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THE PARADOX OF THE PRODUCTIVITY SLOWDOWN IN THE KNOWLEDGE ECONOMY

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The paradox of the productivity slowdown in the knowledge economy*

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Abstract

Paul David's intellectual legacy offers a compelling framework to address the new productivity paradox: the knowledge age is visible everywhere but in the productivity statistics. The apparent and hopefully transient decline in productivity growth rates is due to the diffusion of new knowledge-intensive technologies and the increase in the size of production inputs triggered by the new accounting procedures which capitalize intangible assets. The capitalization of intangible assets has caused a shift effect and an increase in the size of capital inputs which will continue to increase as long as firms continue to introduce and adopt knowledge intensive technologies. Once their diffusion is complete, this shift effect and the apparent productivity decline will cease. We provide empirical evidence at the European sectoral level of the diffusion of intangible assets and its strong and positive effect on total factor productivity when these intangible assets are not capitalized, and its negative effects on total factor productivity when they are capitalized and are included in production function estimates as inputs.

Keywords: Knowledge intensive direction of technological change; Capitalization of intangible assets; Diffusion of intangible assets; Productivity paradox; Productivity slowdown.

JEL classification: O33

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1. Introduction

Paul David's legacy is fundamental for understanding the factors underlying the productivity paradox that characterizes the transition to a knowledge economy. This new productivity paradox refers to the contradiction between the knowledge intensive direction of technological change and the apparent decline in productivity growth rates. Growth accounting exercises and analyses of the relations between technological change and economic growth conducted during the 20th century revealed numerous productivity puzzles including the paradox that emerged at the end of that century which was related to the diffusion of information and communication technologies (ICTs).

Paul David (1990: 355) noted that:

> Many observers of recent trends in the industrialized economies of the West have been perplexed by the conjecture of rapid technological innovation with disappointing slow gains in measured productivity. A generation of economists who were brought up to identify increases in total factor productivity indexes with 'technical progress' has found it quite paradoxical for the growth accountants' residual measure of the 'total advance of knowledge' to have vanished at the very same time that a wave of major innovations was appearing ….

According to Martin Baily and Robert Gordon (1988), the last few decades of the 20th century were characterized by a slowdown in total factor productivity growth rates which was hard to reconcile with evidence about the fast rates of introduction of radical innovations; this prompted the now well-known observation from Robert Solow that "you can see the computer age everywhere but in the productivity statistics".

David (1990) showed that the diffusion of systemic technologies requires a long period of time, and that their introduction and adoption display positive effects on the whole economy only over the long term. He refers to the relevant institutional changes that take place alongside their introduction and adoption and do affect growth accounting. The arguments elaborated by Paul David help our understanding of the latest productivity paradox that you can see the knowledge age everywhere but in the productivity statistics.

Recent empirical evidence suggests that in most advanced countries productivity growth rates have been decreasing since the dawn of the new century. According to Gordon (2016) and the extensive literature on which his approach is founded, declining productivity growth is a reliable sign of a decline in technological opportunities which is supported by Bloom et al. (2020): ideas are becoming more difficult to find. The generation of new knowledge from the recombination of existing knowledge items becomes more difficult due to the increasing number of specialized competencies required: that is, the Renaissance man is dead (Jones, 2009). European level empirical evidence would seem to support these findings and suggests that the productivity slowdown seems driven by a technological gap between the most productive firms and lagging firms (Andrews, Criscuolo and Gal, 2016; Chen and Lee, 2023; Goodridge and Haskel, 2023).

Nevertheless, the advanced economies are characterized by the emergence of a knowledge economy. In the production process, physical capital is being replaced by technological knowledge as the most critical input, along with skilled labor (Antonelli, 2019; Antonelli, Orsatti and Pialli, 2023a). The emergence of the knowledge economy has been accompanied by the new knowledge-intensive and physical-capital-saving direction of technological change in advanced countries exposed to rapid economic globalization and an abundance of knowledge compared to industrializing labor-intensive economies. In this context, the diffusion of knowledge as a capitalized input plays a central role.

This article focuses on the productivity paradox emerging from the growing national accounting practice of capitalizing intangible assets. Precisely, we hypothesize that the capitalization of knowledge items which previously were included in current expenditure (e.g. R&D employees' wages) increases the stock of production inputs but reduces total factor productivity (TFP) as a measure of the residual contribution to productivity. We argue also that the reduction in TFP following the capitalization of intangible capital becomes stronger as intangible intensity increases, which suggests that the transition to intangible capital also affects productivity growth rates. Thus, although the flow of knowledge-related investments boosts productivity, when capitalized and added to the stock of production function inputs it has the paradoxical effect of reducing TFP estimates.

We test our intuitions at the sectoral level using a sample of 11 European countries observed from 1995 to 2019. We use EUKLEMS & INTANProd database which provides national accounting data on financial variables and intangible stock series and enables descriptive analysis of the diffusion of capitalized intangibles. The descriptive evidence on the intensity of intangible capital shows that the elements characterizing the diffusion of new knowledge intensive inputs, which is traditionally used to distinguish low- and high-tech industries, are blurred by late but rapid rates of adoption and increase in intangible assets by traditional manufacturing and service industries.

To estimate sectoral level TFP, we rely on the method proposed by Olley and Pakes (1996) which accounts for unobservable time-varying productivity shocks, since the use of standard ordinary least square (OLS) techniques weakens the consistency of the output elasticities. We estimate two different production functions at the country-industry level to obtain two distinct TFP measures. The first includes only labor and physical capital among the production inputs; the second is augmented with the inclusion of intangible capital.

We provide several results. First, we show that the first measure of TFP is positively correlated with intangible intensity, measured as intangible investment divided by total investment. This result confirms the link between the residual and the investment in knowledge intensive activities found in the literature (Griliches, 1998; Crepon, Duguet and Mairesse, 1998; Bontempi and Mairesse, 2015). Importantly, we show that this correlation is significantly higher than the correlation between the second measure of TFP and intangible intensity. Second, we show that the capitalization of intangible assets affects the rate of increase of TFP, which provides new insights into the positive effects of R&D expenditure on productivity growth (Hall, Lotti and Mairesse, 2013; Mohnen and Hall, 2013). Third, we show that the two estimated TFP measures differ substantially, with the former always larger than the latter, and show also that this difference significantly increases over time. Fourth, we demonstrate that the increasing gap between the two estimated TFP measures is driven by the increased contribution of intangible capital to sectoral value added.

Our empirical evidence shows that the decline in the rates of productivity growth parallels the emergence of the knowledge economy and the diffusion of knowledge capitalized as an intangible asset. Thus, the new productivity paradox: is the knowledge economy the cause of the productivity slowdown?

The rest of the paper is organized as follows. Section 2 proposes the interpretative framework. Section 3 describes the empirical analysis and provides descriptive evidence. Section 4 presents and discusses the results. Section 5 concludes.

2. The interpretative framework

According to Paul David (1975), it is the relative abundance of endowments and the level of input costs, rather than their changes, that account for the direction of technological change. In the U.S. the long-term direction of technological change was induced by the relative abundance of capital, raw resources, and land, and the scarcity of labor. Consequently, the direction of technological change in the U.S. is capital and raw materials intensive, and labor saving. The level inducement theory of technological change enriched by David (1975) was applied by David and Abramovitz to understand the changes in the direction of technological change which occurred in the U.S. economy in the last decades of the 20^{th} century. The accumulation of a large and quite unique stock of knowledge rooted in a peculiar institutional setup changed the direction of technological change dramatically to one based on knowledge and skilled-labor intensiveness and capital saving (Abramovitz and David, 1973a, b, 1996, 1999).

The evidence confirms Abramovitz and David's predictions of a new knowledge intensive direction of technological change in the advanced countries. The use of knowledge as an input enabled by the new technologies is unprecedented. In the new global economy, there is a strong incentive for firms based in advanced countries to make intensive use of an input that, in relative terms, is cheaper than in competing countries. Moreover, the use of knowledge enables localized increasing returns associated to the generation and exploitation of knowledge (David, 1993). The positive relationship between the introduction and adoption of knowledge intensive technologies and productivity should therefore be evident (Antonelli, 2019; Antonelli, Orsatti and Pialli, 2023 a, b).

Accounting procedures are an important institution and are the "carriers of economic history" (David, 1994). The changes to national accounting procedures implemented in 2008 were a major institutional innovation; they allow the inclusion in growth accounting of the increasing role of knowledge as a production input in the advanced countries while also reflecting the advances made in the economics of knowledge. Alongside the well-known limited appropriability, knowledge is characterized crucially by its limited exhaustibility and pervasive effects (Antonelli, Orsatti and Pialli, 2023b).

The traditional accounting procedures established in the 1993 System of National Accounts (SNA) did not included knowledge as a capital input:

> Expenditure by enterprises on activities such as staff training or research and development is […] designed to raise productivity or increase the range of production possibilities in the future […]. However, expenditure on training and research and development does not lead to the creation of assets that can be easily identified, quantified, and valued for balance sheet purposes. (Inter-Secretariat Working Group on National Accounts, and Commission of the European Communities, 1993, para. 51).

In 2008, the SNA added five new broadly defined accounting items: 1) ICT equipment included as a new category under machinery and equipment; 2) intellectual property practices (replacing intangible fixed assets) which include R&D; 3) other intellectual property products (replacing other intangible fixed assets) which include R&D, mineral exploration and evaluation, computer software and databases, literary or artistic originals; 4) mineral exploration and evaluation (replacing mineral exploration to conform to international accounting standards); and 5) computer software modified to include databases (OECD, 2009).

However, the capitalization of intangibles, typically expenditure on R&D and training, and a range of other knowledge intensive activities, transforms labor and wages into long-lasting capital. Knowledge intensive activities mainly comprise wages for workers with high levels of human capital. In traditional accounting procedures, the numbers of these workers add to the size of the labor units (L) which enter the production function. The capitalization of R&D expenditure and other knowledge intensive activities transforms wages into intangible capital whose productive use increases in line with its lower rates of obsolescence (Hall, 2005; de Rassenfosse and Jaffe, 2018). If R&D is included as an expenditure item, the footprint in the production input size of an increase in R&D is represented only by an increase in the labor input of an amount equal to the number of new R&D employees. However, if R&D expenditure is capitalized, the increase in the production inputs given by the increase in capital stock is larger than the asymmetric reduction in the labor input. Indeed, the capitalization of R&D expenses produces an increase in the capital stock (the sum of physical and intangible capital stocks) that is larger than the raw number of R&D expenses for a factor inversely proportional to the depreciation rate.[1] The lower the depreciation rate, the larger the increase in the capital size. Therefore, the capitalization of knowledge items automatically boosts the capital stock, reducing both the 'residual' and the TFP size. Moreover, an increase in the share of total capital produces a multiplicative growth effect which reduces the TFP growth rate over time.

[1]To see this, suppose that a firm employs 100 workers at time *t* and at time *t+1* starts a 5-year R&D project and increases its R&D expenditure by $1M annually. Suppose that the R&D expenditures consist only of the wages paid to the R&D employees, all hired at *t+1*, and that the unit cost of R&D is $100k. At *t+1*, the increase in R&D expenditure increases labor by 10 units and capital by $1M. Labor units increase only in *t+1* and then remain constant until *t+5*. However, the increase in capital cumulates over the entire period. In fact, if the R&D expenditure were capitalized at a constant depreciation rate of 20%, application of standard capitalization practice would imply that the capital stock at *t+5* compared to the capital stock at *t+1* would have increased by $2M (0.8M+0.6M+0.4M+0.2M) while labor would remain constant. At *t+6*, when the R&D project ends and R&D employees terminate their contract, labor is the same as it was at *t* but capital is $2M larger.

The new capitalization procedures trigger a shift effect in accounting which magnifies the size of the inputs that enter the production function: the increase in capital is much larger than the reduction in labor. Moreover, this imbalance increases with a lower rate of obsolescence. The shift effect occurs as long as the firm continues to increase the amount of knowledge intensive activities. The shift effect increases the size of the inputs and, consequently, the levels of expected "equilibrium" output with the perverse consequence of reducing the residual and, hence, the level of TFP. Now, a positive productivity growth trend is contrasted with the negative effects of the increased size of the capital inputs triggered by the new accounting procedures.

The transformation of wages into intangible capital -which adds to tangible capital- causes a shift effect in accounting (Koh et al., 2020) which becomes larger, the larger the increase in the wages paid to workers employed in knowledge intensive activities. As soon as the firm adopts new, more knowledge-intensive technologies and/or increases R&D activities and expenses, this accounting shift effect takes place (Corrado, Hulten and Sichel, 2005, 2009; Corrado et al., 2022).

Consequently, at the aggregate level, the diffusion of knowledge intensive activities drives an increase in the shift effect which keeps increasing with the adoption of new technologies but fades and eventually vanishes as their diffusion is completed. This is the basis for our interpretation of the causes of the new productivity paradox. The introduction and adoption of knowledge intensive technologies and resulting increase in knowledge intensive activities should support increased TFP. However, if these increased knowledge intensive activities are accounted for as intangible capital, their positive effect vanishes and is eclipsed by the increased inputs. Then the fast rates of introduction and adoption of knowledge intensive technologies -and the sustained capitalization of intangible assets which represent a growing and substantial portion of assets in the national accounts- produce a distorting effect on the difference between TFPs estimated from a production function that, respectively, excludes or includes intangible assets among the production inputs, and this difference increases over time proportional to the increase in intangible intensity.

Thus, whether knowledge intensive activities are capitalized or not is crucial. There is robust empirical evidence showing that if knowledge intensive activities are not capitalized, they exert strong positive effects on productivity: the greater the use of knowledge, the better are sales growth rates and TFP (Dettori, Marrocu and Paci, 2012; Marrocu, Paci and Pontis, 2012; Bontempi and Mairesse, 2015; Niebel, O'Mahony and Saam, 2017; Piekkola, 2018). However, if knowledge intensive activities are capitalized, the positive relationship between knowledge intensity and productivity growth becomes much weaker and almost disappears.

Therefore, we test two distinct implications. First, intangible assets exert a positive effect on TFP if measured as flows and not included in capital stocks. Second, capitalization of intangibles and their inclusion in capital stocks figures reduce TFP levels in accounting terms, and the magnitude of this effect increases over time proportional to the increase in intangibles intensity.

3. Data and empirical analysis

The empirical analysis involves four steps. In the first step, we detail the data and provide descriptive evidence on the diffusion of the intensity of intangible capital. In the second step, we estimate TFP measures at the sector-country-year level, respectively excluding and including intangible capital among the production inputs of the estimated production functions. For simplicity, we call the first measure TFP-A, the second TFP-B. The third step provides evidence that intangibles intensity exerts a positive effect on TFP-A. In growth accounting terms, the increased share of intangible capital explains part of the residual contribution to productivity but the impact of intangible intensity on TFP-B is much weaker than on TFP-A. In the final step, we show that the gap between the two TFP measures computed in the second stage (i.e., the difference between TFP-A and TFP-B) increases over time and shows a positive strong correlation with intangible intensity.

3.1. Data and descriptive evidence about the diffusion of intangible assets

We use data from the 2023 release of the EUKLEMS & INTANProd dataset (Bontadini et al., 2023). This dataset combines intangibles investment data from the INTAN-Invest project with sectoral and national accounts figures from EUKLEMS.[2] Specifically, the dataset provides information on sectoral value added, labor compensation, and capital including intangible capital. The dataset disaggregates capital data into: i) ICT capital which includes computer hardware and telecommunications equipment; ii) non-ICT capital which includes dwellings, cultivated biological resources, transport equipment, machinery equipment and weapons, and other buildings and structures; iii) intangible capital which includes R&D expenses, software and databases, and other intellectual property rights

[2]Works using INTAN-Invest data include Corrado et al. (2013), Corrado, Haskel and Jona-Lasinio (2017) and Niebel, O'Mahony and Saam (2017).

products. Our analysis uses an unbalanced panel of 11 countries and 34 industries, spanning 1995 to 2019.[3]

The cross-country and sectoral descriptive evidence suggests that a diffusion process is at work. In a diffusion process, there are two contrasting dynamics: the increase in adopters on the one side and the mirror reduction of the variance of the distribution on the other. At the beginning of the diffusion process, adoption rates increase slowly as the variance of the distribution declines. In the central phase, adoption rates increase sharply as variance declines. In the final phase, rates of increase in adoptions decline, and the variance becomes minimal, that is, all potential adopters share the new technology.

Table 1 reports the country level of intangibles intensity in 1995, measured as intangible capital over total capital, and its change over the period 1995-2019 averaged across industries. A sharp increase in intangibles intensity in the European countries in our sample over the period considered is clear. For example, over the period 1995-2019 Austria's share increased by 61.67%, Belgium's by 84.44%, Germany's by 21.25%, Spain's by 69.45%, and the U.K.'s by 42.56%. In 1995, France's level of intangible intensity was the highest among the countries considered (0.27) and increased by 21.61%. This descriptive analysis suggests the existence of a cross-country diffusion process in which the variance in the distribution of intensity declines along with the increased rate of adoption: laggards adopt the new knowledge intensive technologies at a faster rate than frontrunners. Late adopters such as Spain, Austria, and Belgium exhibit fast rates of adoption and at the end of the period considered reach levels of intensity closer to the levels of the leaders -such as France.

Table 1: Initial level of intangible intensity (1995), final level of intangible intensity (2019) and change from 1995 to 2019 by country

Country	Intangible intensity in 1995	Intangible intensity in 2019	Change from 1995 to 2019
Austria	0.11	0.18	61.67%
Belgium	0.10	0.19	84.44%
Czech Republic	0.08	0.09	5.75%
Finland	0.15	0.21	37.16%

[3]Data are available to 2020 but we dropped 2020 from the analysis to avoid distortions produced by the pandemic crisis. For the respective lists of countries and industries considered in the empirical analysis, see Tables 1 and 2.

France	0.27	0.33	21.61%
Germany	0.15	0.18	21.25%
Italy	0.14	0.16	11.49%
Netherlands	0.19	0.22	18.55%
Spain	0.08	0.14	69.45%
Sweden	0.12	0.11	-5.87%
United Kingdom	0.14	0.20	42.56%

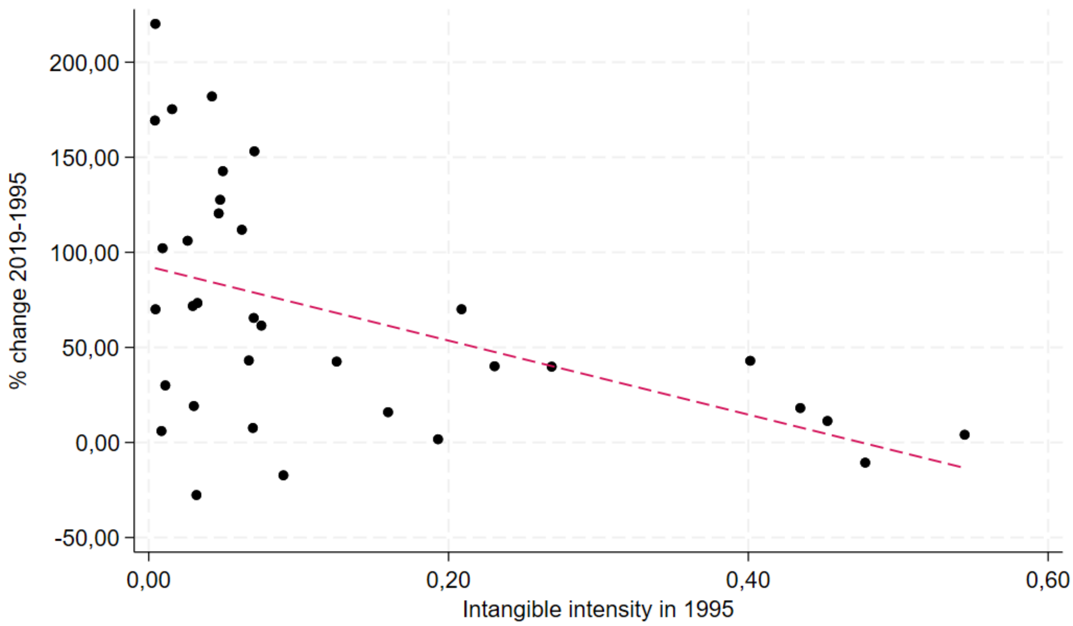
The sectoral breakdown reported in Table 2 provides stronger clues to diffusion process intensity. It shows that the transition to intangible capital affected most sectors and displayed features typical of a diffusion process led by high-tech industries that have been exploiting knowledge intensive inputs since the 1990s. However, in 2019, adoption rates are particularly high in "traditional" low-tech catching up manufacturing sector industries: that is, the variance across industries has declined sharply. For example, intangible intensity in Manufacture of Textiles, Wearing Apparel, Leather and Related Products and Manufacture of Wood, Paper, Printing and Reproduction increased by respectively 142.72% and 71.78% over the period 1995-2019. Adoption rates among so-called high-tech industries are much lower. For example, adoption of intangible inputs shows much lower rates of increase at 39.87% for Manufacture of Electrical Equipment, 40.09% for Manufacture of Motor Vehicles, Trailers, Semi-trailers and of Other Transport Equipment, and 11.30% for Manufacture of Basic Pharmaceutical Products and Pharmaceutical Preparations. The trends are similar in the service sector: laggards showed dramatic increases in rates of adoption over 1994 - Accommodation 220.19% from 0.01%, Warehousing 169.34% from 0.01%, Financial and Insurance Activities 153.13% from 0.07%, and Administrative and Support Service Activities 127.65% from 0.05%. Former leaders such as Computer Programming and Publishing went from high levels (respectively 54% and 40%) of adoption of intangible intensity to low increases of 4.05% for Computer programming and 40% for Publishing. In 2019, rates of adoption and consequent diffusion of intangible capital were substantial for both traditional (physical) capital-intensive sectors and services, with a clear reduction in the high levels of variance observed at the beginning of the process.

Table 2: Initial level of intangible intensity (1995), final level of intangible intensity (2019) and change from 1995 to 2019 by sector

Industry name	Intangible intensity in 1995	Intangible intensity in 2019	Change from 1995 to 2019
C10-C12 - Manufacture of food products; beverages and tobacco products	0.03	0.06	73.34%
C13-C15 - Manufacture of textiles, wearing apparel, leather and related products	0.05	0.12	142.72%
C16-C18 - Manufacture of wood, paper, printing and reproduction	0.03	0.05	71.78%
C19 - Manufacture of coke and refined petroleum products	0.09	0.07	-17.28%
C20 - Manufacture of chemicals and chemical products	0.19	0.20	1.70%
C21 - Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.26	0.50	11.30%
C22-C23 - Manufacture of rubber and plastic products and other non-metallic mineral products	0.07	0.12	65.49%
C24-C25 - Manufacture of basic metals and fabricated metal products, except machinery and equipment	0.07	0.10	43.12%
C26 - Manufacture of computer, electronic and optical products	0.43	0.51	18.12%
C27 - Manufacture of electrical equipment	0.27	0.38	39.87%
C28 - Manufacture of machinery and equipment n.e.c.	0.21	0.35	70.07%
C29-C30 - Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment	0.23	0.32	40.09%
C31-C33 - Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment	0.13	0.18	49.73%
D - Electricity, gas, steam and air conditioning supply	0.03	0.02	-27.65%
E - Water supply; sewerage, waste management and remediation activities	0.01	0.02	102.18%
F - Construction	0.03	0.04	19.17%
G45 - Wholesale and retail trade and repair of motor vehicles and motorcycles	0.02	0.04	175.29%
G46 - Wholesale trade, except of motor vehicles and motorcycles	0.06	0.13	111.87%
G47 - Retail trade, except of motor vehicles and motorcycles	0.03	0.05	106.10%
H49 - Land transport and transport via pipelines	0.01	0.01	30.01%
H50 - Water transport	0.01	0.01	6.02%
H51 - Air transport	0.01	0.01	70.05%
H52 - Warehousing and support activities for transportation	0.00	0.01	169.34%
H53 - Postal and courier activities	0.04	0.12	182.00%
I - Accommodation and food service activities	0.01	0.01	220.19%
J58-J60 - Publishing, motion picture, video, television programme production; sound recording, programming and broadcasting activities	0.40	0.57	42.96%
J61 - Telecommunications	0.08	0.12	61.47%
J62-J63 - Computer programming, consultancy, and information service activities	0.54	0.57	4.05%
K - Financial and insurance activities	0.07	0.18	153.13%
M - Professional, scientific and technical activities	0.48	0.43	-10.61%
N - Administrative and support service activities	0.05	0.11	127.65%
P - Education	0.16	0.19	15.92%
R - Arts, entertainment and recreation	0.07	0.07	7.64%
S - Other service activities	0.05	0.10	120.46%

Figure 1 depicts the convergence process across industries in the form of a scatterplot of the relationship between the change in intangible intensity over the period 1995-2019 and the initial level of intangible intensity. It shows a clear negative relationship between the two variables, indicating catch-up across industries over the 25-year period and a diffusion process typified by slow rates of increased adoption in the early years, followed by rapid increases and then a steady convergence towards saturation. This descriptive evidence on adoption rates of intangible assets suggests that their -distorting- effects on TFP will fade with completion of the new knowledge economy diffusion process.

Figure 1: Relationship between the change in intangible intensity over the period 2019-1995 and the level of intangible intensity in 1995 across industries



3.2. Econometric analysis

To obtain our TFP measures we use two versions of a traditional log-linearized Cobb-Douglas production function. The first production function includes labor and physical capital as the only production inputs and is specified as follows:

$$y_{ict} = \alpha + \beta_1 l_{ict} + \beta_2 k_{ict}^{TANG} + \mu_{ict} + e_{ict} \tag{1}$$

where y is the log of value added in volumes at 2015 prices for each industry i, in country c, at time t; l_{ict} is the log of the labor input, measured in hours worked; k_{ict}^{TANG} is the log of the tangible capital stock in volumes at 2015 prices; the term μ_{ict} is the productivity shock term which is known to the firms but not to the econometrician; e_{ict} is the error term. The coefficients β_1 and β_2 are the respective output elasticities of labor and tangible capital. We then estimate an augmented version of equation (1), which includes also intangible capital among the production inputs:

$$y_{ict} = \alpha + \beta_1 l_{ict} + \beta_2 k_{ict}^{TANG} + \beta_3 k_{ict}^{INT} + \mu_{ict} + e_{ict} \tag{2}$$

where k_{ict}^{INT} is the log of intangible capital in volumes at 2015 prices and β_3 is the output elasticity of intangible capital.

Based on the literature, OLS estimations are likely to produce inconsistent estimates due to the endogeneity of production input quantities to productivity shocks. That is, firms might respond to productivity shocks by modifying their output and demand for inputs which would cause simultaneity between the output variable and the input variables. To solve endogeneity issues, we employ the Olley and Pakes (1996) estimation method (hereafter OP method). While the OP method was designed for -and has been extensively applied to- the estimation of firm-level production functions (Marrocu, Paci and Pontis, 2012; Ilmakunnas and Piekkola, 2014; Antonelli, Orsatti and Pialli, 2023a; Bloch, Eklund and Piekkola, 2023), recent studies show it is effective also in the case of sectoral level data (Nonnis, Bonfour and Kim, 2023).

The OP method consists of a two-step estimation procedure in which investments proxy for unobserved time-varying productivity shocks.[4] We complement the OP procedure with the correction suggested by Ackerberg, Caves and Frazer (2006) (hereafter ACF). The ACF procedure resolves the potential identification issue of the labor input in the first stage of the control function approach in the OP procedure. The input variable (labor) might be a deterministic function of the state variable (capital) and productivity shocks which would result in nonparametric identification of the coefficient of labor. Therefore, we estimate equations (1) and (2) using the OP method with ACF correction.[5] We include year dummies to control for general business cycle effects on productivity.

[4] We invite the reader to refer to Wooldridge (2009) for a rigorous discussion of production function estimation issues.

[5] We estimated TFP in *Stata* using the command '*prodest*' developed by Rovigatti and Mollisi (2018).

We then calculate our two TFP measures of interest as the difference between the expected and the observed outputs. From Equation (1) we obtain TFP-A. From Equation (2) we obtain TFP-B.

In the second part of the empirical analysis, we test the hypothesis that the growth rate of TFP ($TFPGrowth$) is positively associated to the increase in intangible intensity. Moreover, our hypothesis is that the expected positive association is larger for TFP-A than for TFP-B. Therefore, we estimate two versions of the following bivariate relationship:

$$TFPGrowth_{ict} = \delta_0 + \delta_1 IntangIntensity_{ict-1} + \gamma_{ic} + \chi_{ct} + u_{ict} \quad (3)$$

where $TFPGrowth$ is, alternatively, the growth rate of TFP-A or the growth rate of TFP-B, and $IntangIntensity_{ict-1}$ is the log of the ratio of intangible investments to total investments, measured at time $t-1$ to account for a one-year lag effect of intangible assets capitalization on TFP. We include the terms γ_{ic} and χ_{ct} for industry-by-country and country-by-year fixed effects to allow for industry-country unobservable heterogeneity and country-specific year business cycle effects. Therefore, we estimate a bivariate relationship between the two variables by saturating the specification with a large set of fixed effects. Our results cannot be interpreted as causal due to the presence of time-varying industry-country-specific variables which might be correlated to both intangible intensity and TFP growth; our aim is to provide evidence of a relationship between the two variables to corroborate our reasoning.

In the last part of the analysis, we show that the difference between TFP-A and TFP-B grows over time, and we relate the gap between the two estimated TFP measures ($TFPGap_{ict}$) to the log of intangible intensity. According to our hypotheses, a positive relationship is expected: a larger TFP gap should be positively associated to higher intangible intensity. To test this, we estimate the following equation:

$$TFPGap_{ict} = \delta_0 + \delta_1 IntangIntensity_{ict-1} + \gamma_{ic} + \chi_{ct} + u_{ict} \quad (4)$$

4. Results and discussion

We start by estimating the production functions specified by Equation (1) and Equation (2), respectively, employing the OP method. Appendix Table A1 reports the output elasticities obtained.[6]

Then, we calculate the two TFP measures of interest (i.e., TFP-A and TFP-B) and we estimate two separate versions of Equation (3) in which, alternatively, the growth rates of TFP-A and TFP-B are regressed against the lagged level of intangible intensity. Table 3 reports the results. Columns (1)-(3) refer to the growth rate of TFP-A. Columns (4)-(6) refer to the growth rate of TFP-B. We consider different specifications allowing for various fixed effects combinations. Specifically, columns (1) and (4) refer to the estimated bivariate relationship without including any fixed effects; columns (2) and (5) include industry, country and year-fixed effects; columns (3) and (6) report the results for the more demanding specification in which we add industry-by-country and country-by-year fixed effects. The estimated coefficient of intangible intensity is positive and statistically significant across all specifications. Referring to column 3, after accounting for industry-country unobservable time-invariant characteristics and country-specific year effects, a 1% increase in intangible intensity is associated to a 0.07 percentage point increase in the TFP growth rate. Overall, our findings confirm and support previous evidence on the positive relationship between knowledge intensity and TFP (Griliches, 1998; Crass and Peters, 2014; Bontempi and Mairesse, 2015; Roth, Sen and Rammer, 2023).

Finally, the comparison between the coefficients reported in columns (4)-(6) and the coefficients reported in columns (1)-(3) demonstrates that the positive relationship between intangible intensity and the growth rate of TFP is significantly lower when the TFP measure is obtained from estimating the augmented production function (i.e., TFP-B). Referring to column (6), in fact, a 1% increase in intangible capital is associated to a 0.02 percentage points increase in the TFP growth rate, significantly lower than the 0.07 coefficient reported in column (3).

[6] Specifically, Table A1 column (1) presents the results for Equation (1) with labor and physical capital the only inputs of the production function estimated. Column (2) estimates the production function defined by Equation (2) where the production inputs include intangible capital, physical capital, and labor. The respective output elasticities of labor and physical capital in column (1) are 0.58079 and 0.3821; in column (2) the respective output elasticities of physical capital and labor are 0.50811 and 0.3434. In column (2) the output elasticity of intangible capital is 0.2214.

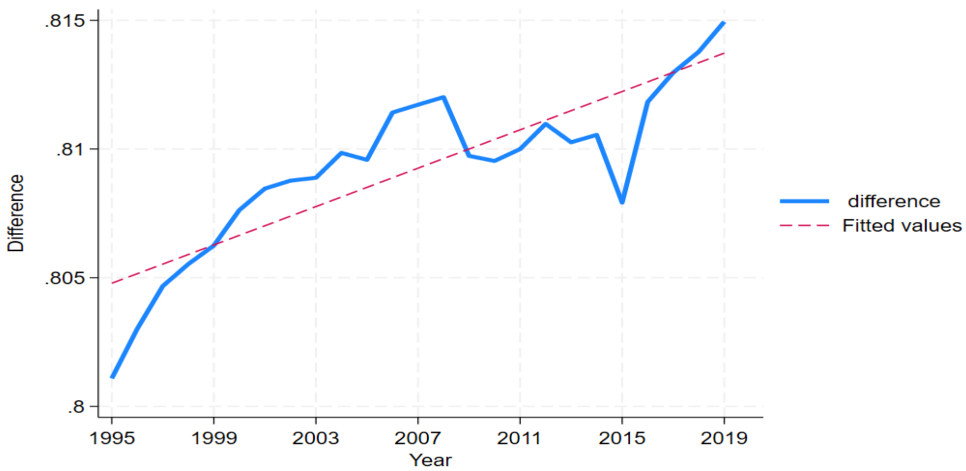
Table 3: TFP growth and intangible intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable:		TFP-A growth rate (the production function excludes intangible capital)			TFP-B growth rate (the production function includes intangible capital)	
Intangible intensity	0.005***	0.020***	0.067***	0.002***	0.007***	0.018***
	(0.001)	(0.004)	(0.013)	(0.001)	(0.001)	(0.003)
Industry, country, year FEs		Yes			Yes	
Industry-by-year FEs			Yes			Yes
Country-by-year FEs			Yes			Yes
N	5,994	5,994	5,994	5,578	5,578	5,578

Notes: Columns (1)-(3) refer to TFP-A, obtained from Equation (1); columns (4)-(6) refer to TFP-B, obtained from Equation (2). ***, **, and * significance at the 1%, 5%, and 10% levels.

We then look at the evolution of the difference between the two TFP measures over time. Figure 2 plots the difference between TFP-A and TFP-B over the period 1995-2019 (blue line); the dotted red line shows the linear fit of the series. First, the difference is always positive, demonstrating that including intangible capital among the production inputs of the production function reduces the size of the estimated TFP. On average, the difference between the two TFP measures is 0.81 log points over the period 1995-2019. Second, the plot shows that the difference between the two measures increased steadily over the period 1995-2019. Specifically, the gap increased by 1.7% between 1995 and 2019, suggesting that the capitalization of intangible assets might have a distorting effect on the estimate of TFP growth.

Figure 2: Evolution of the difference between the two TFP measures



Notes: The figure shows the evolution over 1995-2019 of the difference between TFP-A and TFP-B. The dotted red line shows the linear fitted values of the series.

Finally, we show that the gap observed in Figure 2 is explained in part by the increase in intangible intensity. Table 4 reports the results from estimates of several versions of Equation (4). Table 4 column (1) presents the results of the bivariate relationship between the TFP gap (the difference between the log of TFP-A and the log of TFP-B) and intangible intensity; column (2) includes separate industry, country and year fixed effects; column (3) adds industry-by-country and country-by-year fixed effects. The estimates in columns (1)-(3) confirm the positive and statistically significant relationship between intangible intensity and TFP gap. Referring to the full specification in column (3), a 10% increase in intangible intensity is associated to an ~0.5% increase of the TFP gap.

Table 4: TFP gap and intangible intensity

	(1)	(2)	(3)
Intangible intensity	0.003^{***}	0.012^{***}	0.049^{***}
	(0.001)	(0.004)	(0.013)
Industry, country and year FE		Yes	
Industry-by-country FE			Yes
Country-by-year FE			Yes
N	5,578	5,578	5,578
R^2	0.004	0.019	0.094

Notes: Table 4 presents the results of estimating equation (4). Column (1) does not include fixed effects, column (2) includes industry, country and year fixed effects, column (3) includes industry-by-country and country-by-year fixed effects. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

5. **Conclusion**

In this paper, we contend that the contemporary productivity paradox, where the impact of knowledge is pervasive but not reflected in productivity metrics, can be explained by the combined influence of the introduction and diffusion of knowledge-intensive technologies and the implementation of new accounting methods that enable the capitalization of a diverse range of intangible assets in growth accounting assessments. The capitalization of knowledge triggers a shift effect on the size of inputs which persists for as long as the diffusion of new knowledge intensive technologies continues, and is a major reason for the apparent decline in the rates of increase of TFP and its relationship with knowledge intensity.

The capitalization of intangible assets promotes an increase in total capital that is much greater than the reduction it induces in other inputs, thus producing a progressive reduction in the estimated residual and a slowdown in the growth rates of estimated TFP. The diffusion of the knowledge economy and the knowledge intensive technologies which support it extends this shift which persists as long as new firms increase their use of intangible inputs that substitute tangible capital and labor.

Once the introduction and diffusion of new knowledge intensive technologies slows, the perverse effects of the capitalization of knowledge should cease and stop its -apparent- negative effects.

We provide evidence of the role of intangible capital in TFP growth at the sectoral level across European countries over the last 25 years. We employ EUKLEMS & INTANProd data and analyze the evolution of TFP for 11 European countries and 34 industries over the period 1995-2019. We show that the share of intangible capital in total capital follows a typical diffusion process which favors convergence of most industries towards the high levels of adoption observed in the 1990s among high-tech industries in advanced countries; over the period 1995-2019, most European economies and industries show a generally strong increase in average adoption levels and a reduction in the variance among them. We compute two measures of TFP based on estimation of two distinct production functions – one that does not include and the other that includes intangible capital among the production inputs – and we provide fourfold evidence. First, an increase in intangible intensity is positively related to TFP growth, especially if TFP is obtained from the estimate of the former production function. Second, the former measure of TFP is always greater than the latter. Third, the difference between the two measures of TFP increased over time and, fourth, is positively associated to higher intangible intensity.

Paul David (1990) showed that in the context of the economic effects of the introduction of the dynamo and the computer, the relationship between technological change and economic growth needs to take account of the time lags related to the -slow- diffusion of new systemic technologies and the institutional changes accompanying the introduction of technological innovations (David, 1994).

Appendix

Table A1: Production function estimation results

	(1)	(2)
l	0.579*** (0.000)	0.511*** (0.000)
k^{TANG}	0.382*** (0.000)	0.344*** (0.000)
k^{INT}		0.221*** (0.000)
Observations	6,997	6,897
Number of units	309	297

Notes: Table A1 reports the results for estimating equations (1) and (2) using the OP method. Year dummies are included. Standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

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