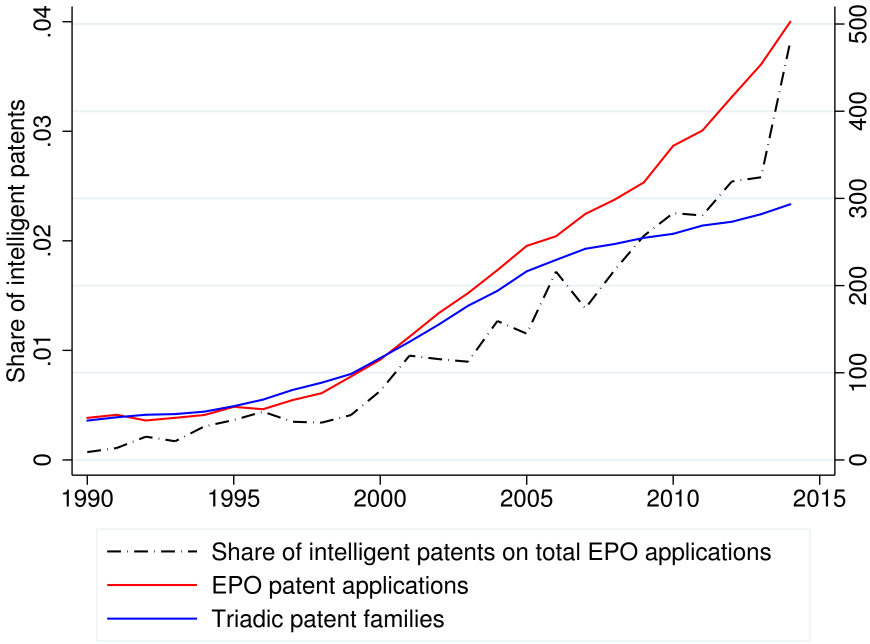
Table 1: **Summary statistics (1990-2014)**

	Mean	Stand. Deviation	Median	Min	Max
TFP	0.98	0.08	0.99	0.55	1.32
EPO patent applications					
Intelligent patents	62.8	145.5	10.0	0.0	1128.0
Intelligent patents per employee (millions)	3.00	4.2	1.33	0.0	37.7
Intelligent patents on total applications (%)	1.5	2.2	1.0	0.00	31.1
Intelligent patent stock	258.7	649.9	31.5	0.32	5048.1
OECD triadic patent families					
Intelligent patents	25.8	74.3	2.0	0.0	560.0
Intelligent patent stock	163.7	427.4	18.3	0.0	2866.5

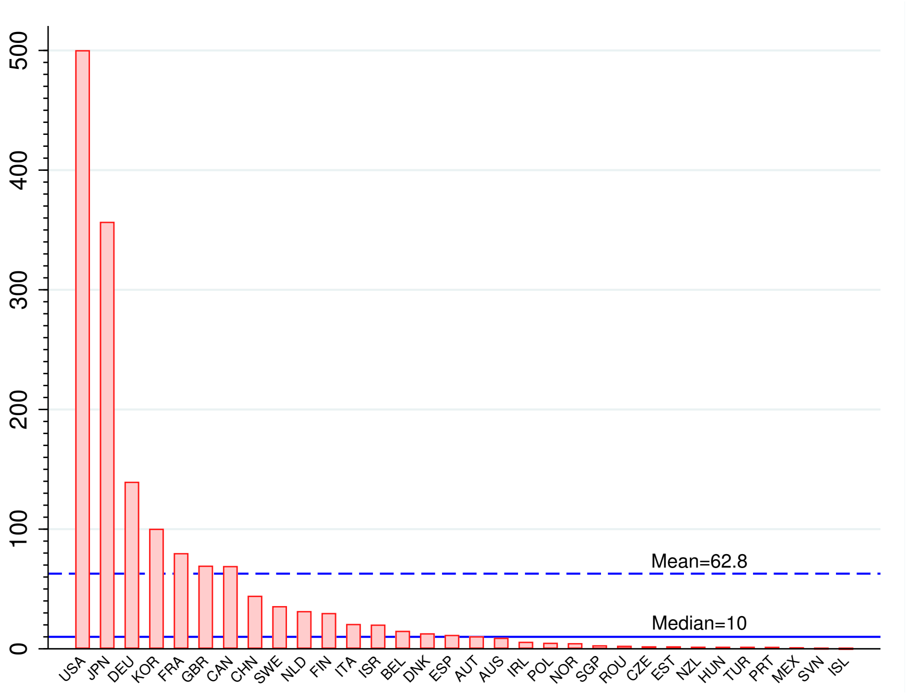
Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). Data on triadic patent families have been extracted with own elaborations from the OECD Triadic Patent Families database. TFP and employment data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).

Figure 1: **Intelligent patents 1990-2014 (un-weighted means)**



Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). Data on triadic patent families have been extracted with own elaborations from the OECD Triadic Patent Families database. TFP data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).

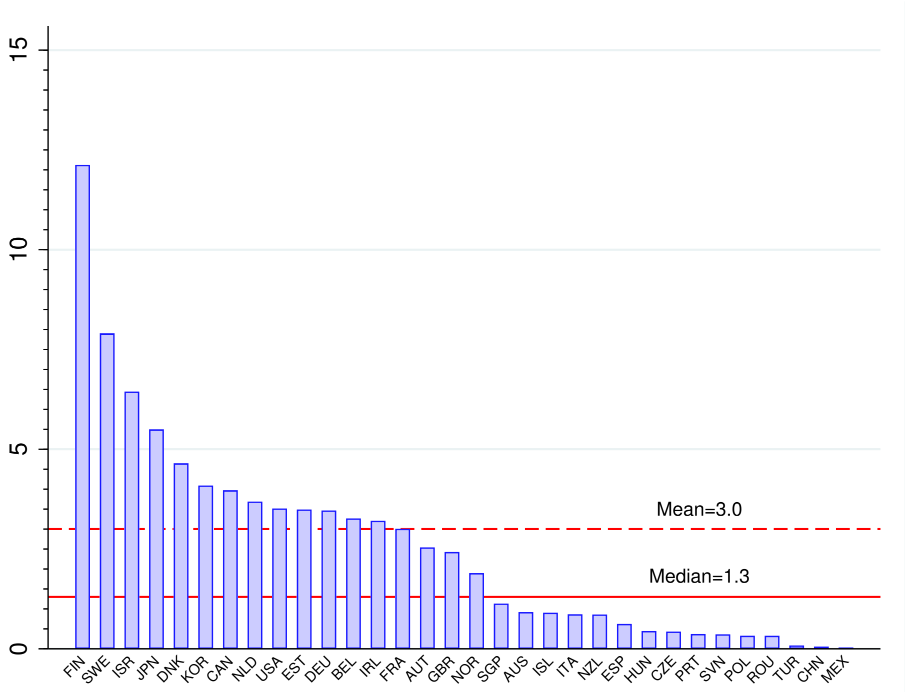
Figure 2: **Intelligent patent counts by country (mean 1990-2014)**



Country list: AUS: Australia AUT: Austria; BEL: Belgium; CAN: Canada; CHN: China; CZE: Czech Republic; DEU: Germany; DNK: Denmark; ESP: Spain; EST: Estonia; FIN: Finland; FRA: France; GBR: Great Britain; HUN: Hungary; IRL: Ireland ISL: Iceland ISR: Israel; ITA: Italy; JPN: Japan; KOR: Korea; MEX: Mexico; NLD: Netherlands; NOR: Norway; NZL: New Zealand; POL: Poland; PRT: Portugal; ROU: Romania; SGP: Singapore; SVN: Slovenia; SWE: Sweden; TUR: Turkey; USA: United States of America.

Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). TFP data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).

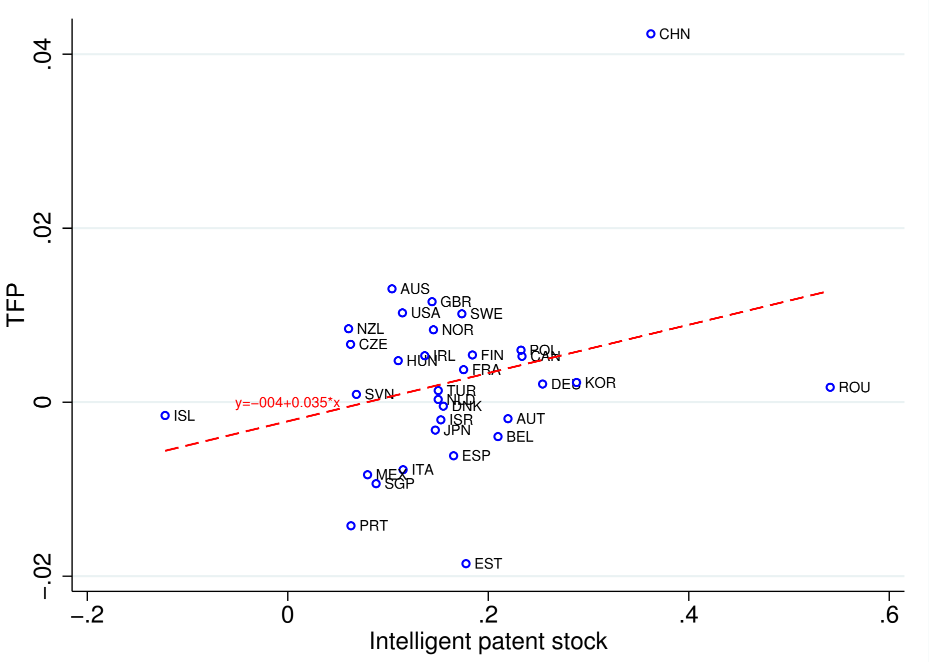
Figure 3: **Intelligent patent counts per million worker by country (mean 1990-2014)**



Country list: AUS: Australia AUT: Austria; BEL: Belgium; CAN: Canada; CHN: China; CZE: Czech Republic; DEU: Germany; DNK: Denmark; ESP: Spain; EST: Estonia; FIN: Finland; FRA: France; GBR: Great Britain; HUN: Hungary; IRL: Ireland ISL: Iceland ISR: Israel; ITA: Italy; JPN: Japan; KOR: Korea; MEX: Mexico; NLD: Netherlands; NOR: Norway; NZL: New Zealand; POL: Poland; PRT: Portugal; ROU: Romania; SGP: Singapore; SVN: Slovenia; SWE: Sweden; TUR: Turkey; USA: United States of America.

Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). TFP data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).

Figure 4: **Correlation between TFP and intelligent patent stock (avg % changes 1990-2014)**



Notes: Average rates of change in logged variables between 1990 and 2004 by country. Country list: AUS: Australia AUT: Austria; BEL: Belgium; CAN: Canada; CHN: China; CZE: Czech Republic; DEU: Germany; DNK: Denmark; ESP: Spain; EST: Estonia; FIN: Finland; FRA: France; GBR: Great Britain; HUN: Hungary; IRL: Ireland ISL: Iceland ISR: Israel; ITA: Italy; JPN: Japan; KOR: Korea; MEX: Mexico; NLD: Netherlands; NOR: Norway; NZL: New Zealand; POL: Poland; PRT: Portugal; ROU: Romania; SGP: Singapore; SVN: Slovenia; SWE: Sweden; TUR: Turkey; USA: United States of America.

Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). TFP data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).

Table 2: **Baseline findings and measurement issues (long-run estimates)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intelligent patent stock	0.061***	0.083***	0.040**	0.045**	0.065***	0.042**	0.061***	0.037**
	[0.004]	[0.001]	[0.030]	[0.018]	[0.002]	[0.022]	[0.004]	[0.031]
	Baseline	Baseline	Relative TFP	Relative TFP / No US	No US	Patent counts per worker	Stock (10%)	Stock (40%)
Patent data	EPO applic.	Triadic families	EPO applications					
Adjustment par. (α_2)	-0.110***	-0.124***	-0.183***	-0.186***	-0.110**	-0.120**	-0.110***	-0.107***
R-squared	0.34	0.28	0.23	0.24	0.34	0.34	0.32	0.33
Obs.	563	490	563	540	540	465	563	563

Notes: The dependent variable is the level of TFP. The long-run coefficient of the explanatory variable is derived from Error Correction Mechanism (ECM) estimates ($\gamma = -\alpha_3/\alpha_2$). Country-specific fixed effects and year dummies are included in all specifications. *p*-values of significance obtained with the delta method are reported in brackets. ***,**,* significant at 1, 5 and 10% respectively.

Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). Data on triadic patent families have been extracted with own elaborations from the OECD Triadic Patent Families database. TFP data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).

Table 3: **Productivity effects of intelligent patent stock: Econometric checks**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intelligent patent stock	0.061*** [0.004]	0.051** [0.011]	0.021** [0.015]	0.027** [0.034]	0.037** [0.029]	0.029* [0.090]	0.034** [0.048]	0.046** [0.027]	0.020*** [0.000]
Controls	No	No	No	No	Traditional patents (NS)	ICT patents (NS)	Human capital (NS)	Robot stock (NS)	No
Adjustment par (α_2)	-0.110***	-0.140***	-0.461***	-0.551***	-0.701***	-0.666***	-0.696***	-0.489	-0.188***
Estimator	FE-OLS	FE-OLS	FE-OLS	MG	MG	MG	MG	MG	MO-OLS
CSD control	TD	TD	CCE	CCE	CCE	CCE	CCE	CCE	CCE
Parameters	Homogeneous	Homogeneous	Homogeneous	Heterogeneous across countries	Heterogeneous across countries	Heterogeneous across countries	Heterogeneous across countries	Heterogeneous across countries	Heterogeneous across countries and over time
Serial correlation	No	Yes	No	No	No	No	No	No	No

Notes: The dependent variable is the level of TFP (logs). The long-run coefficient of the explanatory variable is derived from Error Correction Mechanism (ECM) estimates ($\gamma = -\alpha_3/\alpha_2$). *p*-values of significance obtained with the delta method are reported in brackets. All specifications use: *i*) country-specific measures of TFP benchmarked to 1 in 2011; *ii*) the stock of intelligent patents obtained with the perpetual inventory method and a depreciation of 0.15; *iii*) no control for serial correlation except in col. 3 where we allow for two-year lags of the first-differenced variables. Cross-sectional dependence (CSD) controls: TD= time dummies. CCE= common correlated effects. FE-OLS= Fixed Effect OLS estimator. MG= Mean Group estimator. MO-OLS= Mean Observation OLS estimator. NS= not significant. ***,**,* significant at 1, 5 and 10% respectively.

Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). TFP and human capital data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015. Traditional patent applications and ICT patent applications data come from OECD Directorate for Science, Technology and Industry Economic Analysis & Statistics Division, Patent Database. Robot data come from IFR database (IFR, 2018).

Table 4: **Variation of TFP explained by intelligent patent stock (by country groups)**

	Cumulative change in intelligent patent stock (1)	Mean-group Elasticity (2)	Explained TFP variation (3)
Total	278%	0.027**	8%
OECD	272%	0.031**	8%
EU	289%	0.028*	9%
US	263%	0.128**	34%

Notes: Column 1 reports the cumulative rate of change in intelligent patent stock between 1990 and 2014. Column 2 reports the long-run elasticity based on MG-CCE estimates as of column (4), Table 3. Column (3) reports the product between the values in columns (1) and (2). The total sample includes 32 countries. The OECD group includes 30 countries (total sample less China and Singapore). The group of the EU member states includes 18 countries (Great Britain is included). **,* significant at 5 and 10% respectively.

Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). TFP data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).

Figure 5: **Intelligent patent stock and productivity J-curve**

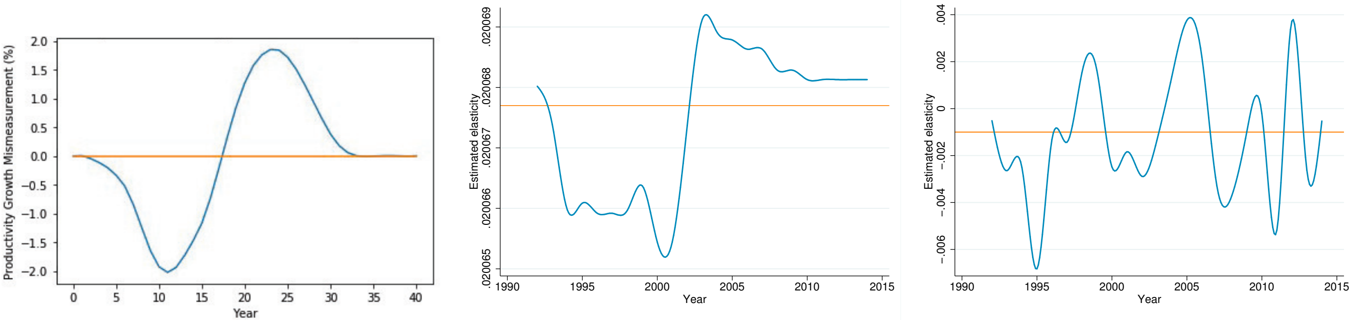


Figure 5.A: Theoretical pattern (source: Brynjolfsson et al., 2020)

Figure 5.B: Elasticity of TFP to intelligent patent stock (source: own estimates)

Figure 5.C: Elasticity of TFP to ICT patent stock (source: own estimates)

A Appendix

Table A.1: Summary statistics by country (average 1990-2014)

		Intelligent patent counts	Intelligent patents per employee	% rate of change in intelligent patents
1	AUS	9.3	0.9	14.6
2	AUT	10.5	2.5	21.7
3	BEL	15.1	3.3	20.2
4	CAN	69.2	4.0	16.9
5	CHN	44.4	0.1	37.0
6	CZE	2.2	0.4	0.0
7	DEU	139.7	3.5	23.7
8	DNK	13.0	4.6	14.5
9	ESP	11.7	0.6	20.4
10	EST	2.1	3.5	9.6
11	FIN	30.0	12.1	16.9
12	FRA	80.0	3.0	16.5
13	GBR	69.6	2.4	9.0
14	HUN	1.8	0.4	14.6
15	IRL	5.9	3.2	14.6
16	ISL	0.2	0.9	0.0
17	ISR	20.3	6.4	9.6
18	ITA	20.8	0.9	7.5
19	JPN	356.9	5.5	13.4
20	KOR	100.4	4.1	24.0
21	MEX	1.3	0.0	7.2
22	NLD	31.6	3.7	11.2
23	NOR	4.8	1.9	13.9
24	NZL	1.9	0.9	2.0
25	POL	5.1	0.3	33.0
26	PRT	1.7	0.4	-8.1
27	ROU	2.6	0.3	97.3
28	SGP	3.0	1.1	5.7
29	SVN	0.4	0.4	69.3
30	SWE	35.7	7.9	18.3
31	TUR	1.8	0.1	20.1
32	USA	500.3	3.5	10.4
	TOTAL	62.8	3.00	15.4

Notes: Own elaborations on data on EPO patent applications from EPO (2017) and employment from the Penn World Tables, release 9 (Feenstra et al., 2015).

Table A.2: Parameter estimates, FE-OLS, MG-CCE and MO-OLS regressions (long-run coefficients)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Section A – FE-OLS + TD					
Intelligent patent stock	0.061***					0.055**	0.036*	0.059***	0.053**
	[0.004]					[0.015]	[0.075]	[0.002]	[0.030]
Traditional patent stock		0.048*				0.019			
		[0.078]				[0.522]			
ICT patent stock			0.044***				0.030*		
			[0.005]				[0.085]		
Human capital				-1.001*				-1.074**	
				[0.058]				[0.024]	
Robot stock					0.013				-0.007
					[0.539]				[0.757]
R-squared	0.336	0.328	0.344	0.332	0.34	0.337	0.349	0.345	0.349
Obs	563	563	563	563	463	563	563	563	463
				Section B – FE-OLS + CCE					
Intelligent patent stock	0.021**					0.004	0.023**	0.018**	0.044***
	[0.015]					[0.495]	[0.012]	[0.014]	[0.000]
Traditional patent stock		-0.019				-0.008			
		[0.445]				[0.745]			
ICT patent stock			0.008				0.001		
			[0.517]				[0.916]		
Human capital				-1.734***				-1.666***	
				[0.000]				[0.000]	
Robot stock					-0.013				-0.031**
					[0.445]				[0.043]
R-squared	0.624	0.686	0.629	0.654	0.57	0.779	0.723	0.757	0.707
Obs	563	563	563	563	463	563	563	563	463
				Section C – MG-CCE					
Intelligent patent stock	0.027**					0.037**	0.029*	0.034**	0.046**
	[0.034]					[0.029]	[0.090]	[0.048]	[0.027]
Traditional patent stock		0.001				-0.015			
		[0.962]				[0.794]			
ICT patent stock			0.005				0.002		
			[0.827]				[0.906]		
Human capital				0.084				-0.079	
				[0.786]				[0.862]	
Robot stock					-0.005				-0.028
					[0.860]				[0.234]
	0.013	0.013	0.011	0.013	0.014	0.008	0.01	0.009	0.009
	563	563	563	563	459	558	558	558	454
				Section D – MO-OLS					
Intelligent patent stock	0.020***					0.010***	0.020***	0.019***	0.050***
	[0.000]					[0.000]	[0.000]	[0.000]	[0.000]
Traditional patent stock		-0.057***				-0.036***			
		[0.000]				[0.000]			
ICT patent stock			0.010***				-0.001*		
			[0.000]				[0.070]		
Human capital				-0.254***				-0.711***	
				[0.000]				[0.000]	
Robot stock					-0.008*				-0.067***
					[0.070]				[0.000]
	563	563	563	563	463	563	563	563	463

Notes: The dependent variable is the level of TFP (logs). The long-run coefficient of the explanatory variable is derived from Error Correction Mechanism (ECM) estimates ($\gamma = -\alpha_3/\alpha_2$). *p*-values of significance obtained with the delta method are reported in brackets. All specifications use: *i*) country-specific measures of TFP benchmarked to 1 in 2011; *ii*) the stock of intelligent patents obtained with the perpetual inventory method and a depreciation of 0.15; *iii*) no control for serial correlation. TD= time dummies. CCE= common correlated effects. FE-OLS= Fixed Effect OLS estimator. MG= Mean Group estimator. MO-OLS= Mean Observation OLS estimator. ***,**,* significant at 1, 5 and 10% respectively.

Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). TFP and human capital data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015. Traditional patent applications and ICT patent applications data come from OECD Directorate for Science, Technology and Industry Economic Analysis & Statistics Division, Patent Database. Robot data come from IFR database (IFR, 2018).

Table A.3: Estimated variation of TFP explained by intelligent patent stock

		Cumulative change in intelligent patent stock	Elasticity	Significance	Explained TFP variation
1	AUS	239%	0.135	Yes	32%
2	AUT	373%	0.002	No	.
3	BEL	419%	0.001	No	.
4	CAN	491%	0.030	Yes	15%
5	CHN	579%	-0.256	No	.
6	CZE	75%	0.097	No	.
7	DEU	585%	0.014	Yes	8%
8	DNK	264%	-0.027	No	.
9	ESP	380%	-0.064	No	.
10	EST	124%	0.514	No	.
11	FIN	424%	0.040	Yes	17%
12	FRA	403%	0.055	Yes	22%
13	GBR	331%	0.050	No	.
14	HUN	187%	0.008	No	.
15	IRL	287%	-0.012	No	.
16	ISL	-159%	3.227	No	.
17	ISR	336%	-0.008	No	.
18	ITA	265%	0.078	No	.
19	JPN	339%	-0.029	No	.
20	KOR	605%	-0.042	No	.
21	MEX	72%	0.106	No	.
22	NLD	345%	0.051	No	.
23	NOR	218%	0.040	No	.
24	NZL	91%	-0.044	No	.
25	POL	233%	0.135	Yes	31%
26	PRT	44%	0.546	No	.
27	ROU	271%	-0.015	No	.
28	SGP	167%	0.393	Yes	66%
29	SVN	116%	-0.002	No	.
30	SWE	365%	0.091	Yes	33%
31	TUR	165%	-0.001	No	.
32	USA	263%	0.128	Yes	34%
	Mean	278%	0.027		8%
	Median	235%	0.030		7%

Notes: Elasticities are derived from by MG-CCE estimates, see column (4), Table 3.
Sources: Data on EPO patent applications in the technology areas of the 4IR are taken from EPO (2017). TFP data are taken from the Penn World Tables, release 9 (Feenstra et al., 2015).