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# Productivity & Innovation Competencies in the Midst of the Digital Transformation Age: A EU-US Comparison

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**The Productivity Challenge:**
Jobs & Incomes in the Dawning Era of Intelligence Robots

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DG ECFIN's Fellowship Initiative 2018-2019 "The Productivity Challenge: Jobs and Incomes in the Dawning Era of Intelligent Robots" has solicited contributions examining current and possible future productivity developments in Europe. In view of possible hysteresis effects after the crisis and in the general context of ageing populations and globalisation, the aim has been to re-examine the ongoing trends and drivers and to identify policies to tap fully the potential for inclusive productivity growth. The fellowships have been awarded to prominent scholars in the field to interact with staff in ECFIN and other Commission colleagues, and to prepare final reports on specific research questions within this general topic.



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European Commission
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# Productivity and Innovation Competencies in the Midst of the Digital Transformation Age
## A EU-US Comparison

Bart van Ark[1,2], Klaas de Vries[1] and Abdul Erumban[1,2]

**Abstract**

This paper reviews the latest evidence on productivity growth by industry and innovation competencies by occupation to observe whether, beneath the productivity slowdown of the past decade in both the European Union and the United States, signs can be detected of structural performance improvements due to digital transformation.

We find that in the United States, the digital-producing sector has continued to contribute strongly to aggregate productivity in recent years. While labour productivity growth in the US was only 0.6 percent from 2013-2017, as much as 0.5 percentage point (or 86 percent) was coming from digital-producing industries representing only 8.2 percent of US GDP. Other industries, which account for the remaining 92 percent of the US economy, including some of the most digital intensive-using industries, have seen a dramatic decline in their contribution to productivity growth.

In the European Union, the digital-producing sector has seen a strong decline in its contribution to productivity growth, which by 2013-2017 was only one third of the US contribution at 0.15 percentage points. However, the most digital intensive-using industries contributed 4 times as much to labor productivity as in the United States, driving overall labour productivity growth from 2013-2017 up to 0.9 percentage point – 0.3 percentage points higher than in the US.

A positive factor, both in the EU and in the US, is that total factor productivity (TFP) growth in the most intensive digital-producing industries, notably trade and business services has improved. Digital intensive-using manufacturing industries generally contribute less to productivity than digital intensive-using services, partly because of slower productivity growth and partly because of their smaller size.

A novel measure of innovation competencies by occupation shows that, when applied to industries, those industries with the highest competencies, also show positive productivity contributions, and the most intensive digital-using industries are strongly represented in this category.

Overall, while the evidence is still thin due to time lags in the data, there are signs of positive contributions to productivity growth related to digital transformation even though those effects are still not widespread observable across the economy.

**JEL Classification:** O40, O47, O30.

**Keywords**: New technologies, productivity growth, innovation competencies, digital transformation, Van Ark.

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# 1. INTRODUCTION

After almost a decade of slow growth, Europe's economies showed solid signs of recovery in 2016, 2017 and the first half of 2018. In addition to a job recovery, there were also some signs of slightly faster productivity growth during this period (van Ark et al., 2018). The latter was a welcome departure from a long slowdown in productivity since the middle of the previous decade (Cette et al., 2016; van Ark, 2016a; van Ark and O'Mahony, 2016). However, as labour productivity typically behaves pro-cyclically, it would be premature to mark the rise in output per hour at the aggregate level as a structural improvement. Indeed the latest update of The Conference Board Total Economy Database (April 2019) points at another significant weakening in labour productivity growth in the EU-28 in 2018, in parallel with an above average growth in total hours worked, while projections for 2019 seem to deliver a modest productivity improvement at best (Charts 1a and 1b, and Table 1).

However, before discarding the recent productivity uptick as a purely cyclical aberration, it is important to look under the hood of the aggregate growth measures for signs of structural improvements. In particular the rapid acceleration of digital technology would have made us expect that at least some productivity improvements from that phenomenon would have emerged by now.

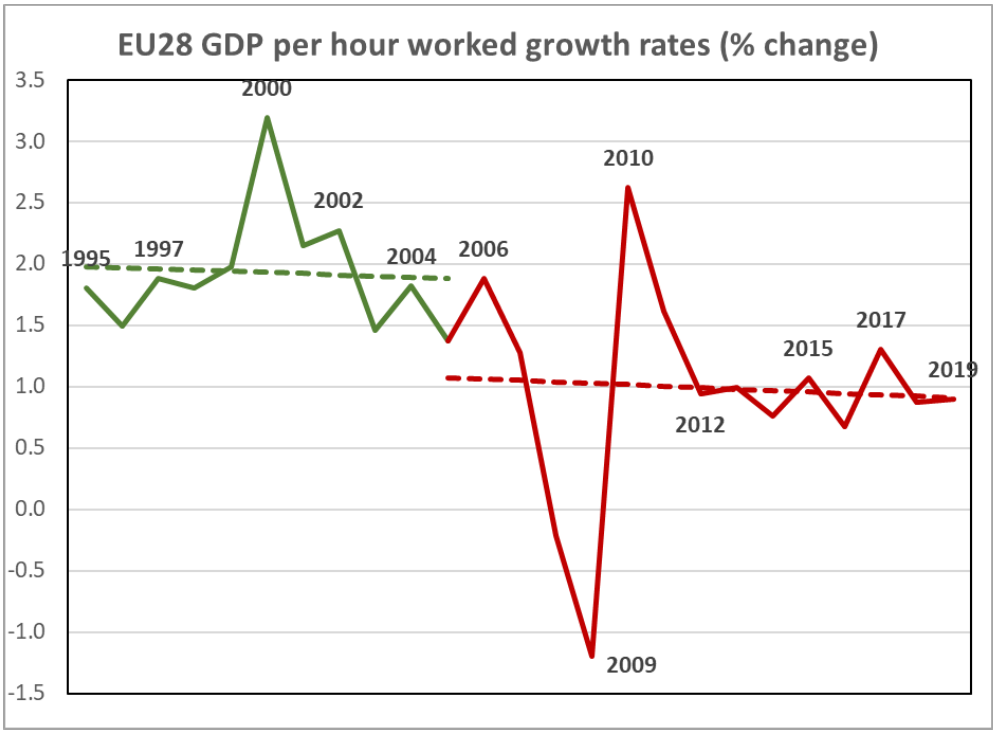
Our **hypothesis** in this paper is that the recent productivity developments may be pointing towards a possible tipping point at which the economies in Europe and the United States are experiencing more widespread impacts from the adoption and absorption of digital technology on productivity and GDP growth.

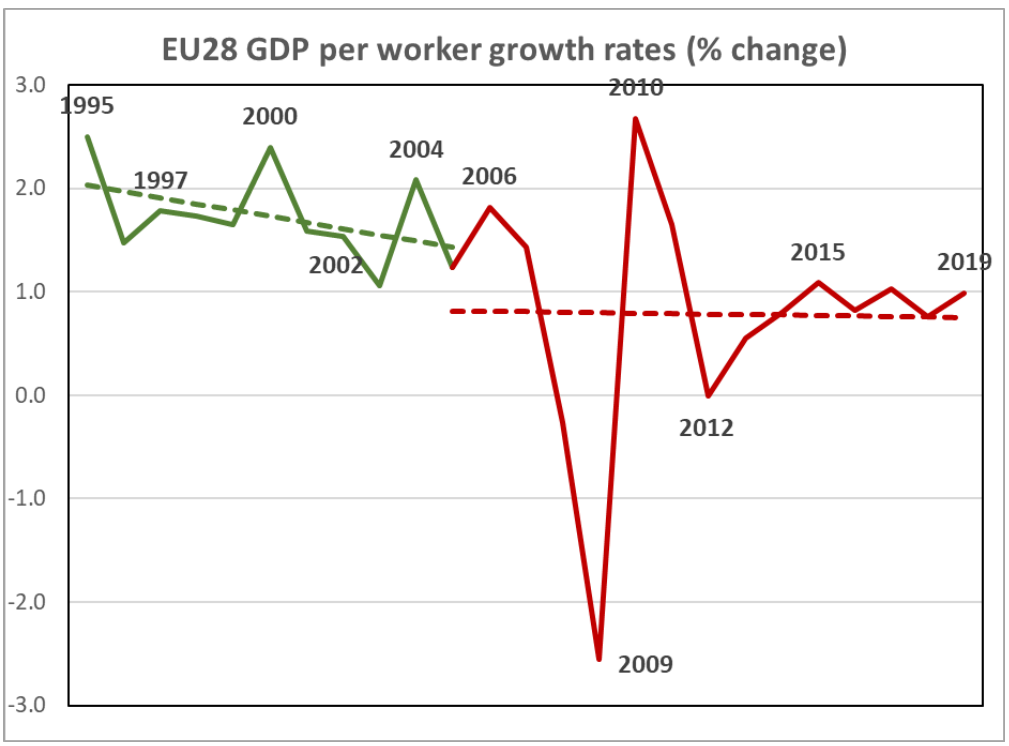
In **Section 2** we review some of the latest literature providing insights on the productivity impacts of general purpose technologies (GPTs), including the notion of time lapses through which digital technologies result in faster productivity growth. We also look at what the literature shows on patterns by which innovation and productivity effects emerge across industries and disperse across the economy.

In **Section 3** we provide an empirical analysis of productivity growth by industry data to observe whether we can detect a distinct pattern across groups of industries which may point in the direction of a structural improvement in recent years. We use a recently developed taxonomy on digital intensity by industry to see if the most digital-intensive industries have experienced a better performance in terms of labour productivity growth since 2007.

In **Section 4** of the paper we move to the labour and skills portion of the digital economy. We employ a new dataset which The Conference Board developed on innovation competencies by occupation on the basis of data from the O*Net database on occupation-specific descriptors in the United States. Our aim is to observe whether such competencies especially point at stronger productivity effects by industry.

Charts 1a and 1b**: EU-28, GDP per worker and GDP per hour, 1995-2019, %**




Note: 2019 is based on forecasted values
Source: The Conference Board Total Economy Database (adjusted version) April 2019

Table 1: **Growth of GDP per Hour Worked and Total Working Hours, 2015-2019**

| | GDP per Hour Worked (% change) | | | | | Total Hours worked (% change) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 2015 | 2016 | 2017 | 2018 | 2019* | 2015 | 2016 | 2017 | 2018 | 2019* |
| United States | 0.9 | 0.4 | 1.0 | 0.9 | 1.3 | 2.1 | 1.3 | 1.4 | 2.1 | 1.3 |
| EU 28 | 1.0 | 0.6 | 1.3 | 0.7 | 0.9 | 1.1 | 1.4 | 1.3 | 1.2 | 0.7 |
| Euro Area | 0.7 | 0.5 | 1.0 | 0.2 | 0.6 | 1.2 | 1.5 | 1.4 | 1.7 | 0.8 |
| Austria | 1.6 | 0.0 | 0.9 | 1.0 | 0.2 | -0.4 | 2.1 | 1.6 | 1.7 | 1.2 |
| Belgium | 1.3 | 0.2 | 0.2 | -0.1 | 0.6 | 0.4 | 1.3 | 1.5 | 1.5 | 0.7 |
| Bulgaria | 3.1 | 3.5 | 2.0 | 3.1 | 3.3 | 0.4 | 0.4 | 1.8 | 0.0 | 0.3 |
| Cyprus | 0.5 | 0.1 | 0.4 | 0.2 | 0.4 | 1.4 | 4.7 | 4.0 | 3.6 | 2.8 |
| Croatia | 4.7 | 2.8 | 1.3 | 0.3 | 0.7 | -2.2 | 0.7 | 1.6 | 2.3 | 2.0 |
| Czechia | 5.0 | -0.4 | 2.4 | 0.9 | 2.3 | 0.3 | 2.9 | 1.9 | 2.0 | 0.4 |
| Denmark | 1.4 | 0.5 | 1.1 | 0.6 | 1.0 | 0.9 | 1.9 | 1.1 | 0.9 | 0.8 |
| Estonia | -0.5 | 3.0 | 2.0 | 5.2 | 2.3 | 2.4 | 0.5 | 2.8 | -1.3 | 0.4 |
| Finland | 0.6 | 2.5 | 1.7 | -0.3 | -0.3 | -0.1 | 0.3 | 0.9 | 2.6 | 2.1 |
| France | 0.8 | 0.0 | 1.3 | 0.6 | 1.1 | 0.3 | 1.1 | 0.8 | 0.9 | 0.3 |
| Germany | 0.6 | 1.4 | 0.9 | 0.0 | 0.5 | 1.1 | 0.8 | 1.3 | 1.4 | 0.6 |
| Greece | -1.7 | -0.6 | -0.8 | 0.3 | -0.2 | 1.2 | 0.4 | 2.3 | 1.7 | 1.9 |
| Hungary | 1.3 | -1.4 | 3.2 | 4.4 | 3.3 | 2.2 | 3.7 | 0.9 | 0.6 | 0.4 |
| Ireland | 4.2 | 1.3 | 4.0 | 0.3 | 1.1 | 4.1 | 3.6 | 3.1 | 6.3 | 3.2 |
| Italy | 0.2 | -0.4 | 0.6 | -0.2 | 0.0 | 0.7 | 1.6 | 1.0 | 1.1 | 0.0 |
| Latvia | 3.5 | 2.3 | 5.6 | 2.8 | 1.8 | -0.5 | -0.3 | -0.9 | 1.9 | 1.3 |
| Lithuania | -0.7 | -1.0 | 7.0 | 1.8 | 3.2 | 2.7 | 3.4 | -2.7 | 1.6 | -0.4 |
| Luxembourg | 0.8 | -0.6 | -1.3 | -1.1 | 0.1 | 3.1 | 3.0 | 2.9 | 3.8 | 2.4 |
| Malta | 6.8 | -1.7 | 4.0 | 1.3 | 0.2 | 3.6 | 7.6 | 2.6 | 5.2 | 4.1 |
| Netherlands | 1.0 | 0.2 | 0.9 | 0.3 | 0.4 | 1.0 | 2.0 | 1.9 | 2.4 | 1.4 |
| Poland | 1.9 | 2.1 | 4.5 | 6.2 | 3.2 | 1.9 | 0.9 | 0.2 | -1.0 | 0.4 |
| Portugal | 0.0 | 0.1 | -0.6 | 0.1 | -0.1 | 1.8 | 1.8 | 3.4 | 2.0 | 1.6 |
| Romania | 5.6 | 4.6 | 4.2 | 3.8 | 4.3 | -1.6 | 0.2 | 2.7 | 0.3 | -0.4 |
| Slovakia | 2.5 | 1.5 | 2.5 | 3.0 | 3.0 | 1.7 | 1.6 | 0.7 | 1.1 | 1.1 |
| Slovenia | 0.6 | 3.4 | 3.8 | 2.6 | 0.3 | 1.7 | -0.3 | 1.0 | 1.8 | 2.8 |
| Spain | 0.5 | 0.5 | 1.1 | -0.2 | 0.8 | 3.1 | 2.7 | 1.9 | 2.8 | 1.5 |
| Sweden | 2.9 | 0.1 | 0.6 | 0.2 | 1.0 | 1.5 | 2.6 | 1.5 | 2.1 | 0.9 |
| United Kingdom | 0.8 | 0.4 | 0.8 | 0.5 | 0.2 | 1.5 | 1.4 | 1.1 | 0.8 | 0.5 |

Note: 2019 is based on forecasted values
Source: The Conference Board Total Economy Database, April 2019

In the final section, **Section 5**, of the paper we conclude with a projection of productivity growth and other growth sources. We argue that while it obviously is early days to fully confirm (or reject) the notion of a structural strengthening in productivity, the evidence in this paper suggests that policy makers should take note of this possibility and devise policies that leverage the potential of a structural productivity revival emerging.

# 2. THE PRODUCTIVITY PARADOX OF THE NEW DIGITAL ECONOMY: RECAP OF THE LITERATURE

It is well known that general purpose technologies (GPTs), defined as new methods of producing and inventing new goods and services which are important enough to have a long-term aggregate impact on the economy, can take a significant amount of time to translate to faster productivity growth at the aggregate level of the economy. This is inherent to the three critical characteristics of a GPT as identified by Bresnahan and Trajtenberg (1996):[1]

1) Pervasiveness – The GPT should spread to most sectors.
2) Improvement – The GPT should get better over time and, hence, should keep lowering the costs of its users.
3) Innovation spawning – The GPT should make it easier to invent and produce new products or processes.

Historical analysis has focused on productivity trends in previous technology phases (Crafts, 2004; Bakker et al., 2017). Recent literature has suggested that the "information and communication technology (ICT) revolution" can also be characterised as a general purpose technology in the same vein as steam technology, electricity or the combustion engine. For example, Hempell (2006) concludes that "investment in information and communication technologies (ICT) are closely linked to complementary innovations and are most productive in firms with experience from earlier innovations.". In an analysis of the evolution of the Internet, Simcoe (2015) argues that the modularity of the internet has prevented a fall in return to investments in innovation by "facilitating low-cost adaptation of a shared general-purpose technology to the demands of heterogeneous applications." And, in a recent review of the data, Liao et al (2016) conclude that:

> *"… ICT investment does contribute to productivity but not in the usual manner – we find a positive (but lagged) ICT effect on technological progress. We argue that for a positive ICT role on growth to actually take place, a period of negative relationship between productivity and ICT investment together with ICT-using sectors' capacity to learn from the embodied new technology was crucial. In addition, it took a learning period with appropriate complementary co-inventions for the new ICT-capital to become effective and its gains to be realised. Our findings provide solid, further empirical evidence to support ICT as a general purpose technology."*

During the current phase of what we define as the New Digital Economy (NDE)[2], which refers to the combination of mobile technology, ubiquitous access to the internet, and the shift toward storage, analysis, and development of new applications in the cloud, the question arises if the NDE is an extension of the

[1] See also Jovanovic and Rousseau, 2005.

[2] Van Ark et al. (2016) and van Ark (2016b)

previous phase of ICT technology, or whether we are starting a new GPT-phase altogether fueled by artificial intelligence and robotics. The latter issue is extensively discussed in a new volume of papers issued by the National Bureau of Economic Research (Agrarwal et al, 2019). In the introduction of the volume, the editors argue that "(H)uman intelligence is a general purpose tool. Artificial intelligence, whether defined as prediction technology, general intelligence, or automation, similarly has potential to apply across a broad range of sectors." (p. 4).

In our view the shift in the target of digital automation from substituting for horse power (such as in CNC machinery), to routine administrative tasks (such as in office software) to substituting for human intelligence (such as with artificial intelligence and robotics) – despite being increasingly pervasive and potentially disruptive from a societal point of view – does not fundamentally alter the underlying source of this technology, namely the exponential growth in computing power. We therefore will treat the entire ICT era in this paper as one General Purpose Technology. However, the distinction in periodisation, especially before 2007 and thereafter, allows us to tease out some of the productivity effects from the Old Digital Economy, driven by the introduction of the PC and the rise of the internet, vis-à-vis the New Digital Economy.

The time lag factor also plays an important role in the evolutionary school literature on technological change. For example, Perez (2002) speaks of an "installation phase" versus a "deployment phase" of new technological paradigm. During the installation phase, new business spending on machinery, innovation, organisational and management changes exceed the overall output recovery. During this phase, the famous Schumpeter credo of "creative destruction" may put more emphasis on creation than on destruction, and hence low productivity firms can survive – especially in the past decade's environment of low interest rates, credit growth, and weak wage growth where cheap workers could still be relied upon (see also Andrews et al., 2017). During the deployment phase, however, the fruits of the new technology become more widespread and less productive firms will lose out on the competition and make room for the reallocation of resources to more productivity firms and industries.

Beyond the time lag in the diffusion of the technology, there can also be a time lag in the absorption of new technologies. Evidence from recent business studies suggest that the absorption of new digital technologies has been particularly slow in the New Digital Economy. Indeed "digitisation", related to the adoption or increase in use of digital technology, which creates value through new products, new processes, business models and organisational structures, needs to be distinguished from "digital transformation". The latter aims at leveraging digital technologies and the data they produce to connect organisations, people, physical assets and processes, etc. which drives long-term value and productivity (Young, 2016). Digital transformation involves a wide range of complexities raising the cost of transition "that can include an initial duplication of structures and investment, cannibalisation of incumbent business, and the diversion of management attention. towards those new technologies." (McKinsey, 2018). More specifically, as to the most recent wave of artificial intelligence (Brynjolfsson et al., 2019) state that:

> *The most impressive capabilities of AI, particularly those based on machine learning, have not yet diffused widely. More importantly, like other general purpose technologies, their full effects won't be realised until waves of complementary innovations are developed and implemented. The adjustment costs, organisational changes, and new skills needed for successful AI can be modeled as a kind of intangible capital.*

It follows that while new digital technologies have rapidly diffused across the economy, the absorption and translation into better business performance has been quite slow and uneven. This is not an unusual phenomenon. Harberger (1998) speaks of two types of growth. One is characterised as "mushroom" growth in which a limited number of sectors, industries or firms experience a much better productivity performance than others. In today's world it means that the exciting prospects about productivity effects from driverless cars, robotics, and artificial intelligence may have caused an exaggeration of the macro productivity impact of mushroom growth. The second type of growth is what Harberger calls “yeasty” growth once the productivity improvements spread more widely across the economy. Even though we may not yet be fully harvesting the yeast effects of digital transformation, accelerated investment and business spending on ICT assets, cloud and digital services across many industries and rising wage premiums on skilled labour coupled with stronger demand bode well for a broader emergence of automation and digitisation.

A very important portion of the wide dispersion of the productivity effects of new digital technology relates to the firm level. In particular studies at the OECD and MIT have pointed at the rising gap between the top echelon of high-performing firms and the rest (Andrews et al. 2017; Autor et al. 2017). In this study we do not look at this important source of productivity divergence but focus one level higher by looking at performance across industries and its link to the aggregate economy.

# 3. AN INDUSTRY PERSPECTIVE ON PRODUCTIVITY GROWTH IN THE DIGITAL ECONOMY

To detect structural trends in productivity improvements from a General Purpose Technology perspective, a useful starting point is to apply a taxonomy of digital intensity by industry. For this we follow the taxonomy recently developed by the OECD (Calvino et al., 2018). The study uses multiple dimensions relating to technology, market and human capital-related features:[3]

- Share of ICT tangible and intangible (i.e. software) investment;
- Share of intermediate purchases of ICT goods and services;
- Stock of robots per hundreds of employees;
- Share of ICT specialists in total employment; and
- Share of turnover from online sales.

The taxonomy is available for time periods, 2001-2003 and 2013-2015, but for this study we use the taxonomy for the 2013-2015 period only.[4] Using an overall summary indicator (the “global taxonomy”), industries at the ISIC Rev. 4 level are distinguished into four groups organised from the lowest to the highest quartile by industry: low, medium-low, medium-high and high digital intensive industries. For this study we collapsed the four groups into two, combining high and medium-high into “most digital intensive-using” industries, and low and medium-low into “least digital intensive-using” ones. Furthermore, we separate out

[3] In an earlier study, Van Ark et al (2016) developed a taxonomy based solely on a ICT service and investment intensity. The OECD grouping largely comparable to van Ark et (2016). There are some exceptions though. They are petroleum, chemical, rubber and plastics, utilities, transport services, and arts and entertainment, which have moved from most intensive category in van Ark et al (2016) to least intensive group in the OECD. Similarly, other manufacturing, health, and other services have moved from least intensive to most intensive groups. Moreover, three sectors, which OECD identify as ICT intensive, are considered in our grouping as ICT producing sectors, which are electrical and optical equipment, publishing, telecom IT. The general impact of the shift from van Ark et al (2016) to OECD taxonomy is a marginally higher contribution from ICT intensive sectors and a consequent decline in less intensive ones.

[4] It may be noted that the use of OECD’s 2013-2015 taxonomy compared to 2001-2003 one has a minor impact on our final digital grouping and the results. The main difference between the taxonomies for the two periods is that the human health activities sector moves from medium-high to medium-low group in the later period, and arts, entertainment, and recreation sector moves from medium-low to medium-high.

four industries that are defined as producing digital goods and services (electrical and optical equipment, publishing, audiovisual and broadcasting activities, telecom services and IT and other information services) as a third group because of their very different productivity dynamics. Hence, our most and least digital-intensive industries are identified as "using" industries compared to producing industries.

Exhibit 1: **Digital industry taxonomy**

| NACE SECTORS | | Used in this study | OECD (2018)* | Van Ark et al (2016) |
|---|---|---|---|---|
| A | Agriculture, forestry & fishing | LDIU | LOW | LIIU |
| B | Mining & quarrying | LDIU | LOW | LIIU |
| 10-12 | Food, beverages & tobacco | LDIU | LOW | LIIU |
| 13-15 | Textiles & leather | LDIU | M-LOW | LIIU |
| 16-18 | Wood, paper, printing & media | MDIU | M-HIGH | MIIU |
| 19 | Coke & petroleum products | LDIU | M-LOW | MIIU |
| 20-21 | Chemicals | LDIU | M-LOW | MIIU |
| 22-23 | Rubber & plastics; non-metallic mineral | LDIU | M-LOW | MIIU |
| 24-25 | Basic metals & metal products | LDIU | M-LOW | LIIU |
| 26-27 | Electrical & optical equip. | DP | M-HIGH | IP |
| 28 | Machinery & equipment n.e.c. | MDIU | M-HIGH | MIIU |
| 29-30 | Transport equipment | MDIU | HIGH | MIIU |
| 31-33 | Other manufacturing | MDIU | M-HIGH | LIIU |
| D-E | Electricity, gas & water supply | LDIU | LOW | MIIU |
| F | Construction | LDIU | LOW | LIIU |
| G | Trade | MDIU | M-HIGH | MIIU |
| H | Transportation & storage | LDIU | LOW | MIIU |
| I | Accommodation & food services | LDIU | LOW | LIIU |
| 58-60 | Publishing & broadcasting | DP | M-HIGH | IP |
| 61 | Telecommunications | DP | HIGH | IP |
| 62-63 | IT & information services | DP | HIGH | IP |
| K | Financial & insurance activities | MDIU | HIGH | MIIU |
| L | Real estate activities | LDIU | LOW | LIIU |
| M-N | Professional services | MDIU | HIGH | MIIU |
| O | Public administration & defence | MDIU | M-HIGH | MIIU |
| P | Education | LDIU | M-LOW | LIIU |
| Q | Health & social work | LDIU | M-LOW | LIIU |
| R | Arts, entertainment & recreation | MDIU | M-HIGH | MIIU |
| S | Other services | MDIU | HIGH | LIIU |

Note: * Based on OECD's 2013-2015 grouping. LDIU=Least digital intensive using, DP=Digital Producing, MDIU=Most digital intensive-using, M-LOW=Medium Low, M-HIGH=Medium High, LIIU=Least ICT intensive-using and MIIU=Most ICT intensive -sing

Sources: OECD (2018), Van Ark et al (2016)

Exhibit 1 compares the taxonomy used for this study with that of the OECD (2018). The last column compares with a taxonomy developed for an earlier study by Van Ark et al (2016) which is only based on a combination of investment intensity on ICT assets and spending intensity on digital services (mainly data services and telecommunication expenses). The comparison shows that despite the addition of other dimensions to the OECD taxonomy, the latter is largely comparable to our earlier one.[5] The general impact of the shift from van Ark et al (2016) to OECD taxonomy is a marginally higher contribution from ICT intensive sectors and a consequent decline in less intensive ones.

Chart 2a compares the contribution of the three groups of industries (digital producing, most digital intensive-using and least digital intensive-using) to labour productivity growth for US, the European Union and the Euro Area from 1996-2017. We distinguish between the two subperiods, 1996-2006 representing the Old Digital Economy-era and 2007-2017 representing the New Digital Economy era.

Chart 2a shows the dramatic decline in labour productivity between the pre- and the post 2007-period, which has been well documented before. In line with our earlier work (Van Ark et al. 2016, Van Ark, 2016b) we find that productivity slowdown since 2007 has been accompanied by a slowdown in all three groups, but with the largest slowdown in the most digital intensive-using group. In our earlier work we have attributed this counterintuitive effect to a time-lag in productivity effects from digital technology due to its general purpose-nature as well as to the delaying effects from the digital transformation process.

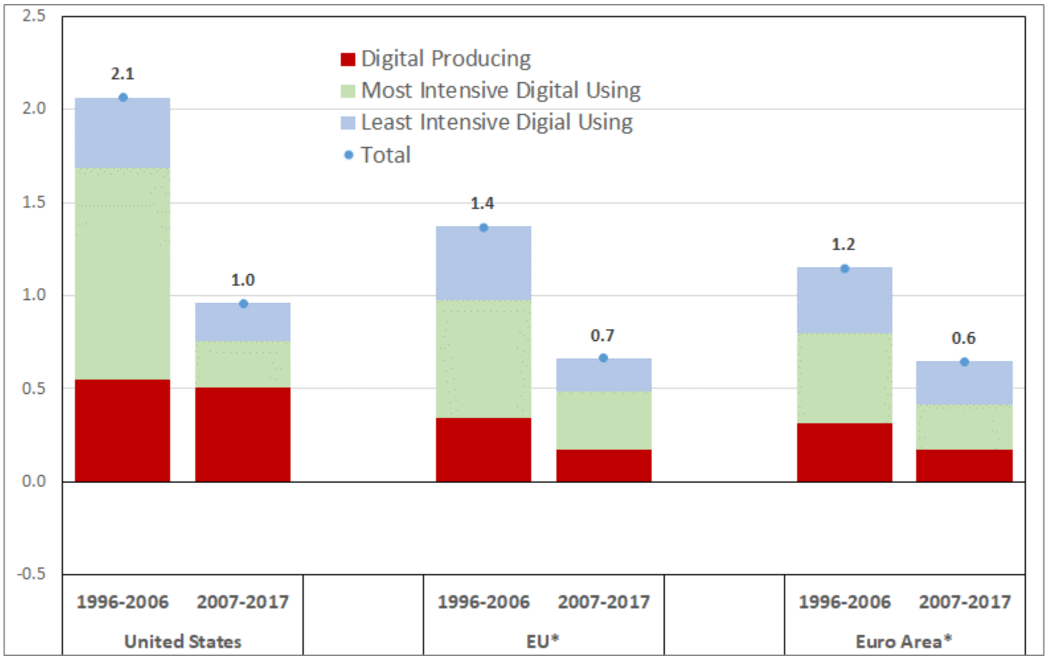
Chart 2a also shows that the slowdown in US labour productivity has been much larger than in the EU or the Euro Area, and that the impact from the decline in intensive digital-using industries was especially large in the US. In order to isolate possible large negative effects from global financial crisis, Chart 2b removes the period 2008-2012 from by comparing results for the last five years 2013-2017 with those for the 2003-2007 period – one decade before when the productivity effects of the Old Digital Economy were playing out.[6] When looking at Chart 2b it becomes clear that the slowing US productivity trend pushed the growth in output per hour (0.6 percent) during the most recent period, 2013-2017 even below that of the European Union (0.9 percent) and the Euro Area (0.8 percent).

[5] There are some exceptions though between OECD (2018) and Van Ark et al. (2016). These include petroleum, chemical, rubber and plastics, utilities, transport services, and arts and entertainment, which have moved from most intensive category in van Ark et al (2016) to least intensive group in the OECD study. Other manufacturing, health, and other services have moved from least intensive to most intensive groups. Moreover, three sectors, which OECD identify as most digital-intensive, are considered in our grouping as digital-producing sectors, which are electrical and optical equipment, publishing, telecom IT.

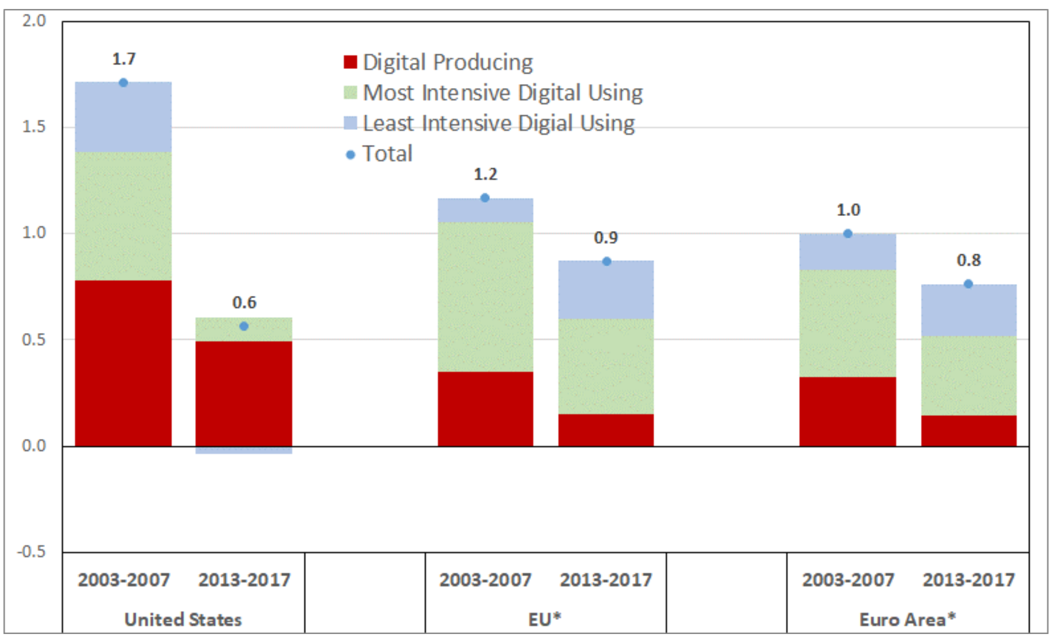
[6] While the productivity slowdown in the US started around 2005, in Europe the strong productivity period was extended to 2007 mostly because of cyclical effects especially in Germany. Hence we chose the period 2003-2007 here, with the implication that, had we chosen the 2003-2005 period, the US productivity growth rate would have been even higher and the decline even more pronounce than currently in Chart 2b.

Charts 2a and 2b: **Growth of output per hour and contributions from digital-producing and most and least intensive-using sectors, in %**

a) 1996-2006 and 2007-2017




b) 2003-2007 and 2013-2017




Notes: For taxonomy used see exhibit 1; for the aggregation method and United States, see appendix; EU aggregate is based on 19 countries and Euro Area aggregate on 16 countries, as data for Luxembourg, Cyprus, Malta, Ireland, Estonia, Lithuania, Latvia, Croatia & Bulgaria were not available for the entire period.

Sources: Conference Board calculations using data from Eurostat; BEA; BLS

The large fall in US productivity growth from 2013-2017 appears almost entirely due to the virtual collapse of productivity contributions from both intensive- and less-intensive digital-using sectors. Collectively, the most intensive digital-using industries contributed only 0.11 percentage point from 2013-2017 and the least intensive digital-using industries even contributed negatively by -0.05 percentage points. In contrast, the digital producing sector in the US, which accounts for only 8.4 percent of the value of GDP on average from 2013-2017, did account for the bulk of overall labour productivity growth from 2013-2017 (0.49 percentage points – or almost 90% of aggregate productivity growth). In contrast, the productivity growth contribution from intensive digital-using industries in Europe has begun to experience signs of improvement and is only slightly below the productivity contributions from 2003-2007. Also, compared to the United, the productivity contribution from the most digital intensive-using industries was four times larger than in the United States from 2013-2017.

It is useful to also take a look at the performance of the separately identified ICT-producing sector. While the contribution of digital-producing industries to productivity growth in the European Union and the Euro Area has dropped off significantly over the past decade, it held ground in the United States and contributes as much as three times more to productivity growth compared to the EU. While the differences in contributions by industry will be discussed in more detail below, the divergence in terms of digital-producing industries feeds directly into current debates about the predominance of digital production in the United States. The large share of external demand for US-based digital products and services may be one reason for its continued strength, while digital-using industries in Europe and the rest of the world may have benefited significantly from the strong performance of the US digital producing sector.

Table 2 compares the productivity contributions from digital producing and most and least intensive-using groups for individual European economies and the United States. The country estimates suggest the productivity contribution from the digital producing sector dropped significantly in all European countries, and especially strongly in Czechia, Finland and Sweden. The most intensive digital-using sector performed comparatively well in some Northern European countries (Sweden, UK) and Eastern European economies (Czechia, Poland and Slovenia).

Table 2: **Growth of GDP per hour worked and contributions from digital-producing and most and least intensive-using sectors, in %**

| | | Total | Digital Producing | Most Intensive Digital Using | Least Intensive Digital Using |
|---|---|---|---|---|---|
| United States | 1996-2006 | 2.06 | 0.55 | 1.14 | 0.38 |
| United States | 2007-2017 | 0.96 | 0.51 | 0.25 | 0.21 |
| United States | 2003-2007 | 1.71 | 0.78 | 0.60 | 0.33 |
| United States | 2013-2017 | 0.57 | 0.49 | 0.11 | -0.04 |
| EU* | 1996-2006 | 1.37 | 0.34 | 0.63 | 0.40 |
| EU* | 2007-2017 | 0.66 | 0.17 | 0.31 | 0.18 |
| EU* | 2003-2007 | 1.17 | 0.35 | 0.70 | 0.12 |
| EU* | 2013-2017 | 0.87 | 0.15 | 0.45 | 0.27 |
| Euro Area* | 1996-2006 | 1.15 | 0.32 | 0.48 | 0.36 |
| Euro Area* | 2007-2017 | 0.65 | 0.17 | 0.24 | 0.23 |
| Euro Area* | 2003-2007 | 1.00 | 0.32 | 0.51 | 0.17 |
| Euro Area* | 2013-2017 | 0.76 | 0.15 | 0.37 | 0.25 |
| Germany | 1996-2006 | 1.47 | 0.37 | 0.43 | 0.67 |
| Germany | 2007-2017 | 0.92 | 0.28 | 0.28 | 0.36 |
| Germany | 2003-2007 | 1.42 | 0.36 | 0.51 | 0.55 |
| Germany | 2013-2017 | 0.96 | 0.17 | 0.44 | 0.34 |
| United Kingdom | 1996-2006 | 1.73 | 0.35 | 1.01 | 0.37 |
| United Kingdom | 2007-2017 | 0.23 | 0.09 | 0.41 | -0.28 |
| United Kingdom | 2003-2007 | 1.22 | 0.31 | 1.26 | -0.34 |
| United Kingdom | 2013-2017 | 0.81 | 0.08 | 0.66 | 0.07 |
| France | 1996-2006 | 1.62 | 0.37 | 0.62 | 0.63 |
| France | 2007-2017 | 0.62 | 0.16 | 0.22 | 0.23 |
| France | 2003-2007 | 0.91 | 0.35 | 0.41 | 0.15 |
| France | 2013-2017 | 1.00 | 0.19 | 0.26 | 0.55 |

| | | rTotal | Digital Producing | Most Intensive Digital Using | Least Intensive Digital Using |
|---|---|---|---|---|---|
| Italy | 1996-2006 | 0.26 | 0.21 | 0.08 | -0.03 |
| Italy | 2007-2017 | 0.13 | 0.10 | 0.15 | -0.13 |
| Italy | 2003-2007 | 0.00 | 0.19 | 0.19 | -0.39 |
| Italy | 2013-2017 | 0.37 | 0.06 | 0.42 | -0.10 |
| Spain | 1996-2006 | -0.50 | 0.14 | 0.35 | -0.98 |
| Spain | 2007-2017 | 1.08 | 0.13 | 0.28 | 0.67 |
| Spain | 2003-2007 | 0.15 | 0.25 | 0.68 | -0.77 |
| Spain | 2013-2017 | 0.49 | 0.20 | 0.34 | -0.04 |
| Poland | 1996-2006 | 3.42 | 0.41 | 1.62 | 1.38 |
| Poland | 2007-2017 | 2.19 | 0.30 | 1.05 | 0.83 |
| Poland | 2003-2007 | 1.92 | 0.21 | 1.03 | 0.68 |
| Poland | 2013-2017 | 1.97 | 0.19 | 0.86 | 0.93 |
| Netherlands | 1996-2006 | 1.88 | 0.35 | 1.06 | 0.46 |
| Netherlands | 2007-2017 | 0.87 | 0.12 | 0.46 | 0.29 |
| Netherlands | 2003-2007 | 1.97 | 0.43 | 0.81 | 0.73 |
| Netherlands | 2013-2017 | 1.00 | 0.13 | 0.50 | 0.37 |
| Belgium | 1996-2006 | 1.41 | 0.21 | 0.60 | 0.60 |
| Belgium | 2007-2017 | 0.44 | 0.11 | 0.33 | -0.01 |
| Belgium | 2003-2007 | 1.70 | 0.20 | 0.88 | 0.62 |
| Belgium | 2013-2017 | 0.67 | 0.12 | 0.53 | 0.02 |
| Sweden | 1996-2006 | 2.73 | 0.74 | 1.30 | 0.70 |
| Sweden | 2007-2017 | 0.59 | 0.32 | 0.58 | -0.31 |
| Sweden | 2003-2007 | 2.52 | 0.98 | 1.33 | 0.21 |
| Sweden | 2013-2017 | 1.32 | 0.32 | 0.99 | 0.01 |

Table 2 continued

| | | Total | Digital Producing | Most Intensive Digital Using | Least Intensive Digital Using | | | Total | Digital Producing | Most Intensive Digital Using | Least Intensive Digital Using |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Romania | 1996-2006 | 3.30 | 0.31 | 1.03 | 1.96 | Hungary | 1996-2006 | 1.96 | 0.79 | 0.63 | 0.54 |
| Romania | 2007-2017 | 3.62 | 0.34 | 0.81 | 2.47 | Hungary | 2007-2017 | 0.15 | 0.17 | -0.20 | 0.17 |
| Romania | 2003-2007 | 4.74 | 0.57 | 1.50 | 2.67 | Hungary | 2003-2007 | 2.65 | 0.66 | 0.22 | 1.76 |
| Romania | 2013-2017 | 3.23 | 0.12 | -0.04 | 3.15 | Hungary | 2013-2017 | 0.77 | 0.31 | -0.23 | 0.69 |
| Austria | 1996-2006 | 1.68 | 0.21 | 0.81 | 0.66 | Denmark | 1996-2006 | 1.11 | 0.33 | 0.50 | 0.28 |
| Austria | 2007-2017 | 0.66 | 0.13 | 0.39 | 0.15 | Denmark | 2007-2017 | 0.70 | 0.29 | 0.12 | 0.29 |
| Austria | 2003-2007 | 1.78 | 0.33 | 0.95 | 0.50 | Denmark | 2003-2007 | 1.02 | 0.46 | 0.80 | -0.24 |
| Austria | 2013-2017 | 0.84 | 0.06 | 0.27 | 0.51 | Denmark | 2013-2017 | 1.20 | 0.25 | 0.28 | 0.66 |
| Czechia | 1996-2006 | 3.03 | 0.51 | 1.94 | 0.58 | Finland | 1996-2006 | 2.29 | 1.08 | 0.71 | 0.50 |
| Czechia | 2007-2017 | 1.13 | 0.32 | 0.91 | -0.10 | Finland | 2007-2017 | 0.44 | 0.23 | 0.18 | 0.03 |
| Czechia | 2003-2007 | 4.27 | 0.82 | 2.64 | 0.82 | Finland | 2003-2007 | 2.40 | 1.23 | 0.78 | 0.39 |
| Czechia | 2013-2017 | 1.50 | 0.30 | 0.83 | 0.37 | Finland | 2013-2017 | 0.90 | 0.45 | 0.22 | 0.24 |
| Portugal | 1996-2006 | 1.36 | 0.22 | 0.94 | 0.20 | Slovakia | 1996-2006 | 4.27 | 0.37 | 1.60 | 2.30 |
| Portugal | 2007-2017 | 0.06 | -0.05 | 0.35 | -0.25 | Slovakia | 2007-2017 | 2.02 | 0.33 | 0.46 | 1.23 |
| Portugal | 2003-2007 | 1.11 | 0.18 | 0.58 | 0.34 | Slovakia | 2003-2007 | 4.62 | 0.60 | 1.90 | 2.12 |
| Portugal | 2013-2017 | -1.12 | -0.11 | 0.17 | -1.17 | Slovakia | 2013-2017 | 1.75 | -0.03 | 0.62 | 1.16 |
| Greece | 1996-2006 | 1.39 | 0.21 | 0.33 | 0.84 | Slovenia | 1996-2006 | 2.48 | 0.44 | 1.22 | 0.83 |
| Greece | 2007-2017 | -1.25 | -0.13 | -0.73 | -0.38 | Slovenia | 2007-2017 | 0.71 | 0.17 | 0.49 | 0.04 |
| Greece | 2003-2007 | 0.97 | 0.22 | 0.28 | 0.48 | Slovenia | 2003-2007 | 3.31 | 0.60 | 1.46 | 1.26 |
| Greece | 2013-2017 | -0.14 | -0.02 | -0.21 | 0.09 | Slovenia | 2013-2017 | 1.65 | 0.21 | 0.98 | 0.46 |

Notes: For taxonomy used see exhibit 1; for the aggregation method and United States, see appendix; EU aggregate is based on 19 countries and Euro Area aggregate on 16 countries, as data for Cyprus, Malta, Ireland, Estonia, Lithuania, Latvia, Croatia & Bulgaria were not available for the entire period.

Sources: Conference Board calculations using data from Eurostat; BEA; BLS

To exploit the full richness of the labour productivity data by industry, we also developed so-called Harberger diagrams for this study. A Harberger diagram plots the cumulative contribution of individual industries to aggregate productivity growth, against the cumulative share of these industries in aggregate value added (Harberger, 1998; Timmer et al., 2010). It helps us understand how concentrated or widespread productivity growth across sectors. Charts 3a and 3b provide two examples of Harberger diagrams for the EU and the US, comparing the labour productivity contributions for the 2003-2007 and 2013-2017 periods. In Table 3 we further provide the key summary statistics from the Harberger approach for the growth of labour productivity in the EU, the US and the 19 economies in the EU.[7]

While both EU and the US both saw a slowdown in labour productivity as exemplified by the vertical axis, the share of value added representing industries that contributed positively to labour productivity pulled back in the US from 78 percent (2003-2007) to 45 percent (2013-2017). In contrast, industries representing 73 percent of value added in the EU were generating positive productivity growth rates from 2013-2017, up from 55 percent from 2003-2007. However, some heterogeneity was again visible between European countries. Notably Germany and the UK saw a drop in the contribution of most intensive digital-using industries, but not as large as in the United States.

In the US, only 49 percent of value added of the most intensive digital-using industries contributed positively to productivity growth from 2013-2017, which mainly represented two industries (trade and business services). In contrast in the EU, 92 percent of value added in the most intensive digital-using industries contributed positively to labour productivity from 2013-2017. In addition to trade and business services those industries in the EU also included finance and public administration. Manufacturing industries that were digital intensive users generally contributed much less to productivity growth than services, with the exception of digital producing manufacturing industries such as ICT equipment.

[7] Harberger diagrams may also be developed for total factor productivity growth. However, due to the shorter recent period, with data only up to 2015/2016, we will develop those later as the 2017 EUKLEMS data become available.

Chart 3a: **European Union, 2003-2007 and 2013-2017**

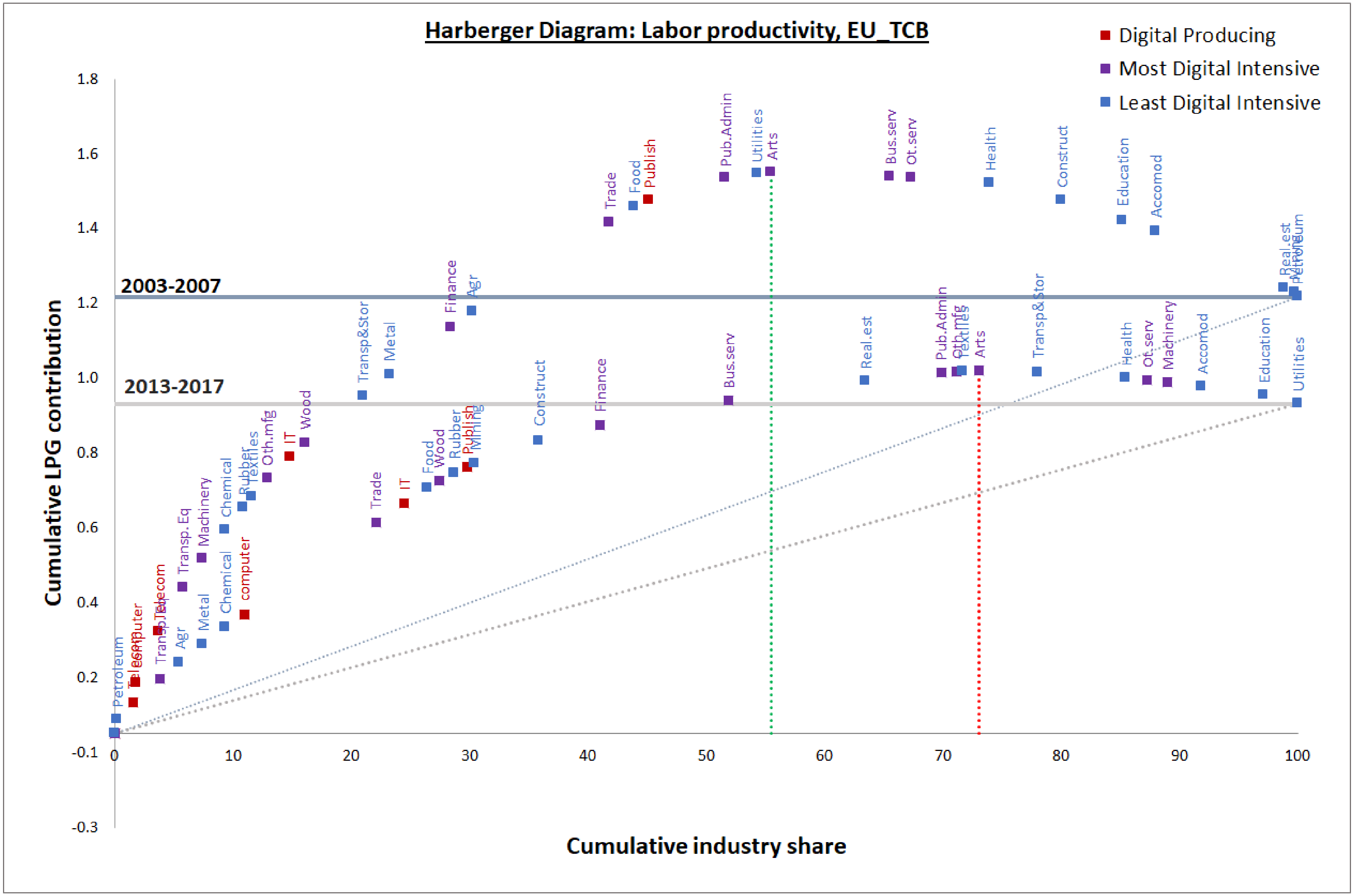


Chart 3b: **United States, 2003-2007 and 2013-2017**

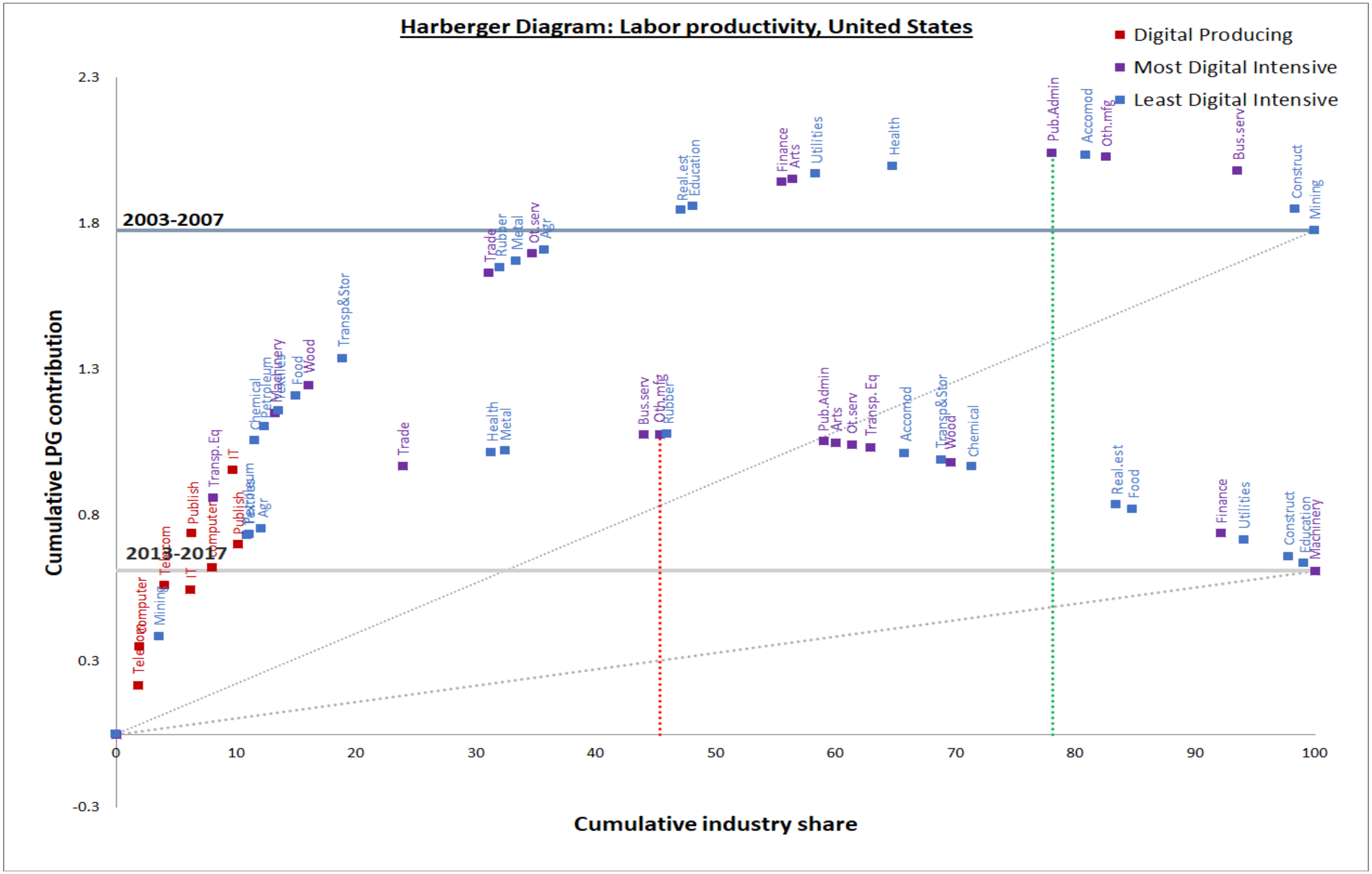


Table 3: **Summary metrics from Harberger diagrams, labour productivity growth, 1996-2006, 2007-2017, 2003-2007 and 2013-2017**

| Country/Region | Period | Aggregate labour productivity growth rate (%) | Cumulative value added share of industries with positive contributions to labour productivity growth in each group (%) | | | |
|---|---|---|---|---|---|---|
| | | | Total | Digital Producing | Most Intensive Digital Using | Least Intensive Digital Using |
| EU | 1996-2006 | 1.4 | 65.0 | 100.0 | 77.5 | 49.8 |
| | 2007-2017 | 0.7 | 74.7 | 100.0 | 68.0 | 77.0 |
| | 2003-2007 | 1.2 | 55.5 | 100.0 | 72.3 | 35.3 |
| | 2013-2017 | 0.9 | 73.1 | 100.0 | 91.8 | 53.8 |
| EA | 1996-2006 | 1.2 | 66.4 | 100.0 | 77.4 | 52.4 |
| | 2007-2017 | 0.7 | 64.8 | 84.2 | 63.6 | 63.4 |
| | 2003-2007 | 1.0 | 56.8 | 100.0 | 72.3 | 37.6 |
| | 2013-2017 | 0.8 | 70.2 | 84.4 | 88.2 | 53.0 |
| Germany | 1996-2006 | 1.5 | 74.6 | 100.0 | 57.9 | 86.8 |
| | 2007-2017 | 0.9 | 77.1 | 100.0 | 59.9 | 90.1 |
| | 2003-2007 | 1.4 | 74.3 | 100.0 | 63.3 | 81.1 |
| | 2013-2017 | 1.0 | 64.9 | 100.0 | 59.9 | 64.0 |
| France | 1996-2006 | 1.6 | 72.8 | 100.0 | 72.8 | 69.0 |
| | 2007-2017 | 0.6 | 69.0 | 100.0 | 66.1 | 67.7 |
| | 2003-2007 | 0.9 | 75.9 | 100.0 | 100.0 | 52.0 |
| | 2013-2017 | 1.0 | 82.6 | 100.0 | 83.4 | 79.9 |
| United Kingdom | 1996-2006 | 1.7 | 76.6 | 100.0 | 96.7 | 57.7 |
| | 2007-2017 | 0.3 | 57.0 | 100.0 | 77.9 | 33.4 |
| | 2003-2007 | 1.2 | 75.9 | 100.0 | 95.7 | 56.6 |
| | 2013-2017 | 0.8 | 66.8 | 74.9 | 94.8 | 42.2 |
| Italy | 1996-2006 | 0.3 | 64.2 | 100.0 | 74.9 | 51.3 |
| | 2007-2017 | 0.1 | 51.5 | 87.0 | 73.7 | 29.9 |
| | 2003-2007 | 0.0 | 53.0 | 58.4 | 74.2 | 35.1 |
| | 2013-2017 | 0.4 | 61.3 | 88.1 | 67.9 | 53.4 |
| Netherlands | 1996-2006 | 1.9 | 79.4 | 100.0 | 97.4 | 58.2 |
| | 2007-2017 | 0.9 | 71.8 | 86.1 | 63.4 | 79.0 |
| | 2003-2007 | 2.0 | 62.6 | 100.0 | 67.3 | 52.6 |
| | 2013-2017 | 1.1 | 72.0 | 86.6 | 63.9 | 79.1 |

Table 3 (continued)

| Country/Region | Period | Aggregate labour productivity growth rate (%) | Cumulative value added share of industries with positive contributions to labour productivity growth in each group (%) | | | |
|---|---|---|---|---|---|---|
| | | | Total | Digital Producing | Most Intensive Digital Using | Least Intensive Digital Using |
| Finland | 1996-2006 | 2.3 | 77.7 | 100.0 | 77.9 | 72.7 |
| | 2007-2017 | 0.5 | 54.5 | 100.0 | 58.4 | 43.5 |
| | 2003-2007 | 2.4 | 67.9 | 100.0 | 77.3 | 53.3 |
| | 2013-2017 | 0.9 | 52.0 | 100.0 | 60.5 | 38.7 |
| Sweden | 1996-2006 | 2.7 | 87.3 | 100.0 | 100.0 | 75.3 |
| | 2007-2017 | 0.5 | 58.5 | 68.8 | 97.5 | 25.1 |
| | 2003-2007 | 2.5 | 71.9 | 100.0 | 100.0 | 45.0 |
| | 2013-2017 | 1.3 | 68.7 | 75.4 | 100.0 | 41.5 |
| United States | 1996-2006 | 2.1 | 79.4 | 100.0 | 74.4 | 81.8 |
| | 2007-2017 | 1.0 | 86.5 | 100.0 | 97.4 | 70.5 |
| | 2003-2007 | 1.7 | 78.1 | 100.0 | 75.4 | 77.3 |
| | 2013-2017 | 0.6 | 45.3 | 100.0 | 48.8 | 29.9 |
| Portugal | 1996-2006 | 1.4 | 60.0 | 86.0 | 81.4 | 40.9 |
| | 2007-2017 | 0.1 | 51.9 | 16.8 | 82.7 | 31.0 |
| | 2003-2007 | 1.1 | 64.1 | 83.9 | 47.8 | 75.1 |
| | 2013-2017 | -1.1 | 46.3 | 15.8 | 83.2 | 21.1 |
| Spain | 1996-2006 | -0.5 | 56.3 | 79.0 | 79.6 | 38.8 |
| | 2007-2017 | 1.1 | 72.6 | 52.8 | 83.5 | 67.0 |
| | 2003-2007 | 0.2 | 52.2 | 80.4 | 78.5 | 32.2 |
| | 2013-2017 | 0.5 | 49.3 | 49.8 | 74.0 | 32.6 |
| Greece | 1996-2006 | 1.2 | 71.9 | 80.0 | 79.3 | 66.3 |
| | 2007-2017 | -1.2 | 44.4 | 0.0 | 42.0 | 49.0 |
| | 2003-2007 | 0.8 | 53.8 | 80.6 | 62.3 | 46.2 |
| | 2013-2017 | -0.1 | 42.4 | 76.3 | 21.3 | 52.8 |
| Romania | 1996-2006 | 3.6 | 86.8 | 100.0 | 96.6 | 81.1 |
| | 2007-2017 | 3.9 | 90.2 | 100.0 | 80.9 | 94.1 |
| | 2003-2007 | 4.3 | 75.9 | 90.8 | 78.1 | 73.2 |
| | 2013-2017 | 3.2 | 74.0 | 73.8 | 51.9 | 87.4 |

Table 3 (continued)

| Country/Region | Period | Aggregate labour productivity growth rate (%) | Cumulative value added share of industries with positive contributions to labour productivity growth in each group (%) | | | |
|---|---|---|---|---|---|---|
| | | | Total | Digital Producing | Most Intensive Digital Using | Least Intensive Digital Using |
| Hungary | 1996-2006 | 2.1 | 69.5 | 100.0 | 65.7 | 67.5 |
| | 2007-2017 | 0.2 | 43.7 | 84.8 | 22.5 | 55.6 |
| | 2003-2007 | 2.6 | 67.3 | 86.1 | 40.8 | 85.2 |
| | 2013-2017 | 0.8 | 59.3 | 70.2 | 44.4 | 71.1 |
| Slovak Republic | 1996-2006 | 4.3 | 87.9 | 83.8 | 90.9 | 86.2 |
| | 2007-2017 | 2.0 | 66.7 | 62.4 | 49.6 | 82.2 |
| | 2003-2007 | 4.6 | 77.7 | 100.0 | 100.0 | 57.7 |
| | 2013-2017 | 1.7 | 62.9 | 31.6 | 55.9 | 73.0 |
| Czech Republic | 1996-2006 | 3.1 | 72.9 | 100.0 | 93.6 | 54.8 |
| | 2007-2017 | 1.2 | 79.6 | 100.0 | 94.6 | 64.1 |
| | 2003-2007 | 4.3 | 71.5 | 100.0 | 80.6 | 60.4 |
| | 2013-2017 | 1.5 | 76.9 | 100.0 | 82.2 | 68.6 |
| Poland | 1996-2006 | 3.6 | 89.4 | 100.0 | 96.0 | 82.8 |
| | 2007-2017 | 2.2 | 85.6 | 100.0 | 85.1 | 84.4 |
| | 2003-2007 | 2.0 | 85.2 | 45.1 | 100.0 | 76.8 |
| | 2013-2017 | 2.0 | 80.4 | 82.8 | 79.1 | 81.3 |
| Denmark | 1996-2006 | 1.2 | 63.4 | 100.0 | 74.3 | 51.6 |
| | 2007-2017 | 0.8 | 70.5 | 100.0 | 43.4 | 87.6 |
| | 2003-2007 | 1.1 | 57.3 | 100.0 | 58.0 | 52.1 |
| | 2013-2017 | 1.1 | 85.9 | 100.0 | 74.3 | 93.2 |
| Belgium | 1996-2006 | 1.4 | 65.9 | 84.2 | 73.8 | 57.5 |
| | 2007-2017 | 0.4 | 63.1 | 47.7 | 98.5 | 32.5 |
| | 2003-2007 | 1.7 | 86.4 | 100.0 | 98.6 | 74.5 |
| | 2013-2017 | 0.7 | 62.1 | 43.5 | 98.5 | 30.2 |
| Slovenia | 1996-2006 | 2.5 | 83.2 | 100.0 | 77.2 | 85.5 |
| | 2007-2017 | 0.7 | 62.0 | 65.5 | 93.7 | 36.1 |
| | 2003-2007 | 3.4 | 85.4 | 100.0 | 96.2 | 75.0 |
| | 2013-2017 | 1.6 | 77.7 | 68.5 | 96.4 | 64.0 |

Notes: For taxonomy used see exhibit 1; for the aggregation method and United States, see appendix; EU aggregate is based on 19 countries and Euro Area aggregate on 16 countries, as data for Cyprus, Malta, Ireland, Estonia, Lithuania, Latvia, Croatia & Bulgaria were not available for the entire period.
Sources: Conference Board calculations using data from Eurostat; BEA; BLS

# 4. INNOVATION COMPETENCIES AND PRODUCTIVITY

Economic growth is the sum of two key trends in the economy: the increase in the employment and the rise in labour productivity. The dynamics of employment and productivity growth are both severely impacted by the digitisation of the economy. In this section our focus is on the workforce and more specifically on how innovation competencies of the workforce align to the needs of the digital transformation process.

To measure the extent to which people competencies relate to industry productivity growth, we apply a novel approach developed by The Conference Board to assess the innovation potential of occupations (Hao et al., 2018). The Innovation Potential of Occupations (IPO) Dashboard assigns an innovation potential score to each occupation. The score is an average of a broader set of twelve competencies which are based on 200+ variables on job characteristics for 700+ occupations from the O*NET database, the primary US source of information on occupations (US Bureau of Labor Statistics). On the basis of a literature review, The Conference Board study selected 65 innovation-related job characteristics from the O*NET database and then applied factor analysis to ultimately group them into 12 competencies:

1. STEM
2. Adaptability/Flexibility
3. Autonomy
4. Empowerment
5. Decision Making
6. Cooperative teams and group interaction
7. Creativity
8. Mistake handling
9. Learning culture
10. Conflict handling
11. Enterprising
12. Deal with external customers

Each occupation is then assigned an innovation potential score. Using the IPOP Dashboard, the individual scores for each competency can be aggregate to provide an overall innovation score for each occupation. This score then highlights the strengths and weaknesses of each occupation related to innovation. One of the insights of quantifying competencies is that the innovation potential of occupations is more widely dispersed than is mostly assumed. For example, while a sales manager may not at face value be assumed to contribute to the innovative potential of an organisation, this occupation does get a relatively high IPO score, higher than for example a physicist. This is related to the sales managers crucial role in representing the customer's voice in both the beginning and the end of an innovation cycle.

Using tabulations of occupations by industry for individual countries, we construct weighted IPO averages by industry by country. In this exploration we focus on the UK, US and Sweden. After we harmonised the industry data to conform to the International Standard of Industry Classification (ISIC) revision 4, the results can be presented for 15 aggregate sectors for the three countries for the year 2017 (Table 4). A relatively higher ranking is reflective of a higher number of workers with occupations that have a high innovation potential score. In general, it seems that service industries score better on this index than goods producing industries. For the US and the UK, for which we have more detailed data than the 15 sectors shown in table 5, we find that services industries such as advertising and market research, legal, accounting and management consulting as well as research and development have a relatively high innovation potential. Conversely, at the lower end of the list are agricultural industries, as well as goods producing industries such as clothing, food and drinks and basic metals manufacturing.

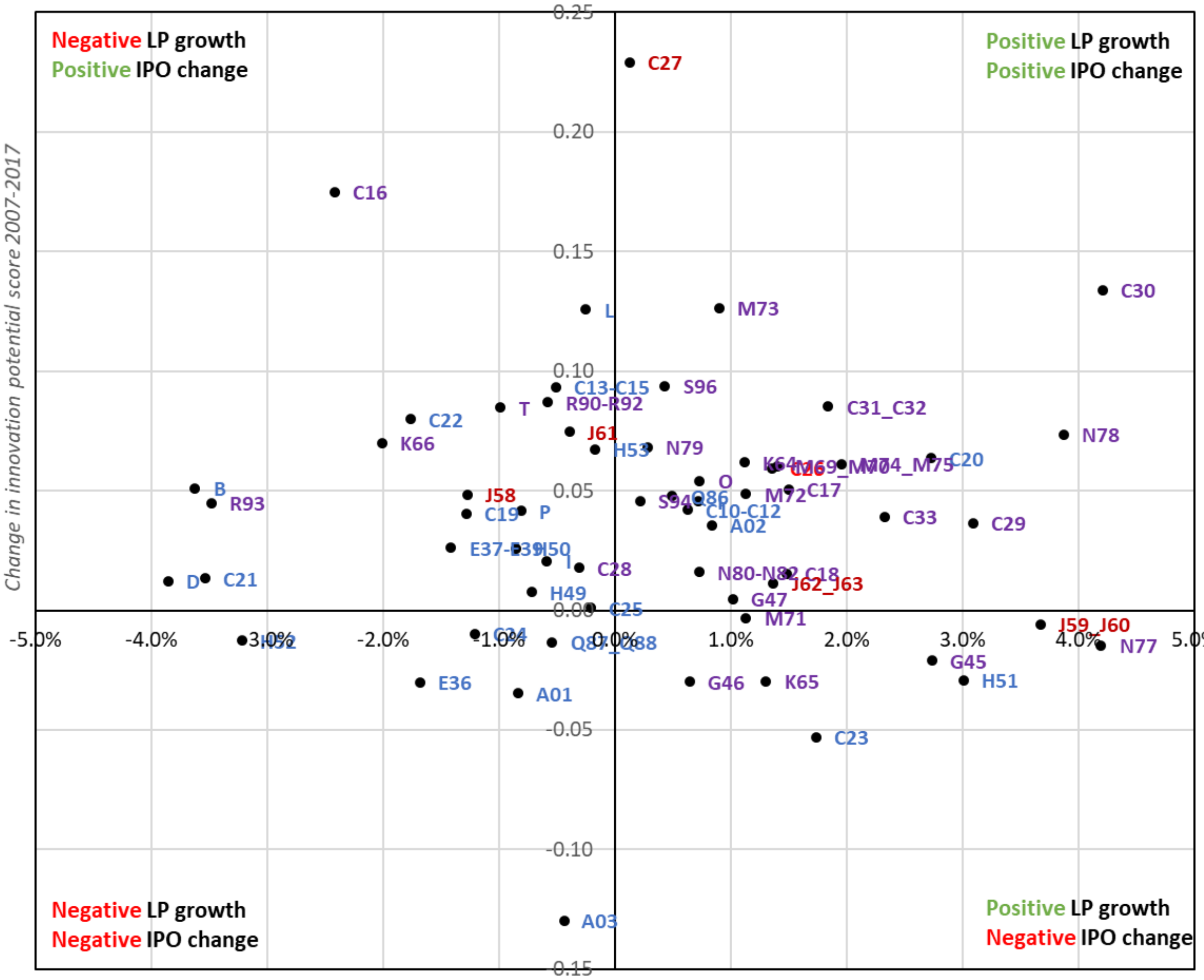
Table 4: **Innovation Potential Score by industry, Sweden, UK and US, 2017**

| | United Kingdom | Sweden | United States |
|---|---|---|---|
| A - Agriculture, forestry and fishing | 15 | 14 | |
| B+C - Mining, Quarrying, Manufacturing | 13 | 13 | 12 |
| D+E - Utilities | 10 | 9 | 10 |
| F - Construction | 11 | 11 | 11 |
| G - Wholesale and retail trade | 8 | 6 | 8 |
| H - Transport and storage | 14 | 12 | 14 |
| I - Hotels and restaurants | 12 | 15 | 13 |
| J - Information & Communication | 3 | 4 | 3 |
| K - Finance | 2 | 2 | 2 |
| L - Real estate | 1 | 10 | 7 |
| M+N - Business services | 7 | 8 | 6 |
| O - Public administration and defense | 4 | 3 | 4 |
| P - Education | 5 | 1 | 1 |
| Q - Human health and social work | 6 | 5 | 5 |
| R+S+T+U Entertainment, other services | 9 | 7 | 9 |

Notes: For methodology used see Appendix; US data is based OES survey, which excludes agriculture.
Source: The Conference Board Innovation Potential of Occupations Dashboard; Office for National Statistics (UK), Statistics Sweden, Bureau of Labor Statistics and the Bureau of Economic Analysis (US).

Using data on output per hour we compare to what extent the changes in IPO scores are related to changes in labour productivity at the industry level. Chart 4 presents data for the United Kingdom for the period between 2007 and 2017.

Chart 4: **Scatter plot of the change in IPO score and productivity growth by detailed industry for the period 2007-2017, United Kingdom**



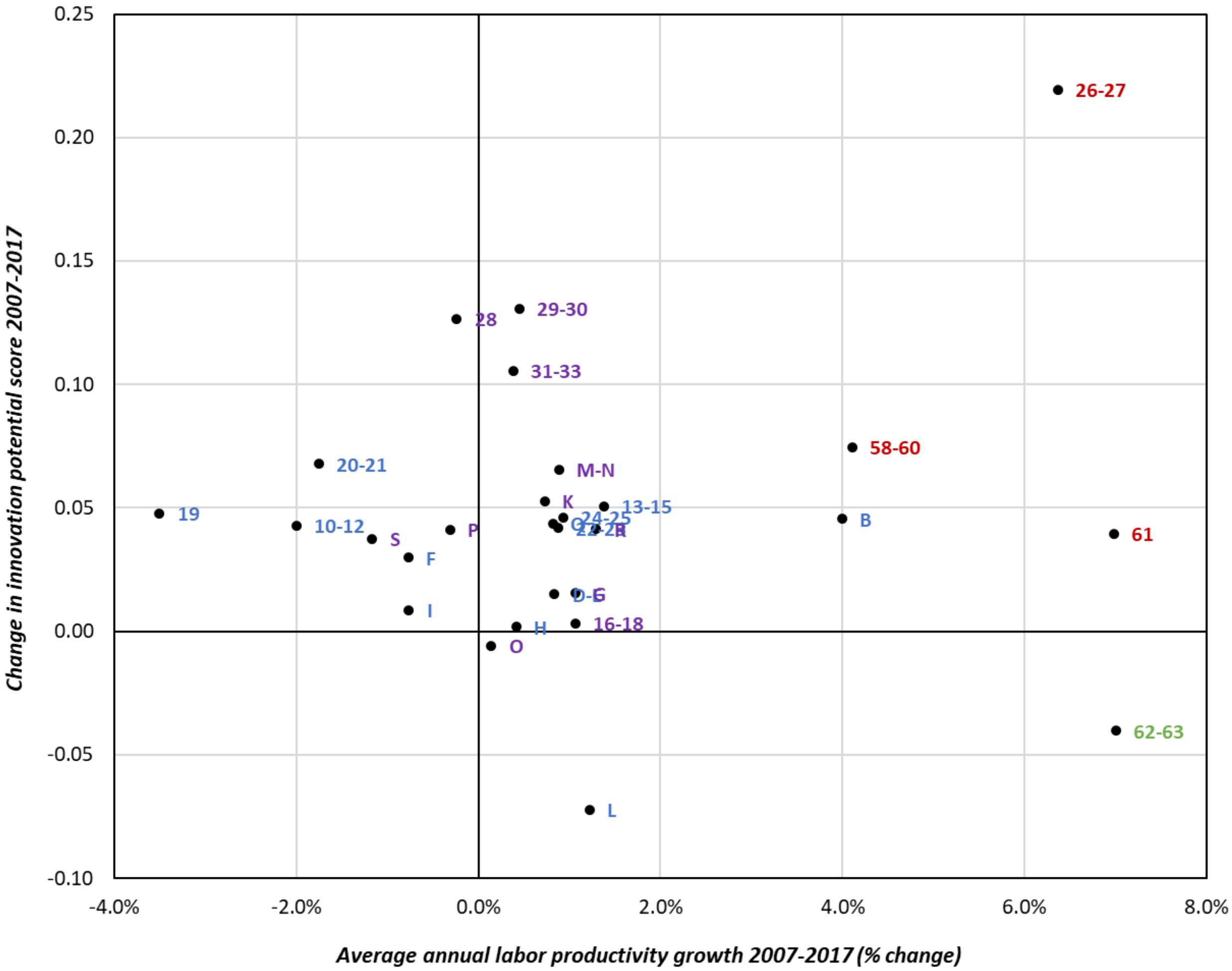

Average annual labor productivity growth 2007-2017 (% change)

Notes: For the underlying methodology used see the appendix; Data is shown here on the level of 63 individual industries, based on the ISIC rev.4 classification. Industry codes are given in Exhibit 1; Dark red denotes digital producing, purple refers to most digital intensive-using and blue refers to least digital intensive-using industries.

Source: The Conference Board Innovation Potential of Occupations Dashboard; Office for National Statistics.

The chart shows that most industries were able to employ more workers with higher innovative potential scores (north of the x-axis), even though some of those industries were not able to improve their productivity growth rates (northwest quadrant). However, most of the dots are in the northeast quadrant which combined an improved IPO score with positive productivity growth. The latter group represents a wide array of industries, including transport equipment manufacturers, construction and most business services. These industries for about 55% of total hours worked and 47% of value added. Importantly, many of the industries in the north-east quadrant are identified as part of the group of most intensive-digital using industries.

Chart 5: **Scatter plot of the change in IPO score and productivity growth by detailed industry for the period 2007-2017, United States**




Notes: For the underlying methodology used see the appendix; Data is shown here on the level of 29 individual industries, based on the ISIC rev.4 classification, based on the ISIC rev.4 classification. Industry codes are given in Exhibit 1; Dark red denotes digital producing, purple refers to most digital intensive-using and blue refers to least digital intensive-using industries.

Source: The Conference Board Innovation Potential of Occupations Dashboard; Bureau of Labor Statistics and the Bureau of Economic Analysis.

The results for the US (Chart 5) show a similar picture, though there are fewer industries with a decline in IPO score and more industries in the northeast quadrant of positive IPO change and positive productivity growth. These industries represent 59% of total hours worked and 58% of value added. However, current estimations are based 29 industries, hampering a full comparison with the UK for which we have greater detail (See appendix for details). Digital-producing industries, especially in manufacturing, are characterised by very strong innovation competencies and strong productivity growth, whereas several other digital-intensive using industries in manufacturing (e.g. machinery) also show strong innovation competencies but much weaker productivity performance.

# 5. CONCLUSIONS

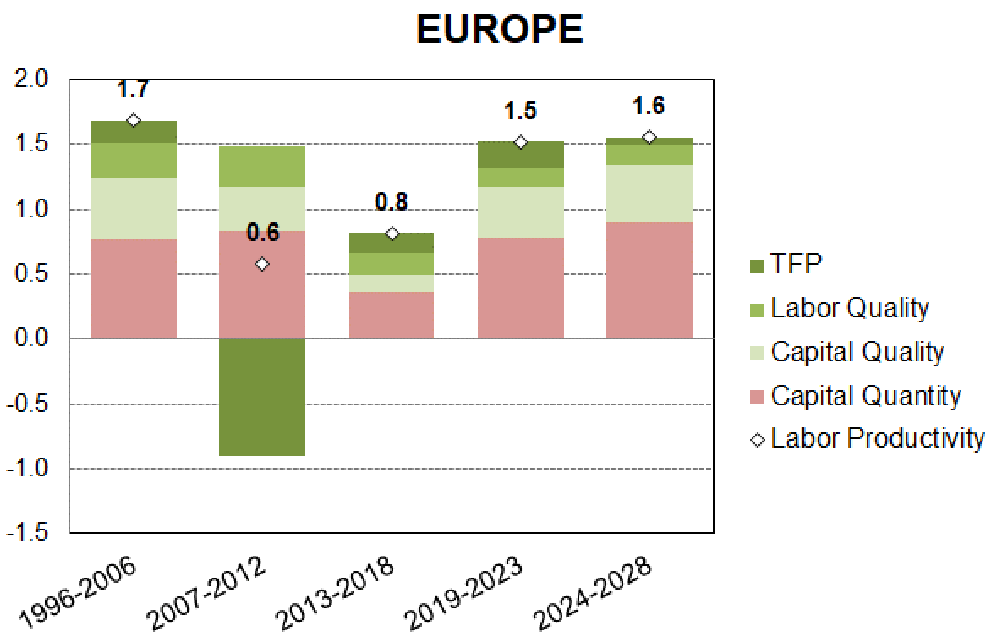
Despite improved productivity growth in 2016 and 2017 in Europe and the US, the productivity paradox of the New Digital Economy, pointing at the notion of increasing business spending on ICT assets and digital services without a noticeable increase in productivity in most advanced economy, is far from resolved. Nevertheless this paper provides some early evidence that underneath the macro-economic numbers signs of structural changes can be detected. However, we observe substantial differences in the way the digital economy is evolving. In the US most of the positive contribution to productivity growth is coming from the digital producing sector. Europe has an advantage in the most intensive digital-using sector, which has been driving the largest part of labour productivity growth in recent years. We also find that improved innovation competencies of the workforce are mostly related to faster growth in labour productivity, even though more research is needed to identify causality.

Overall, while the evidence is still thin due to time lags in the data, there are signs of positive contributions to productivity growth related to digital transformation even though those effects are still not widespread observable across the economy. In line with Brynjolfsson et al. (2019) we agree that time lags are the most important reason for the slow emergence of the productivity effects of digital transformation.

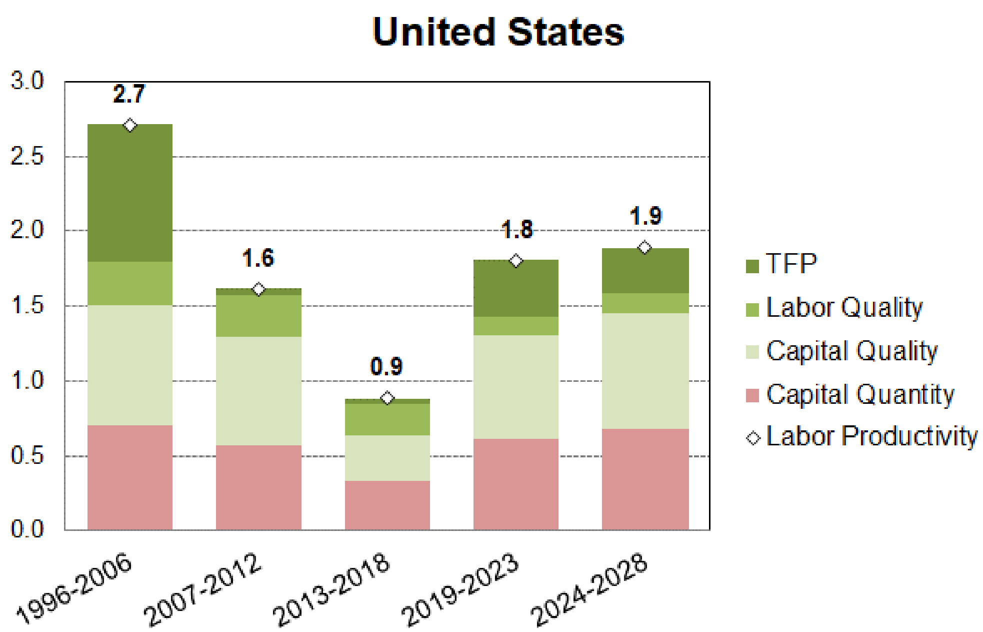
TFP growth is the critical factor in improving the labour productivity growth performance of the EU and US economies (Charts 6a and 6b). Current projections for the next 10 years point at significant improvements in the contribution of capital quality (which mostly reflects the shift towards digital assets) but only a very modest improvement in total factor productivity, especially in Europe. Hence TFP improvements, which cover a wide range of factors including innovation, competition and other regulatory matters, have to become a critical focus of business strategy and policy.

Charts 6a and 6b: **Growth Accounting Projections, 1996-2028, Europe and USA, % growth**

a) Europe




b) United States




Note: Europe including EU-28 plus Iceland, Norway and Switzerland
Source: The Conference Board Global Economic Outlook, November 2018

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# APPENDIX

## Aggregate productivity data for digital producing and using groups

The OECD distinguishes 35 industries in their sectoral taxonomy of digital intensity. We bring this down to 29 industries according to the availability of data. These industries along with their codes and descriptions are listed in Exhibit 1. For each digital grouping we use the commonly used Tornqvist method of aggregation, which is a weighted average of underlying industry productivity growth rates with the weights being value added shares. That is, aggregate productivity growth for the digital groupings $d$ is derived as:

$$\Delta \ln PROD_d = \sum_{\mathrm{i}} \overline{\mathrm{w_i}}\, \Delta \ln PROD_{\mathrm{i}}$$

where $PROD$ denotes either labour productivity or total factor productivity of digital grouping $d$ or industry $i$, and $\overline{\mathrm{w_i}}$ represents the share of industry $i$ in aggregate value added for the digital grouping and the bar denotes the use of two-period averages.

## Innovation Potential Score by Industry methodology and sources

The idea of aggregating occupational IPO scores by industry is relatively straightforward. What is needed is detailed data on the number of workers by occupation by industry, so that a weighted average of the IPO score for industry $i$ across various occupations can be calculated as:

$$IPO_i = \sum_{o} emp\_s_o^i \cdot IPO_o$$

where $emp\_s_o^i$ denotes the share of the number of workers with occupation $o$ in industry $i$ and $IPO_o$ is the $IPO$ score for occupation $o$. Thus, the industry $IPO$ score is the product of the $IPO$ scores of the occupations that are prevalent in that industry weighted by the number of workers for each occupation.

The biggest challenges are in the availability of detailed tabulations of occupations by industry and perhaps more importantly the crossover from different classification systems used to denote occupations and industries. In the remainder of this section we will focus on the latter issue.

### Table AX1 – Sources used

| | Source | Coverage | # industries (2017) | # occupations (2017) |
|---|---|---|---|---|
| **United States** | Occupational Employment Statistics (OES)[8] | Establishment survey covering only full-time and part-time wage and salary workers in nonfarm industries | 250 NAICS | 809 SOC (US) |
| **United Kingdom** | Annual Population Survey (APS)[9] | People aged 16 or over who did some paid work in the reference week (whether as an employee or self-employed); those who had a | 88 ISIC rev.4 | 369 SOC (UK) |

[8] https://www.bls.gov/oes/home.htm

[9] https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/methodologies/annualpopulationsurveyapsqmi

| | | | | |
|---|---|---|---|---|
| | | job that they were temporarily away from (for example, on holiday); those on government-supported training and employment programs and those doing unpaid family work (that is, working in a family business) | | |
| **Sweden** | The Swedish Occupational Register[10] | Covers all persons registered as employee, entrepreneur or own account worker in Sweden aged 16 years and over | 15<br>ISIC rev.4 | 430<br>SSYK |

Harmonising occupational classifications

Data on IPO scores are based on variables on job characteristics from the United States O*NET database and are available for 772 occupations using the Standard Occupational Classification (SOC) System, not to be confused with the UK system carrying the same name.[11] Our first step is to map the US SOC to the International Standard of Occupations (ISCO) at the most detailed level possible, to arrive at IPO scores by ISCO occupations.[12] The ISCO classification system is used because it is more internationally recognised and hence assures the availability of concordance tables, which is usually not the case with regards to country specific systems (e.g. to our knowledge there is no concordance table available mapping the UK SOC codes to the US SOC codes).

Luckily the SOC and ISCO systems are relatively similar, though there are some notable differences where one classification provides greater detail for a certain group of occupations than the other. An example is 'University and higher education teachers' in ISCO (code 2310) which maps to 35 occupations in the SOC classification. At the same time, in some cases ISCO provides more detail, for example for SOC occupation 'First-Line Supervisors of Transportation and Material-Moving Machine and Vehicle Operators' (code 53-1031) maps to 17 ISCO occupations. Overall however the SOC system is more detailed, identifying 840 occupations as opposed to 436 in ISCO.[13]

This presents difficulties as our IPO score for ISCO-based occupations is thus based on multiple SOC-based IPO scores (the average ISCO occupation represents 2.4 SOC occupations). However, luckily there is a one-to-one direct match for a large number of occupations (160 of the 422 ISCO-based occupations used in the analysis) and a somewhat smaller number of ISCO-based occupations which map to 2 SOC-based occupations (135) which together account for 70% of all the occupations used in the analysis. However, some problem cases remain like the earlier mentioned 'University and higher education teachers' which is scattered across 35 different SOC codes with a minimum IPO score of -0.18 and maximum of 0.76. In this case our approach of taking a simple average (at 0.46) is less suitable. This is also the reason why we refrained from using the publicly available EU-wide Labor Force Survey data on occupations by industries as it distinguishes only 40 occupations with the average ISCO (2-digit) occupation representing 26 SOC occupations (the maximum number is 76 for 'Stationary plant and machine operators' (code 81) ). In other words, each ISCO-based IPO score would have been based on the simple average of 26 SOC-based scores, which we do not deem to give reliable results. Therefore, we take a more targeted approach by

[10] https://www.scb.se/en/finding-statistics/statistics-by-subject-area/labour-market/employment-and-working-hours/the-swedish-occupational-register-with-statistics/

[11] For the US please refer to https://www.bls.gov/soc/2010/home.htm; for the UK please refer to https://www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc

[12] For more information on the ISCO please refer to https://www.ilo.org/public/english/bureau/stat/isco/index.htm

[13] Note that the Innovation Potential scores are based on 772 occupations as some occupations are left out due to data constraints while the military (20 SOC occupations) are also excluded in the IPO analysis.

focusing only on those countries for which publicly available detailed data is available, which in this study are the US, UK and Sweden.

The next step then is to map the ISCO classification to national occupational classification systems as they are used in the UK and Sweden. As mentioned earlier, just as the US the UK labels their system SOC, though the UK system is more closely related to the ISCO, as such that both the UK SOC and ISCO identify 9 major groups that are roughly equal in terms of characteristics (as opposed to 23 major groups in the US SOC). The Swedish occupational classification system SSYK is largely based on ISCO. We use the concordance tables that are produced by the respective Statistical Offices (e.g. UK SOC-ISCO and SSYK-ISCO).

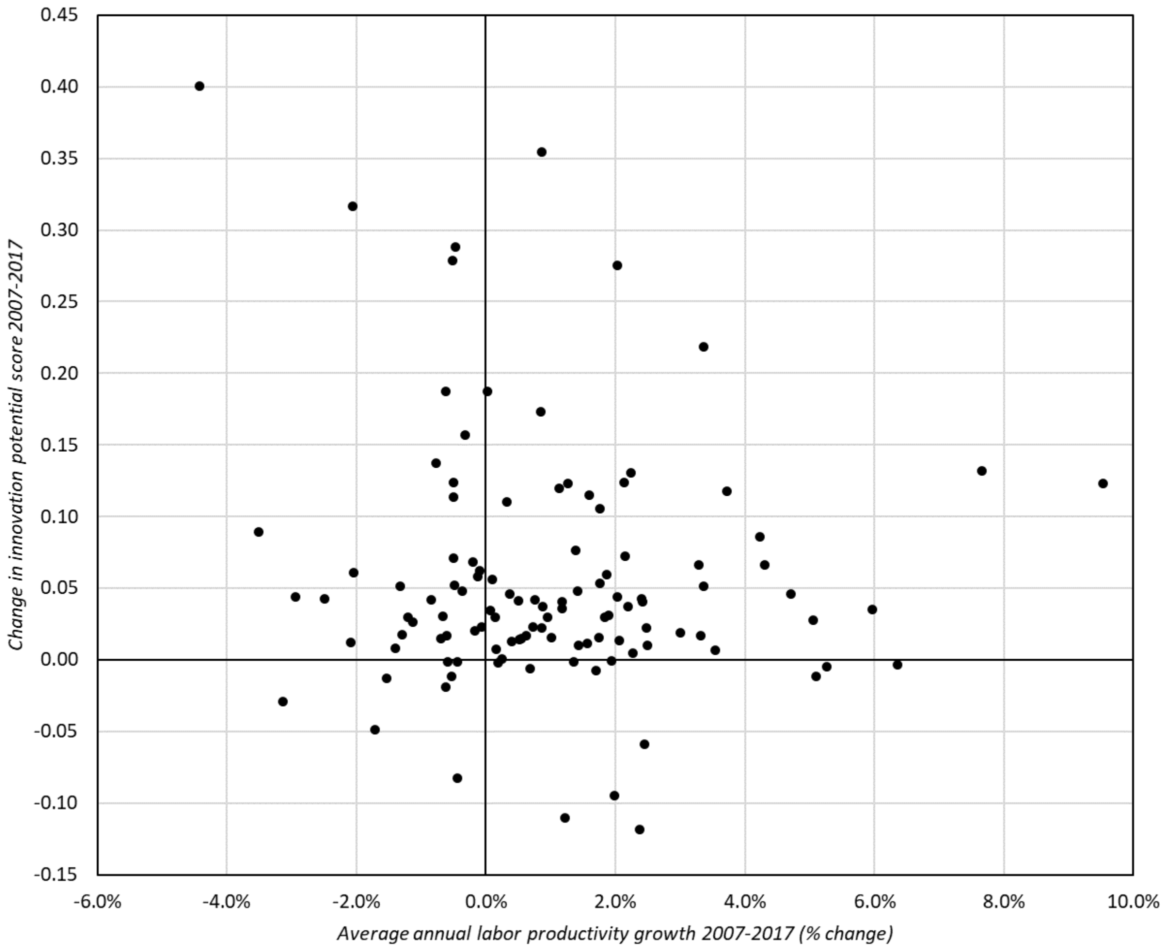
Harmonising industry classifications

While data for the UK and Sweden are organised according to the industries as defined in the International Standard of Industry Classification (ISIC) revision 4, the US data on the other hand are based on the North American Industry Classification System (NAICS). The occupation-by-industry data for the US provides detail for 250 industries, which is enough detail to provide a good crossover to ISIC industries. However, the value added data that is used in the productivity analysis has somewhat reduced detail with about half of that number of industries, hence we opted for a more aggregated and therefore 'safer' set of 29 ISIC industries for the productivity analysis, as opposed to the 63 industry detail for the UK.

Another option is to use the BLS industry productivity data, as that would avoid the problem associated with matching the and NAICS and ISIC classifications.[14] However out of the 250 industries from the occupation-by-industry data from the OES, the BLS only provides labour productivity data for 114 industries, hence it does not cover the total economy. The scatter plot below (Chart AX2) provides the data for those 114 industries (NAICS codes are left out for ease of exposition) and seems to provide roughly the same picture as the figure based on 29 ISIC industries.

[14] Data is available from https://www.bls.gov/lpc/tables_by_sector_and_industry.htm

Chart AX2 – **Scatter plot of the change in IPO score and productivity growth by detailed NAICS industry for the period 2007-2017, United States**




Source: The Conference Board calculations using data from The Conference Board Innovation Potential of Occupations Dashboard and productivity data from the Bureau of Labor Statistics.

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