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Artificial intelligence and productivity: an intangible assets approach

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Abstract: Can artificial intelligence (AI) raise productivity? If we regard AI as a combination of software, hardware, and database use, then it can be modelled as a combination of the deployment of intangible and tangible assets. Since some are measured and some are not, then conventional productivity analysis might miss the contribution of AI. We set out whether there is any evidence to support this view.

Keywords: productivity growth, intangibles, AI
JEL classification: O47, E22, E01

I. Introduction

What is the possible impact of AI on productivity growth? As described in Susskind (2020), AI is not new. Alan Turing told the London Mathematical Society in 1947 that he had conceived of a computing machine that could exhibit intelligence. A 1956 conference at Dartmouth College, including Claude Shannon (the father of information theory), proposed studying 'artificial intelligence'. At the same time, computing power has been improving apace, now linked together by the Internet. Is there anything special about AI?

The second wave of AI (Baruffaldi *et al.*, 2020; Susskind, 2020) has, however, rekindled interest in this question. One way to see this is in trends in image recognition. Figure 1 shows the changing ability of machines to recognize images, with the

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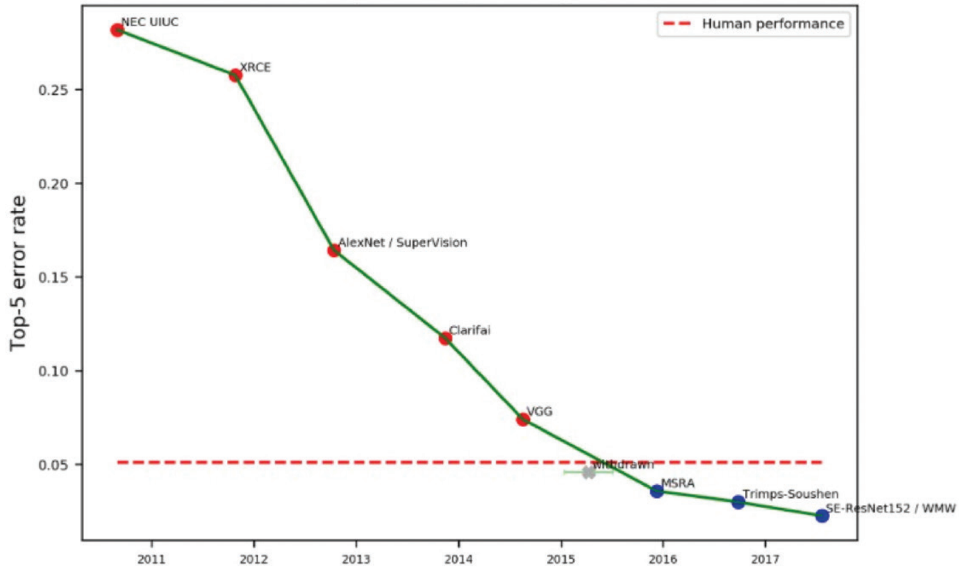
Figure 1: Imagine recognition by computers



Source: https://www.eff.org/ai/metrics#Vision

horizontal dotted line being human performance. Progress here has been very rapid and since around 2015 machines have been better than humans.

The idea that AI technology is potentially important gains additional support when considering the leading companies in today's economy. Table 1 shows the world's top ten companies by market capitalization. As is apparent, these companies are mostly 'hi-tech'. If one thinks about the assets employed by these (mostly digital) companies, they are likely to be 'knowledge-based', centred on data, software, and AI. Indeed, company accounts reveal that the *tangible* capital value for Alphabet is \$20 billion, Microsoft \$5 billion, and Facebook \$11 billion. These are clearly nowhere near their market values. What of their 'intangible' assets, including those derived from AI? They are typically very badly measured in company and national accounts, if measured at all (Lev, 2001; Haskel and Westlake, 2017). Suppose for example, we capitalize the value of reported R&D since birth. The capitalized value of their R&D capital is for Alphabet \$53 billion, Microsoft \$85 billion, and Facebook \$14 billion.[1] Thus understanding their R&D is insufficient as well.

The major puzzle is that at the same time as this technology seems to be accelerating, productivity growth is slowing down. If AI is a potentially general purpose technology, it should be showing up in productivity growth, yet such growth is slowing more or less everywhere. Perhaps AI is not productivity enhancing and productivity growth is over, slowed by falling technical progress and other growth headwinds, such as declining marginal improvements in education attainment (Gordon, 2016; Vollrath, 2020). Perhaps AI is productivity enhancing, but we will have to wait a while for it to show up (Brynjolfsson *et al.*, 2021).

[1] These estimates use a 20 per cent depreciation rate and the net stocks formula set out below.

Table 1: The world's top companies (by market capitalization, 2018)

Company name	Location	Industry	31 March 2018	31 March 2009
			Market capitalization ($billion)	
Apple	USA	Technology	851	94
Alphabet	USA	Technology	719	110
Microsoft	USA	Technology	703	163
Amazon.com	USA	Consumer services	701	31
Tencent	China	Technology	496	13
Berkshire Hathaway	USA	Financials	492	134
Alibaba	China	Consumer services	470	–
Facebook	USA	Technology	464	–
JBMorgan Chase	USA	Financials	375	100
Johnson & Johnson	USA	Healthcare	344	145

Source: Bloomberg and PWC, quoted in Haskel (2019).

This paper attempts to shed some light on these questions. Our first task, if we are to understand these top firms and, by extension, modern economies, is to understand their intangible assets. This leads to a way of understanding AI. Consider facial recognition, which has dramatically improved over the last half decade (Figure 1). Facial recognition improvement is a combination of faster computers, running better software, scanning larger databases. Thus we can think of AI as using a combination of tangible assets (hardware) with measured intangibles (software) and unmeasured intangibles (databases). Our second task is therefore to set out a model that describes what happens when an economy invests in the combination of these assets, some of which are unmeasured. As we shall see, the model predicts the possibility of a rise in measured returns and a fall in measured total factor productivity (TFP) growth (as in the analysis by Brynjolfsson *et al.* (2021)). Third, we use a dataset that measures intangibles and try to uncover these effects.

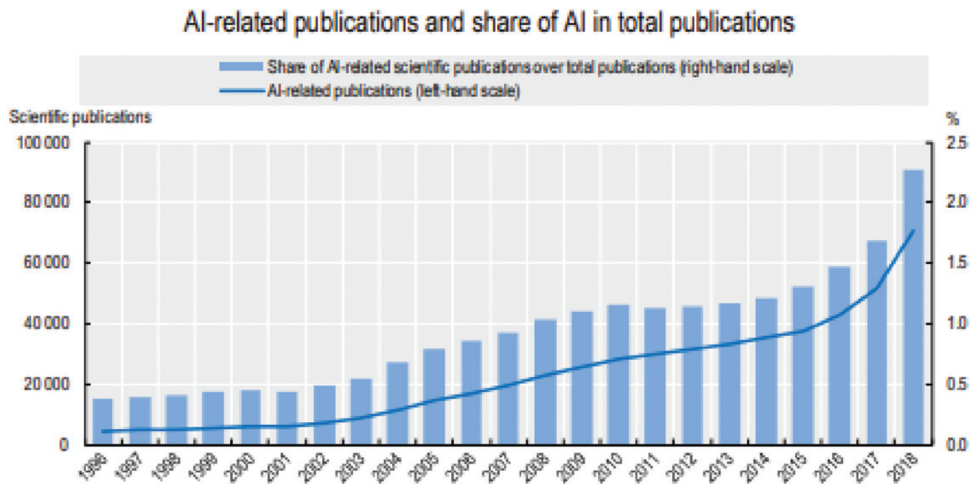
Our main finding is that, on our data at least, there is indeed plenty of unmeasured investment but little sign of a 'J-curve' effect on TFP growth. The upward 'swoosh' of the effects of investments whose returns are long-lasting just is not there. That said, we are still in the early stages of pinning down AI in macroeconomic statistics, and the paper offers a framework and approach for capturing its impact in GDP and productivity growth.

The next section of this paper describes AI. We then set out our model of AI and returns on capital and growth, and then take it to the data in section V. Section VI sets out results and section VII summarizes.

II. AI

The OECD describes AI as 'machines performing human-like cognitive functions (e.g. learning, understanding, reasoning and interacting)' (Baruffaldi *et al.*, 2020). Technologists add that AI methods require larger databases and faster computers than non-AI methods, emphasizing that AI delivers nonlinear improvements over legacy models and systems only once certain technical thresholds are met. Key developments

Figure 2: AI scientific publications



Source: Baruffaldi *et al.* (2020).

in AI began in the 1950s with narrow intelligence and are now progressing towards the goal of general intelligence. Urban (2015)[2] discusses some examples of narrow AI, such as Google's self-driving car, an email spam filter, recommendations on Amazon, Google search and translate, and chess playing. Much harder is 'general AI'; recognizing a picture of a cat, for example, as a cat (not a leopard) or using shadows to pick out the three-dimensionality in such a picture, as a human would, when a computer just sees shades of grey.

Documenting the spread of AI has been done in various places, mostly using keywords to search over patents, open source software, scientific publications, etc. Baruffaldi *et al.* (2020), for example, report the growth of scientific publications related to AI based on a keyword search with agreed keywords. As Figure 2 shows, this has accelerated in 2016.

Another use of AI is in software. Documenting the use of AI in opensource software by searching GitHub repositories (where software projects are held) is one way of counting this. Figure 3 shows that, since 2013, substantial outsized growth in measures of AI software relative to all software.

Is AI a general purpose technology? WIPO (2019) looks at AI patents which specify the use of AI in a particular industry, finding that a wide spread of industries to which AI patents are applied: telecommunications (mentioned in 15 per cent of all identified patent documents), transportation (15 per cent), life and medical sciences (12 per cent), and personal devices, computing and human–computer interaction (HCI) (11 per cent). The trends in such data are set out in Figure 4.

To many, AI means specific business processes and inventions: driverless cars, robots, machine learning. Some real world insight into the general use of the business applications of AI can be obtained from McKinsey, who survey firms using AI and group

[2] https://waitbutwhy.com/2015/01/artificial-intelligence-revolution-1.html

Figure 3: AI use in opensource software

Source: Baruffaldi *et al.* (2020, figure 3.4).

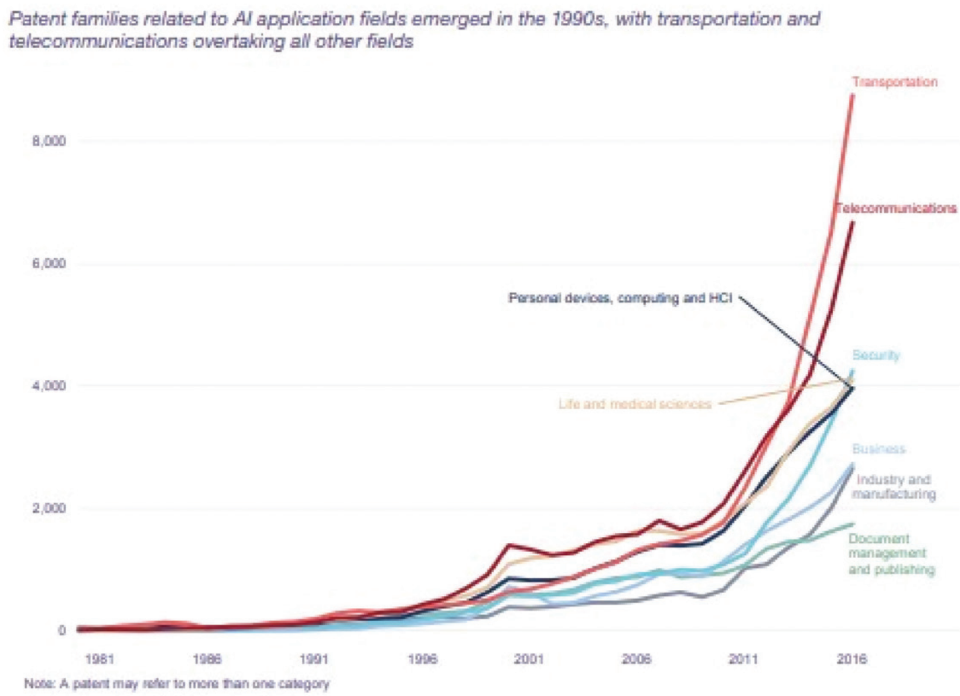
them into industries. The 2019 snapshot suggests wide adoption of natural language capabilities, see Figure 5.

Likewise there is widespread adoption of robotics, see Figure 6.

Urban (2015) discusses what is required to make the transition from narrow to general AI. He suggests it will need a mix of improved hardware and software. For example, he cites estimates that the human brain performs 10 quadrillion (10^{16}) calculations per second, whereas the world's fastest supercomputer can manage 34 quadrillion (but requiring 720 square metres of space for processing and costing $390m). Another way to express this is that a $1,000 computer can perform at the speed of a mouse's brain, about 1,000th of a human level, but if Moore's Law continues the speed should be matched by 2025. He also discusses developing artificial neural networks software as a way of mimicking human intelligence. Quite whether this will duplicate human intelligence as some transhumanists say, is controversial (Jones, 2016),[3] but some indication of the challenges involved can be seen by noting that simulating by software the neurons in a flatworm has only just been achieved. The flatworm has 302 neurons (Fessenden, 2014), but the human brain has 100 billion. Meanwhile, the Blue Brain project (https://www.epfl.ch/research/domains/bluebrain/), to mimic by software a mouse brain (70 million neurons), is still ongoing. Nonetheless, the idea of treating AI as hardware, software, and data seems to have some merit which we explore below.

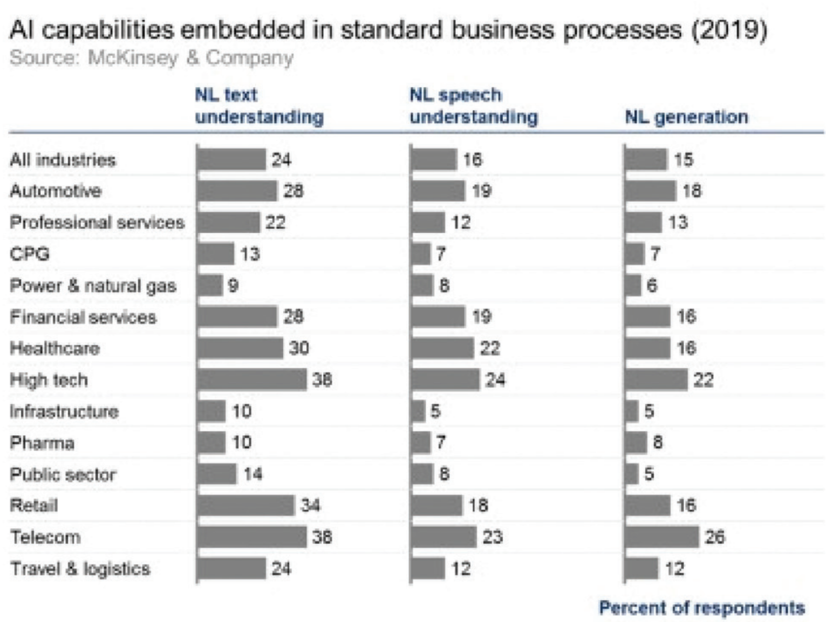
[3] http://www.softmachines.org/wordpress/wp-content/uploads/2016/01/Against_Transhumanism_1.0.pdf

Figure 4: AI patents by technology



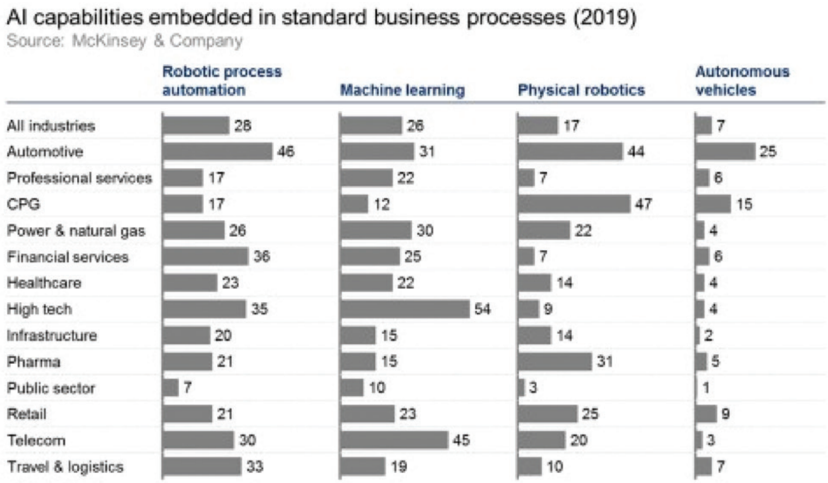
Source: WIPO (2019, Figure 3.18).

Figure 5: AI use in business: natural language



Source: McKinsey quoted in Perrault *et al.* (2019, figure 4.3.3a).

Figure 6: AI use in business: robots



Source: McKinsey quoted in Perrault *et al.* (2019, figure 4.3.3b).

III. Modelling AI and productivity

(i) Summary

As we have seen, then, AI would seem to be a potentially important feature of the economy. But how can we measure it in a coherent way and then work out its effects? In what follows we follow the technologists and think of AI as a bundle of hardware, software, and databases. Thus, we:

- treat spending on AI as an investment in a productive asset;
- set out how such spending would show up in national accounts were it so measured;
- show how omitting such spending affects measured TFP growth.

(ii) AI as an intangible asset

The discussion above suggests that AI might be thought of as spending on software and databases. How long do the services from that spending last? If that spending is 'used up' in, say, a year, it is then an *intermediate expenditure*, like air conditioning. Suppose, though, that it confers enduring benefits, e.g. a new algorithm that searches a new database on customer behaviour and produces information on how better to advertise, and that information lasts for a couple of years before renewed behaviour has to be modelled. In this case, such spending is *investment* which creates capital assets that provide a flow of long-lived services to be used in production ('capital services'). The criterion of long-lasting benefits applies naturally to spending on long-lasting tangible assets, such as buildings, vehicles, and equipment. But if benefits are long-lived (and appropriable),

Table 2: Asset types

Tangible investment	Treated as investment in National Accounts?	Intangible investment	Treated as investment in National Accounts?
Building and structures	Yes	*Computerized information*	
IT equipment (computer hardware, communications equipment)	Yes	Software	1993 SNA. Most OECD countries implements by 2000, but using various methods
Non-computer machinery, equipment, and weapons systems	Yes	Databases	1993 SNA. Very uneven implementation
Vehicles	Yes	*Innovative property*	
		R&D and mineral exploration	2008 SNA. UK implements in 2014
		Creating entertainment, literary, or artistic originals	1993 SNA. US implements in 2013
		Design	No
		Economic competencies:	
		Training	No
		Market research and branding	No
		Business process re-engineering	No

Note: SNA is System of National Accounts.
Source: CHS and authors' summary of national accounts conventions.

then we should treat in the same way firms' expenditures on intangibles such as software and data, as well as other assets such as R&D, product, brand, and organizational development. The Corrado *et al.* (2005, 2009; hereafter CHS) framework, set out in Table 2, expanded national accounts business investment to treat the part of spending on 'intangibles' that was long-lived as investment, and split such intangible spending into three broad groups. They are (i) computerized (digitized) information (software and databases), (ii) R&D, design, and other non-science-based new product development costs, and (iii) brand equity, firm-specific training, and business process reorganization. AI investment fits most naturally into group (i), though the development of new, original algorithms falls in R&D, and applications of existing tools might also be found in market research and IT consulting services (included in organization capital). In any event, AI investments likely are complementary to these and other assets, e.g. a company using AI may also undergo process reorganization and product expansion and/or diversification.

Like tangibles, intangible assets can decline in value. Tangible assets might decline in value due to 'wear and tear', i.e. a physically induced decline, and/or 'obsolescence', i.e. a better product is invented, which is more like a market-based decline. Intangible assets might be less subject to 'wear and tear', but are likely subject to market-based declines: a database goes out of date as consumers change behaviour, trained workers leave the firm, investment cannot be fully appropriated, etc. For both these reasons then the 'capital stock' is likely to experience (economic) depreciation (OECD, 2009).

To build capital stocks then, we start by deflating nominal investment data to obtain real investment for asset a, I_t^a, being $I_t^a = P_t^{Ia} \cdot I_t^a / P_{t,m}^{Ia}$ where $P_{t,m}^{Ia}$ is the measured price index which may or may correspond to the 'true' price index, P_t^{Ia}, depending on, for example, quality adjustment. With this, we can then measure, for each intangible asset type a, its net asset stock R_t^a in period t given by

$$R_t^a = I_t^a + (1 - \delta_a^R) R_{t-1}^a \tag{1}$$

where δ_a^R is its depreciation rate and we assume depreciation is geometric.[4]

Finally, note that Table 2 shows that not all intangible investment is counted as investment by statistical agencies—training and market research, for example. Rather, such spending is treated as an intermediate. We study the consequences for growth and capital returns next.

IV. AI as an investment: consequences for TFP growth

We can get a sense of how important it might be to add these assets by looking at growth with and without their inclusion. A formal model is in the Appendix; here we attempt to describe our work with the minimum of equations.

(i) Outline model and economic interpretation

Value added, Q, is produced in the economy by inputs labour, L, tangible capital, K, and intangible capital, R, used with efficiency A^Q. Output growth in this economy is then

$$dq = \sigma_L^Q dl + \sigma_K^Q dk + \sigma_R^Q dr + da^Q \tag{2}$$

where du is change in natural log of variable u and and σ_X^Q are rental payments to input X as a share of Q; the market is assumed competitive so that rental payments equal output elasticities of the inputs $L,\ K,\ R$. The term da^Q captures changes in the efficiency with which inputs are used plus any effects of input growth over and above those captured by their input shares (e.g. 'spillovers' due to the partial appropriability of intangibles).

As a matter of measurement, however, at least some intangibles are expensed. Thus, both their output and inputs are ignored when measuring value added in which case output growth in this measured economy is

$$dv = \sigma_L^V dl + \sigma_K^V dk + dt_m^{NoIntan} \tag{3}$$

[4] What is the justification of the geometric assumption, especially as one might assume that knowledge, e.g. a mathematical formula, is long-lasting? Let us describe the probability that a given asset type will survive in productive use from t to $t + 1$ as a 'survival' or 'discard' function. Let us describe the productivity of an asset as it ages, conditional on survival, as a 'decay' function. Hulten and Wycoff (1981) showed that when a decay function implying long-lasting productivity (conditional on survival) is interacted with a discard function with a high early failure rate and age cohorts are aggregated, the result is a convex geometric-like profile with relatively rapid depreciation.

where $dt_m^{NoIntan}$ is calculated as a residual. This gives a relation between $dt_m^{NoIntan}$, da, and the other terms

$$dt_m^{NoIntan} = \underbrace{da^Q}_{\text{tech,spillovers}} - \underbrace{\omega_N^Q(dn - dv)}_{\text{missingnewintanoutput}} + \underbrace{\sigma_R^Q dr}_{\text{intanginput}} + \underbrace{(\sigma_X^Q - \sigma_X^V)dx}_{\text{K,Lsharemismeas}} \tag{4}$$

where dn is changes in the output of new intangibles and ω_N^Q their share in Q and x captures the K and L inputs (but not the R input).

What is the economic interpretation of equation (4)? Consider a bank which keeps money safely and also provides an 'app' to customers. The bank's inputs to the output of 'keeping money safe' consist of security guards, L, and a bank vault, tangible capital, K. But the bank also produces the app, whose input is lines of software code, which is intangible capital, R. Treating the intangibles as an intermediate good means ignoring the output component that is the app, i.e. using V and not Q, and the input component that is the flow of intangible capital services, i.e. ignoring $\sigma_R^Q dr$.

These effects are captured in equation (4). The left-hand side is total factor productivity (TFP) as measured, that is, using V as output, and L and K as input. The terms on the right say what this mismeasured term will capture. First, it captures any change in AQ, which could be a change in underlying technical change or efficiency. Second, it captures the missing intangible output, in the bank example, a new app. Third, it captures the missing input of intangibles and finally, because output is mismeasured, so are the shares.

(ii) What does a slowdown in measured TFP growth ($dt_m^{NoIntan}$) indicate?

Equation (4) shows that a slowdown in $dt_m^{NoIntan}$ can occur for a number of reasons. First, da^Q might slow: a slowdown in underlying technical progress, for example. In an important book Robert Gordon (Gordon, 2016) has argued that technical progress consists of, essentially, one big wave around industrialization, electricification, transportation, and IT, that has now run its course. Such an argument has some support in that the slowdown in productivity growth has been common across countries (Bergeaud *et al.*, 2016).

Second, the second set of terms on the right-hand side of equation (4) capture the 'J-curve' effect due to in Brynjolfsson *et al.* (2021).[5] Suppose in the early stages of AI we have substantial investment in databases, software, hardware, and the like that is unmeasured. Then $dn > dv$: intangible investment is growing faster than value added (i.e. too little output counted). This can render $dt_m^{NoIntan} < 0$ even though nothing has happened to da^Q. As that initial burst of investment falls off, this effect falls, and intangible stocks and their payments share start to grow, i.e. $\sigma_R^Q dr$ rises. Thus $dt_m^{NoIntan}$ recovers. Brynjolfsson *et al.* (2021) makes some assumptions on the path of unmeasured

[5] This equation is the same as their A10. This can be seen by using their A4 to substitute into A10 to give, in our notation $da^Q = (Y/Q)(dt_m^{NoIntan}) - \sigma_R^Q dr + \omega_N^Q dn$. Substituting our equation (3) into this expression and using the fact that $Y/Q = 1 - \omega_N^Q$ gives our equation (4).

intangible investment and rates of return to examine this. We use our data on intangibles, measured and unmeasured, to see if, on our data at least, unmeasured intangibles are significant enough to give such effects.

Finally, the framework helps shed some light on some other findings, namely, the divergence between the TFP of 'leader' companies and 'laggards' in similar sectors reported in Andrews *et al.* (2016). This could be due to leaders having faster underlying *da*. Or, it could be due to leaders receiving more unmeasured intangible capital services than laggards (more *dr*); Corrado *et al.* (2021) find evidence that suggests more intangibles are indeed part of the story.

In what follows, we attempt to examine evidence on productivity.

V. Data

This section documents the missing investment and whether it can account for the fall in measured TFP. We start with measuring investment, and ask whether that investment does or does not cover AI. We then seek to measure the real capital stock and services this investment provides and the TFP implications.

(i) Cross-country data

To investigate this we gather country-industry-year data, described more fully in Corrado *et al.* (2019). Our data is from 1995 to 2017 and covers the US plus 10, primarily Western, European countries, namely Austria (AT), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Italy (IT), Netherlands (NL), Sweden (SE), and United Kingdom (UK). Our industries are the 11 NACE A21 industry sectors that represent most non-agricultural private business activity in the two geographies: mining, manufacturing, construction, wholesale and retail trade, transportation and storage, accommodation and food services, finance and insurance, professional services, administrative services, and other services. We drop agriculture, public administration, health, and education since they are dominated by subsidies and public-sector involvement. We also ended up dropping Industry S, Other service activities, since it is poorly measured.

Our building blocks of data are value added, hours, and capital investment and the relevant deflators and labour costs. These are sourced from Eurostat. When we construct gross value added (GVA) we then include capitalized non-national accounts intangibles investment. We compute net stocks by cumulating real investment as in equation (1), with depreciation rates as in Table 3. We then compute *ex post* rental rates for each capital asset so that adjusted nominal value added less labour costs equals total rental costs. Capital services growth is then a rental price-weighted Törnqvist-weighted index of capital asset growth rates. Labour composition is taken from EU-KLEMS. Finally, we aggregate across countries using industry-specific purchasing power parities (PPPs). Hence each aggregate displayed is a bottom-up summation at the asset-industry-country-year level.

Table 3: Geometric depreciation rates for market sector intangibles

Asset type	Depreciation rate
Computerized information	
1. Software	0.315
2. Data and databases	0.315
Innovative property	
3. R&D	0.15
4. Entertainment, literary, and artistic originals	0.20
5. Mineral exploration	0.075
6. Design and other new product development	0.20
Economic competencies	
7. Brands	0.55
8. Organizational capital	
(a) Manager/strategic capital	0.40
(b) Purchased services	0.40
9. Employer-specific human capital	0.40

Note: Line 6 includes new financial products.
Source: Corrado *et al.* (2012).

(ii) How much AI is included as investment already?

Software, data, and databases in the System of National Accounts (SNA)

As set out in Edquist *et al.* (2020*b*), in the SNA (European Commission *et al.*, 2008), assets (entities that give their owner an economic benefit over a period of time) are separated into 'produced' and 'non-produced' assets, with non-produced as those assets not produced as output from a production process. The issue is important in our context because the SNA distinguishes between data and databases. As Ahmad and Schreyer (2016) note, this matters because the SNA argues that databases consist of two components:

(i) the supporting software or database management system (DBMS), which provides or facilitates access to the data: counted as a produced asset; and
(ii) embodied data, counted as a non-produced asset.

Data are a non-produced asset because if data (or information/knowledge in the form of data) were a produced asset then accounts would potentially have to capitalize all forms of information/knowledge, an infeasibly large undertaking. Thus, investment in databases is recommended to include (*a*) the cost of the underlying DBMS, which is software; and (*b*) costs associated with the preparing and transferring of data to the format/structure required by the database, including costs of digitization. This suggests that since (*a*) is already in software database improvement is already captured. That said, recent work by the Office for National Statistics (McCrae and Roberts, 2019), has sought to improve estimates of UK investment by extending coverage of own-account activity to better capture database investment; see also experimental estimates from Statistics Canada (2019).

It is the case, however, that a key aspect of AI activity not addressed in the SNA is data analytics or data science, which is the process of creating or extracting knowledge from data. Is this captured in R&D? In the UK, respondents to the R&D survey are asked about software development but not database development or data science/

analytics. Since software expenditures are already capitalized, reported software development expenditures are then excluded from R&D to avoid double-counting. So if firms report data science activities to be a form of R&D, but not software, they are in R&D.

Edquist *et al.* (2020*a*) look across Europe to see whether occupations typically counted as software-investment building might also be 'database-building'. Software occupations in the UK are mostly in occupations such as IT specialist managers, IT project and programme managers, IT business analysts, architects, and systems designers, programmers and software development professionals, web design and development professionals, IT operations technicians, IT user support technicians, IT engineers. Data for Europe are hard to obtain consistently, but they estimate that perhaps around 55 per cent of employment engaged in data capital formation is already accounted for in the measurement of own-account investment in software and databases in most European countries. The remaining half is, in most cases, unmeasured, and the investment uncapitalized. In addition, the unmeasured element is growing faster than measures recorded in the national accounts in a number of countries. That said, the UK is one country that has incorporated these measures into its National Accounts.

AI counted in other data

AI measured in software occupations would pick up AI produced internally by the firm. Some such expertise might be bought in, and so to some extent AI, in the form of data analytic services, might be bought in as part of management and computer-related consulting services. It might also be included as part of R&D in the computing industry. Corrado *et al.* (2019), following Byrne and Corrado (2017), show some US AI indicators in Figure 7, namely computer design consulting services and computer equipment/software/data-processing R&D. Such indicators are growing very fast in recent periods. We do not have data on computer design consulting services for Europe, but industry-level R&D data in Europe is stable relative to GDP. Consistent then with EU KLEMS patterns (see O'Mahony and Timmer, 2009), ICT investment rates are relatively higher and faster-growing in the US.

Finally, we should mention that we will, of course, obtain different results if we deflate intangibles differently. To guard against this, we use the same deflators for all countries. See the Appendix.

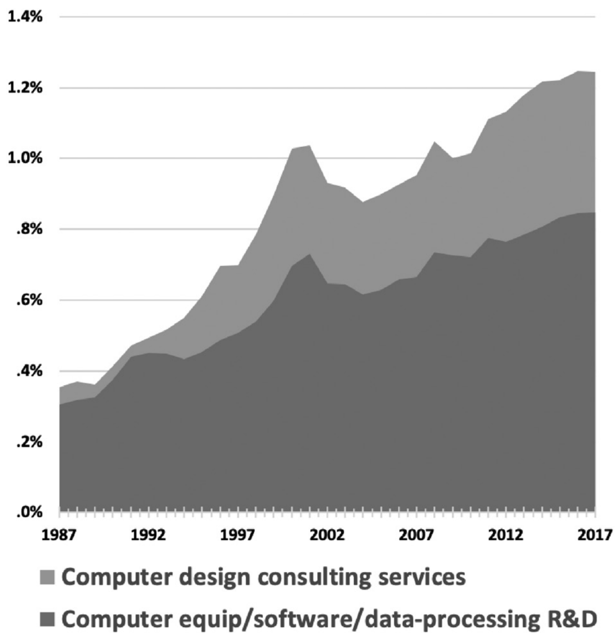
VI. Results

(i) Missing investment

Figure 8 shows shares of tangible and intangible investment across countries from 1997 to 2017. As the graph shows, intangible investment is generally trended upwards and the US invests considerably more intangible investment then the EU. This immediately suggested accounting for intangible investment might potentially be important.

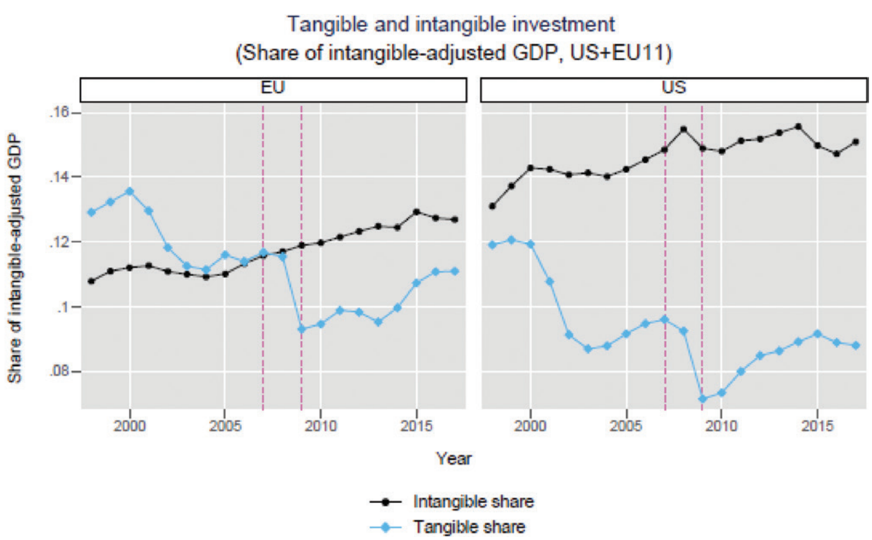
As we have discussed, national accounts do indeed measure intangible investment. Figure 9 plots national accounts intangible investment and the additional investment suggested by CHS set out in Table 2. As the graph shows, the non-national accounts intangible share is higher than the national accounts intangible share, reflecting the fact

Figure 7: Indicators of AI product development in the United States (per cent of GDP)



Source: Authors' elaboration of data developed and described in Byrne and Corrado (2017).

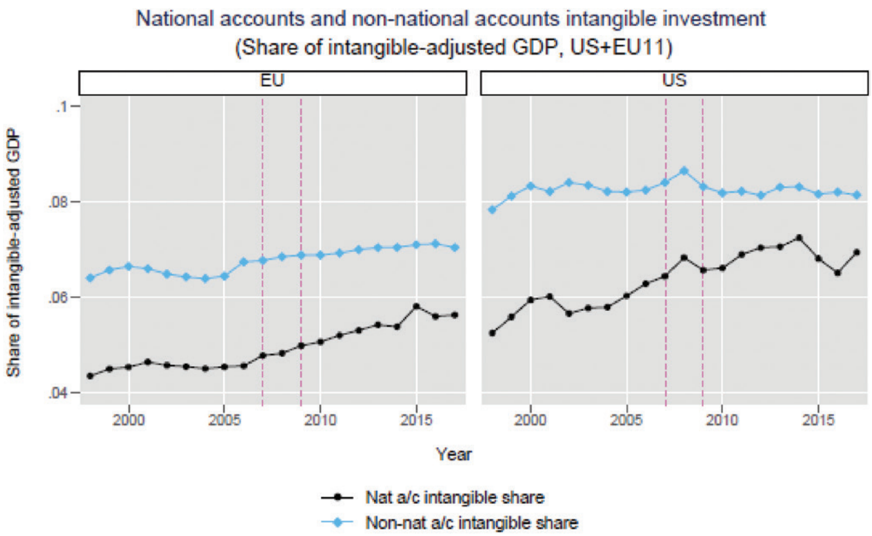
Figure 8: Intangibles and tangibles trends



Note: NonAgBusiness. Industry-specific value added PPPs for EU.
Source: Authors' calculations from www.intaninvest.net.

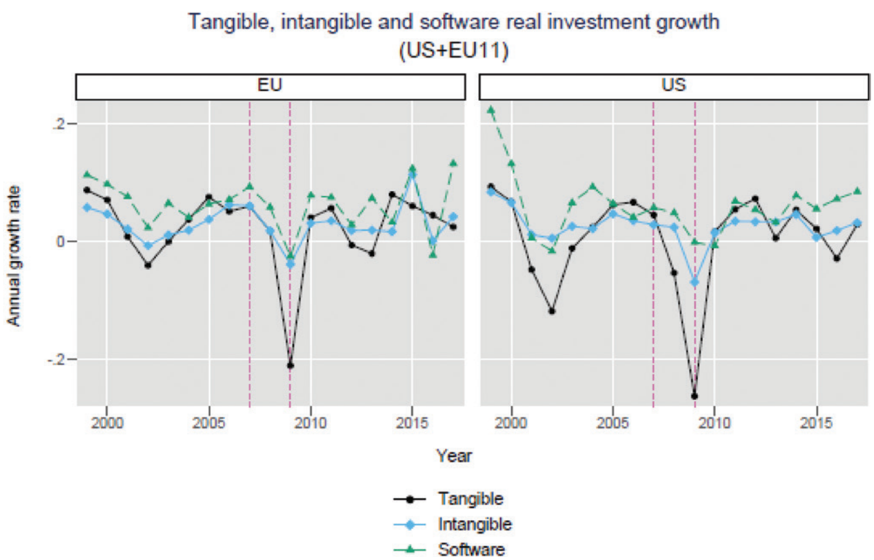
that expenditure on items such as training and design are large. However, the trend is towards relatively more intensive national accounts intangibles measurement.

Figure 9: National accounts and non-national accounts intangibles



Note: NonAgBusiness. Industry-specific value added PPPs for EU.
Source: Authors' calculations from www.intaninvest.net.

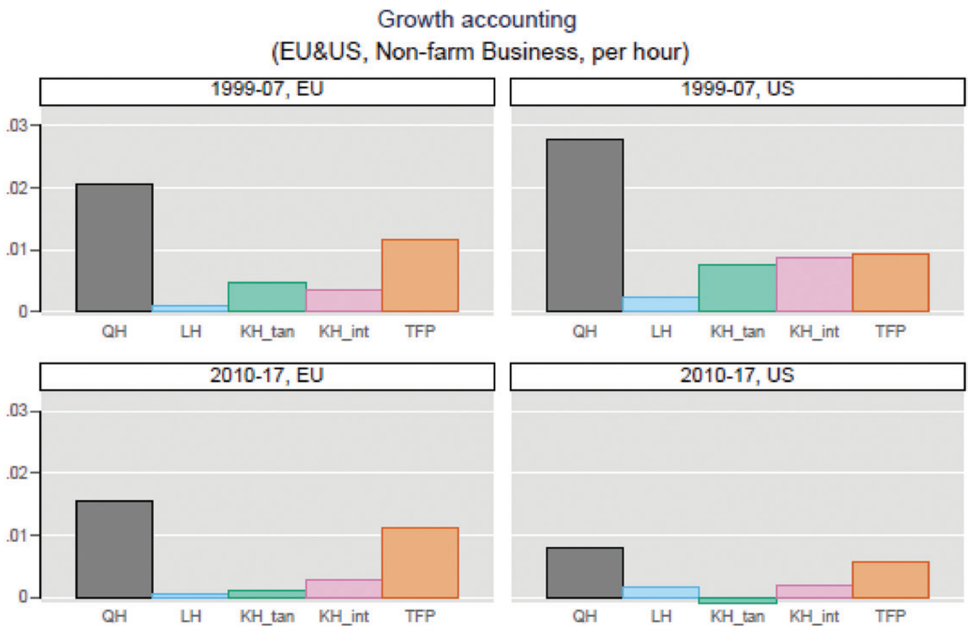
Figure 10: Investment



Source: Authors' calculations from www.intaninvest.net

Finally, Figure 10 shows growth in real investment for tangibles, intangibles, and software. Notice that, particularly in the US, software spending grows particularly strongly at the end of the period. If artificial intelligence is included in such spending this is suggestive. The position seems much more volatile in Europe.

Figure 11: Growth accounting



Source: Authors' calculations from Eurostat and www.intaninvest.net

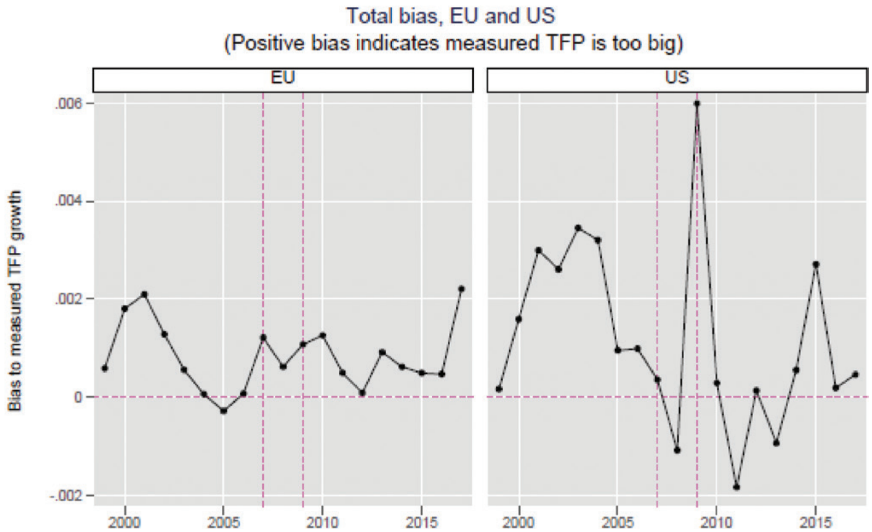
In summary, then, we see quite marked differences across countries. In the US, intangible investment has been strong, with software investment growing particularly strongly relative to the other forms of investment since 2013. In Europe, by contrast, intangible investment, and in particular software, does not seem to have grown particularly differently.

(ii) Biases to TFP growth

To start our examination of total factor productivity, Figure 11 shows growth accounting for the EU and US for the years 1997–2007 and 2010–17 (we omit the recession years of 2008 and 2009). As the top panel shows, labour productivity and TFP were growing at a healthy rate in the run up to the financial crisis. The contributions of both tangible and intangible capital deepening were higher in the US than in Europe, and their contributions exceeded those of labour composition. In the period following the financial crisis, the situation changed. As is well known, labour productivity growth slowed substantially by around 0.5 percentage points per annum (pppa) in Europe and 2pppa in the US. US TFP growth also slowed: if anything European TFP growth was around the same. Intangible capital deepening slowed very strongly in the US, and somewhat in Europe.

Figure 12 shows the biases to measured TFP growth for the EU and the US respectively: these are the terms on the right of equation (4), second line. A positive number indicates that measured TFP growth is too big. Recall that the 'J curve' hypothesis is that measured TFP growth after the financial crisis is too small and then rises, suggesting

Figure 12: Bias to TFP



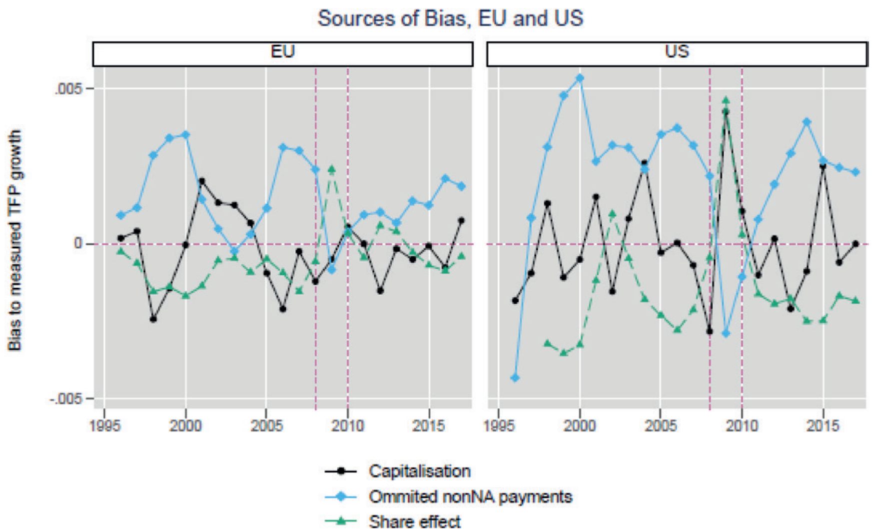
Note: Market sector exAgHeEd.
Source: Authors' calculations from Eurostat and www.intaninvest.net.

that after the financial crisis the bias line should dip and then perhaps rise. At least for the EU, there is not much support for this hypothesis. Note first that the biases are small, at most around 0.2 per cent per annum, but less than this for most of the sample. On average, in the EU the bias is slightly positive but seems to show no particular trend.

Turning to the US, there is a hint of a J-curve effect after the mid-2000s. The bias, which was almost 0.4 per cent per annum fell steadily to around –0.2 per cent per annum in 2011, with the spike in the financial crisis years which presumably reflects mismeasured utilization and the like. Since then, the bias has been moving back towards being positive. This then suggests that the pre-crisis TFP growth slow-down, which has been noted by a number of authors, may be somewhat overstated. That said, the effects do not appear to be all that large.

What is the intuition behind this apparent finding that the positive 'swoosh' of the 'J' appears quite quickly? We can get some insight into this from Figure 13, which shows the different components of the mismeasurement on the right-hand side of equation (4). These are the capitalization effect, the errors-in-shares effect, and the mismeasured capital payments effect. What is notable is that the mismeasured capital payments effect comes in very strongly and quite quickly. The intuition here would seem to be the following. As set out in equation (3), intangibles depreciate quite quickly. That means that a burst in intangible investment rapidly builds up the intangible stock, and the rental price on that stock is relatively large (the per-period rental price of capital has to be large for capital that depreciates to compensate the capital owner for renting out an asset whose value will fall quickly). As a result, the missing rental payments effect comes in very quickly following even unmeasured intangible investment. That means that the second half of the 'J' appears rather quickly after the initial dip.

Figure 13: Bias to TFP, component parts



Note: Market sector exAgHeEd.
Source: Authors' calculations from Eurostat and www.intaninvest.net.

All this suggests that investments in artificial intelligence will have a more substantial 'J effect' the more they are mismeasured and the lower their depreciation rate. Now, it might be that current AI investments are not substantially mismeasured for the simple reason that we might still be too early in the AI investment cycle. As the earlier graphs showed, the 'second wave' of AI might be comparatively recent and so it might be too early to pick up the mismeasurement involved. It might also be that we have mismeasured depreciation rates. At the moment, in our system AI-related investments are given the high depreciation rates the literature has found are appropriate to intangibles. But it may, of course, be the case that artificial intelligence investment has a much lower depreciation rate.

VII. Summary

This paper has reviewed the question of whether investment in AI might or might not raise productivity. While there seems to be plenty of evidence that such investments are large and ongoing, the immediate puzzle is that productivity, far from speeding up, is slowing down. The leading hypothesis to explain this puzzle is the 'J-curve' effect.

Under this hypothesis, investment in AI is mismeasured. Measured output is therefore too low, and hence TFP growth appears to be falling. In the fullness of time, when such investment returns to steady-state levels, the bias to measured output disappears, but by then a capital stock corresponding to the asset of intangible knowledge in artificial intelligence is built up, and the mismeasurement then is the lack of attributing payments to that stock, and TFP growth is too high.

We have set out a framework to illustrate this effect and used a cross-country-industry-year data set for the US and European economies to examine it. To look for unmeasured investment, we have used the CHS approach, which brings into national accounts unmeasured investment in intangible assets which are likely complementary to artificial intelligence, such as design, training, and business process re-engineering. We have also seen that at least some artificial intelligence investment is likely in software investment and is thus already counted. Thus we have harmonized the deflation of software and hardware investment to facilitate comparison across different countries.

At least on these data, we do not find much support for the J-curve view. There is, indeed, plenty of unmeasured investment, but the trend in such investment does not seem to be sufficient to give an effect. In particular, the high depreciation rates mean that the missing capital payments which bias TFP growth up follow quickly after a burst of intangible investment, meaning that the upward-sloping part of the J curve, at least on our data, appears very quickly, too quickly to account for a sustained TFP growth slowdown following the financial crisis. That said, we are in the early stages of measuring AI, and since much of it is taking place within firms on their own account, the detection of such investment is extremely difficult. Nonetheless, the framework presented here and the direction travelled by numerous statistical agencies towards increased collection of this type of investment we believe constitute useful steps forward.

Appendix

(i) Depreciation rates

For convenience, Table 3 reports the geometric depreciation rates for market sector intangibles. The values in Table 3 are relatively high. Geometric depreciation rates used to calculate tangible capital stocks in, for example, EU KLEMS, are typically numbers like 0.033 (non-residential structures), 0.01 (residential structures), 0.12 (machinery), and 0.15 (transport equipment) (Timmer *et al.*, 2007)). These estimates are supported by direct business survey estimates of intangible depreciation rates for the United Kingdom (Awano *et al.*, 2010).

(ii) Industries

Table 4 sets out our industry coverage.

Deflators

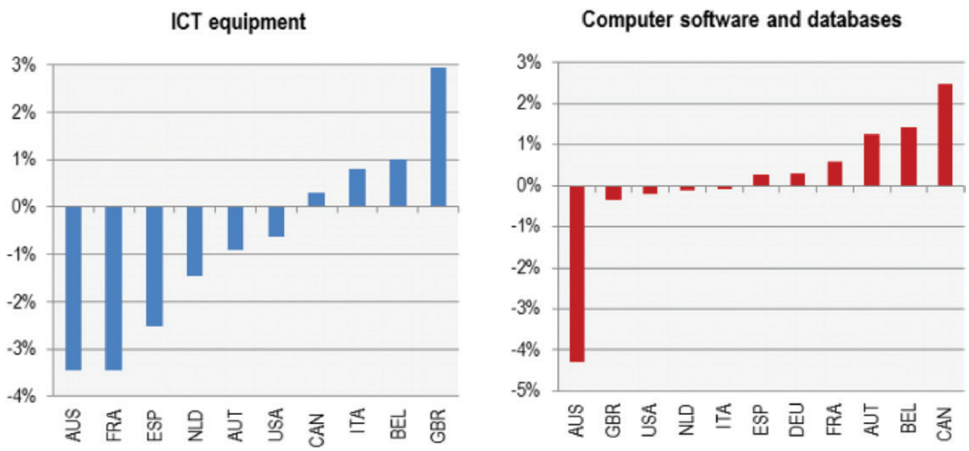
We will obtain different results across countries if use a different deflator for capital goods. For non-computer tangible goods, such as buildings, deflators are uncontroversial, but for computers and intangible investment matters are more difficult. For computers, the main issue is quality adjustment, that is, ensuring $100 of spending today is the 'same' as $100 spent 10 years ago. Software and databases pose similar challenges (likewise, other intangible categories, see Byrne and Corrado (2017)). Figure 14, taken from Ahmad *et al.* (2017), shows how price indices used by national statistical agencies

Table 4: Industry sectors

Sector	Description
A	Agriculture, forestry, and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam, and air conditioning supply
E	Water supply; sewerage, waste management, and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific, and technical activities
N	Administrative and support activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment, and recreation
S	Other service activities
T	Activities of households
U	Activities of extraterritorial organizations and bodies

Note: INTAN-Invest covers all but the dark-shaded industry sectors.
sectors. All shaded sectors (light and dark) are excluded from the data reported in this paper.
Source: NACE Rev. 2 A21 industry sectors as defined in Eurostat (2008).

Figure 14: Average growth, 2010–15, in ICT price index, by country



Source: National statistical agencies, compiled by OECD, reported in Ahmad *et al.* (2017).

differ quite substantially across countries. Thus we harmonize prices across countries, following Colecchia and Schreyer (2002).

(iii) Derivation of equations

Model

A fuller model is as follows. The model has two sectors, an upstream, or knowledge-producing/innovation, sector and a downstream, or knowledge-using/production, sector. The upstream sector takes freely available concepts or ideas—basic knowledge—and produces new 'finished' ideas or new commercial knowledge (e.g. blueprints), Nt. The downstream production sector uses a resulting stock of commercial knowledge as an input to production. That is, the downstream sector rents the knowledge stock, R. Each sector has a production possibilities frontier following Jorgenson (1966) and a flow equation whereby, due to competition, revenue covers costs (we deal with imperfect competition below). Labour is denoted L, new tangible capital, which is investment, I, and the tangible capital stock is K. The downstream sector is a price-taker for knowledge (so that any product market power is located in the innovation sector: this is similar to many models of innovation, e.g. Romer (1990); Aghion and Howitt (2007)). All sectors pay PL and PK, being competitive factor prices for the services of L and K.

Following the net stock equations above, the stock of intangibles evolves as ($\Delta R = N - \delta^R R_{t-1}$) and stock of tangible capital as ($\Delta K = I - \delta^K K_{t-1}$). Let us combine the conventional inputs K and L by X and σ_X, σ_R are rental payments to inputs X and R as a share of value added. A is shift in production function: a combination of exogenous technical progress and true spillovers (i.e increase in knowledge freely available). du is change in natural log of variable u.

The intangibles-producing N-sector has a flow payments and production relation given by

$$P^N N = P^X X^N; \qquad dn = \sigma_X^N dx^N + da^N \tag{5}$$

The tangibles-producing I-sector has a flow payments and production relation given by

$$P^I I = P^X X^I; \qquad di = \sigma_X^I dx^i + da^I \tag{6}$$

GDP and growth accounting when intangibles are intermediates

Suppose we treat intangibles as intermediates to the downstream intangible- and tangible-using production sector which produces consumption goods. So its flow payments include as costs the entire flow of new intangibles $P^N N$, meaning that its value added subtracts $P^N N$ from its sales

$$P^C V^C \equiv P^C C - P^N N; \qquad dc = \sigma_X^C dx^C + \sigma_N^C dn^C + da^C \tag{7}$$

Counting economy-wide value added = sum of industry value-added, i.e.$P^V V \equiv P^C V^C + P^I I + P^N N$, we have

$$\Rightarrow \underbrace{P^V V}_{\text{GDP}} = \underbrace{P^C C}_{\text{consump}} + \underbrace{P^I I}_{\text{invest}}; \qquad \underbrace{dv = \sigma_X^V dx + da^V}_{\text{output = share*input + TFP}} \tag{8}$$

and where $da = \sigma_I^V da^I + \sigma_C^V da^C$. This is the usual model where value added equals consumption and investment, TFP growth is value-added less share-weighted inputs.

GDP and growth accounting when intangibles are capital

Now, if we treat the upstream intangibles-producing N-sector as producing capital, we must amend the downstream C-sector so that it rents the stock of intangibles R,

$$P^C V^C \equiv P^C C; \qquad dc = \sigma_X^C dx^C + \sigma_R^C dr^C + da^C \tag{9}$$

Letting economy-wide value added = sum of industry value-added, i.e. $P^Q Q \equiv P^C V^C + P^I I + P^N N$, gives

$$\underbrace{P^Q Q}_{\text{GDP}} = \underbrace{P^C C}_{\text{consump}} + \underbrace{P^I I}_{\text{taninvest}} + \underbrace{P^N N}_{\text{intaninvest}}; \quad \underbrace{dq = \equiv \omega_C^Q dc + \omega_I^Q di + \omega_N^Q dn = \sigma_X^Q dx + \sigma_R^Q dr + da^Q}_{\text{output = share*input X + share*input R + TFP}} \tag{10}$$

Thus the implications of an intangible/AI economy can be derived from the comparison of the payment flow terms and growth accounting relations.

How growth changes in an intangible/AI economy

The sources of growth change as follows. Measured TFP with no intangibles, $dt_m^{NoIntan}$, is measured output less value added share-weighted conventional K and L inputs (including L and K in the N sector)

$$dt_m^{NoIntan} = dv - \sigma_X^V dx; \tag{11}$$

This gives a relation between $dt_m^{NoIntan}$, da and the missing intangibles as set out in equation (4) in the text.

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