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Virtually everywhere? Digitalisation and the euro area and EU economies

Degree, effects, and key issues

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Abstract

Digitalisation can be viewed as a major supply/technology shock affecting macroeconomic aggregates that are important for monetary policy, such as output, productivity, investment, employment and prices. This paper takes stock of developments in the digital economy and their possible impacts across the euro area and European Union (EU) economies. It also compares how these economies fare relative to other major economies such as that of the United States. The paper concludes that: (i) there is significant country heterogeneity across the EU in terms of the adoption of digital technologies, and most EU countries are falling behind competitors, particularly the United States; (ii) digitalisation is affecting the economy through a number of channels, including productivity, employment, competition and prices; (iii) digitalisation raises productivity and lowers prices, similarly to other supply/technology shocks; (iv) this has implications for monetary policy and its transmission; and (v) structural and other policies may need to be adapted for the euro area and EU countries to fully reap the potential gains from digitalisation, while maintaining inclusiveness.

Keywords: digital technology, technology shocks/adoption/diffusion, productivity, labour market, inflation, human/intangible capital, potential growth.

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Executive summary

The digitalisation revolution is “virtually everywhere” and transforming our economies. A key objective of this paper is to take stock of developments in the digital economy, as well as their possible impacts, across the individual euro area and EU economies. It also looks at how these economies fare relative to other major economies such as that of the United States. Overall, we find significant country heterogeneity across the EU in terms of the adoption of digital technologies – such as robotisation, online platforms and the size of the digital economy – and most EU countries are falling behind competitors such as the United States and Japan. Good governance and efficient institutions tend to be associated with a higher degree of digitalisation.

The extent to which digitalisation affects the economy is an important issue from a central banking viewpoint. In particular, we examine the possible impacts of digitalisation on key variables relevant to monetary policy and its transmission, such as output, investment, productivity, employment, wages and prices. Overall, digitalisation is raising productivity and activity, but may not always increase employment, with impacts on inflation skewed to the downside.

The “productivity paradox” – advances in digitalisation amid a protracted slowdown in productivity growth – is a phenomenon that needs to be better understood. The paradox of low aggregate productivity growth against the background of a growing digital economy seems to be associated with rising productivity dispersion at the firm level, with high-productivity leaders being partly offset by low-productivity laggards. This is accompanied by significant lags between the implementation of digital technologies and their full operationalisation together with the realisation of their potential productivity gains.

From a monetary policy perspective, reaching an inflation objective may become more challenging as the digital economy grows if there are mechanisms, such as increased (online) competition, which lead to lower inflation in the shorter run. However, the impacts of digitalisation on inflation may not be clear-cut, and may differ at short and long horizons. Apart from the possible impact of more flexible (dynamic) pricing which is likely to occur across all time horizons, there may be upward pressure on inflation from digitalisation in the medium to long term via increasing concentration and profit margins.

Digitalisation may affect the transmission of shocks. This may also apply to monetary policy shocks if – in a digital economy – firms are able to change prices more quickly. On the other hand, changes in market power related to digitalisation and “superstar firms” may affect how firms react to changes in costs, in turn affecting the transmission of monetary policy. Different adoption rates and the use of digital technologies across the euro area countries may lead to country heterogeneity regarding monetary policy transmission. The relative importance and impacts of these various channels, and the extent to which digital heterogeneity across the euro area countries matters, is an empirical question that remains open.

The digital economy is a challenge for traditional measurement frameworks. In particular, more work needs to be done on the question of what to count as intangible investment and how to assess the value of data as an asset of the firm. The measurement of inflation in the presence of rapidly improving digital products and the ever-growing importance of digital services and products is a key priority. Some findings suggest that the slowdown in gross domestic product (GDP) growth and productivity, which started before the financial crisis, may be less pronounced under different measurement methodologies for some deflators.

Structural policies may have to be adapted in response to digitalisation. Labour, product and financial market regulations may need to be changed in order to fully reap the potential gains from digital technologies while maintaining inclusiveness and safeguarding vulnerable groups who may experience job insecurity and lower earnings. Access to relevant education and training, along with business models supporting digital skills, tasks and jobs, would seem especially important. Financing of intangible investment, which is hard to collateralise, may be more suited to equity financing than traditional bank financing. These issues may require policies at the EU level as well as the national level.

Digitalisation is indeed “virtually everywhere”, but to differing degrees across EU countries and across continents. Although there are notable digital success stories across the EU, the position of many countries may have to be strengthened as not all of them are near the frontier of dissemination and adoption of digital technologies, while the vanguard of the digital revolution is frequently outside the EU. This may raise the question as to whether the EU needs a more far-reaching digital policy agenda to overcome second-mover disadvantages and to advance closer to the technology frontier in order to remain competitive in global markets.

The COVID-19 pandemic may result in an acceleration in the take-up of digitalisation, which could be a further significant challenge for EU countries, but could also provide opportunities to catch up. Firms, workers and consumers are rapidly becoming more accustomed to, and familiar with, using digital technologies during the pandemic – such as video conferencing, teleworking or working from home and online transactions – which may result in an acceleration of digitalisation, perhaps leading to structural change across economies, with possible implications for labour markets, growth and productivity.

1 Introduction, main findings and policy implications

1.1 Introduction

The digitalisation revolution seems to be “virtually everywhere” and transforming our economies. At the same time, its measurement, and assessing the extent to which it may be transforming and affecting different economies to differing degrees, is challenging. Not least because the creation of satellite “national accounts” of the digital economy is currently ongoing, and such accounts are only available for a small number of countries such as the United States and Canada. Accordingly, one key objective of this paper is to bring together various sources of data and information to take stock of developments in the digital economy, as well as their possible impacts, across the euro area and EU economies and to see how they compare relative to other major economies such as the United States.¹

The extent to which digitalisation affects the economy is an important issue from a central banking perspective. The diffusion of information and communication technology (ICT), along with the spread of ICT-related services, automation and robotisation, artificial intelligence (AI) and the Internet of Things (IoT), amounts to a sequence of supply shocks with potentially pervasive impacts on economic outcomes, which may entail significant structural change. This paper focuses on some of the key variables that may be affected by digitalisation and are important for monetary policy.

Some key effects of digitalisation relevant for monetary policy relate to output, investment and productivity. These effects are due to the transformative nature of digitalisation leading to new forms of output, intangible investment and new ways of doing business. In addition, process and product innovations affect both the digital economy and the production of non-digital output, not least through their impact on downstream sectors.

Similarly, the effects of digitalisation on labour markets, wages and prices are also relevant for monetary policy. The increased use of digital technologies (especially automation) as a substitute for, or to complement, certain types of task and/or job has affected the dynamics of job creation and destruction. Combined with the rise of new “platform-based” activities, this has possible implications for wages and the wage bargaining process, as well as implications for inflation, not least against the background of growing online retail trade and competition.

This paper focuses on the impact of digitalisation on the real and nominal sides of economic activity, but it does not analyse its impacts on the financial sector. We contribute to the understanding of the impact of digitalisation in several ways. First, we provide an in-depth overview of the current thinking on the main

¹ The cut-off date for the data used in this paper was 31 December 2019.

mechanisms through which digitalisation affects output, investment, productivity and employment as well as wages and prices. Second, we summarise some of the main analyses and surveys of digitalisation and its estimated impacts on a range of variables. Third, we report on new analytical work in a number of areas related to digitalisation. Finally, we shed light on the degree of differences across euro area and EU countries, as well drawing a comparison with other major economies in terms of the take-up of digitalisation and its impacts.²

Section 2 of the paper assesses the degree of digitalisation across euro area and EU countries, also using various measures to draw comparisons with other major economies where possible. Section 3 then gives a broad overview of the estimated macroeconomic impacts of digitalisation across a range of key variables such as productivity, output, employment and inflation. The overview is based on a qualitative review of the literature and also refers to an ECB survey of large corporates. It also includes a description of various possible measurement issues relating to the digital economy. Against this background of the macroeconomic impacts of digitalisation, the paper then looks in more detail at the various mechanisms and possible impacts of digitalisation regarding productivity (Section 4), labour markets (Section 5), the supply side (Section 6) and, finally, inflation (Section 7).

1.2 Main findings

We start with a summary of the main findings, which also takes the form of a roadmap of the paper.

The degree of digitalisation may be measured by the adoption and use of digital technologies as discussed in Section 2. The European Commission's Digital Economy and Society Index (DESI) measures broadband coverage (connectivity), human capital (digital skills), use of internet, integration of digital technology and digital public services. In 2019, the index for the euro area and the EU28 was around 55 on a scale of 0 to 100, ranging from above 70 for the highly digital Nordic countries to around 40 for Greece, Romania and Italy at the lower end of the digitalisation scale. Meanwhile, the size of the digital economy – measured as the share in value added of digital-related manufactured goods and services – is larger in the United States than in all EU countries except for Ireland and Finland (representing around 8% of total economy value added in the United States, compared with 6.5% for the EU28 and just over 6% for the euro area). Again, it is the Nordic countries that have some of the largest shares of value added in the digital economy within the EU, while Greece and Italy are among the countries with the smallest shares. Finally, in terms of robotics, the rate of robot adoption in manufacturing in 2017 was highest in Japan, which registered around 27 robots per thousand workers, compared with around 16 for the euro area and the United States, and 14 for the EU. However, turning to euro area countries, Germany is on a par with Japan in terms of robot adoption in manufacturing, and is substantially ahead of the rest of the other large euro area countries. In 2017, in the robot-intensive automotive sector, Germany was ahead of the United States but

² This paper therefore does not examine a range of other issues related to digitalisation, such as fintech, crypto assets, digital currencies, taxation of superstar companies, technology addiction, etc.

behind Japan, while Japan also had the most highly robotised electronics industry. The high levels of robotisation in manufacturing in Japan and Germany are in line with previous findings that adoption of industrial robots rises with population ageing.³

Cloud computing, in turn, has been highlighted as a key digital technology because it is an enabler that precludes reliance on physical capital. It raises the scope for storage and computing capabilities and the adoption of other complex technologies. As shown in Box 1, the use of cloud computing has been linked to higher productivity, and there is considerable heterogeneity across the euro area, with the Netherlands and Estonia showing relatively strong adoption rates of high-level cloud computing by firms in 2018 (up to 70% of firms), while in Germany only 45% of enterprises purchase cloud computing services. Meanwhile, the prices of some categories of cloud computing services have fallen by around 60% over the past ten years, while quality-adjusted prices have declined even more dramatically, declining by approximately 90% over the same period.

The COVID-19 pandemic may result in an acceleration in the take-up of digitalisation. Firms, workers and consumers are rapidly becoming more accustomed to, and familiar with, using digital technologies – such as video conferencing, teleworking or working from home, online banking and online shopping – which may result in an acceleration of digitalisation, possibly leading to structural change across economies, with implications for labour markets, growth and productivity. This may provide challenges among the EU countries but may also provide opportunities for them to catch up and further develop their digital economies.

Section 3 provides an overview of the impacts of digitalisation on key macroeconomic variables based on a comprehensive qualitative review of the literature (while an ECB survey of large firms reported in Box 11 in the Appendix finds similar impacts) and also describes possible measurement issues relating to the digital economy in Box 2. According to the literature, digitalisation tends to raise productivity and activity, but not necessarily employment, with impacts on inflation skewed to the downside. Meanwhile, aggregate wage inflation may rise, an indication that skill shortages associated with digitalisation may have a greater effect on pay than the substitution of capital for labour. These impacts are broadly in line with a survey of large firms on the effects of digitalisation carried out by the ECB in 2018: most firms saw digitalisation having a positive impact on their productivity, driven by the ease of sharing knowledge (especially within the company) and more efficient production processes, while the impact of digitalisation on prices was less clear, with downward pressure being observed mainly in the consumer services segment. Around one-third of survey respondents expected digitalisation to reduce employment over the next three years, while one-fifth foresaw increases in employment. Digitalisation was seen by firms as increasing the ratio of high-skilled to low-skilled workers, the emphasis being on the need to retrain and reassign workers to new tasks supported by digital technologies, with big data and cloud computing the most widely adopted digital technologies. Meanwhile, difficulties in adjusting the organisation of the company, along with the need to recruit and retain highly skilled ICT staff, were regarded as the main obstacles to the adoption of digital technologies.

³ See, for example, Acemoglu and Restrepo (2018b).

Measurement issues relating to digitalisation are also a recurring theme throughout this paper. These are summarised in Box 2, which has a special focus on the measurement of deflators of digital-related products and services as well as the related possible downward bias to the measurement of output.

Turning to the mechanisms through which digital technologies affect key variables, a major effect of digitalisation is via the change in production processes through the adoption of digital technologies in industry and their potential impacts on productivity. This is covered in Section 4. Despite expectations of remarkable productivity growth through technological progress, the past two decades have been characterised by relatively low productivity growth. This is especially the case in the euro area, but is also true of almost all advanced economies and is associated with rising productivity dispersion (frontier firms growing faster than other firms), lower business dynamism and high resource misallocation. These phenomena may be explained by bottlenecks in technology diffusion, rigidities due to financing or other frictions that affect firms' decisions, all of which constrain productivity growth. These factors may be at least partially related to the nature of ICT technology itself, which differs from traditional physical technologies (e.g. machinery and equipment) in that it requires a complex combination of specialised labour, new production processes and managerial capital, posing a challenge to incumbent firms. The crucial role of management may be especially important in explaining why European firms have not benefited from the ICT revolution to the same extent as their US counterparts since around 1995.

Nevertheless, the growing consensus among economists and the private sector seems to be that the productivity gains of the ongoing second stage of the digital revolution, primarily driven by advances in AI, will eventually be realised. This view is supported by historical experience: AI is a general purpose technology (GPT), like electricity or the steam engine, and hence has the potential to revolutionise the way humans live and produce. However, GPTs require a high enough stock of complementary, specialised physical, human and managerial capital to be fully operational. They therefore suffer from implementation lags (electricity is a historical example of a GPT: 30 years after the establishment of portable electricity technologies, over half of US factories were still not electrified).

Technology adoption can be also affected by policy. For example, good governance and efficient institutions tend to be associated with a higher degree of digitalisation. Empirical work, including Box 3 in this section, shows that better institutions and governance – proxied by indicators such as the effective “rule of law” and “control of corruption” – have a positive impact on the rate of adoption of digital technology, which in turn can generate higher productivity. In this connection, Box 10 in the appendix assesses several indicators of trust from the perspective of digitalisation and finds that security concerns can sometimes deter online purchases, while only one-fifth of enterprises in selected EU countries incorporate security risks into their digital-related business processes.

Box 4 analyses productivity for firms in the digital and non-digital sectors across the four largest euro area countries. It focuses on productivity differences across the sectors and the churning across the productivity

distribution. The analysis results in two main findings: (i) digital firms are on average less productive than their non-digital counterparts across the productivity distribution, with the exception of those digital firms at the top of the productivity distribution where the productivity differential vis-à-vis non-digital firms widens considerably; and (ii) there is non-negligible churning at the top of the productivity distribution for both types of firms, with incumbent productivity leaders slowly losing their leadership status and new leaders arising over time.

Different types of technological change can have different effects on labour. As shown in Section 5, which considers the historical effects of technology on labour, fear of technological immiseration of workers has tended to accompany technological progress (as illustrated for instance by the Luddite movement in Northern England in the early 1800s). However, technology has not created mass unemployment. That is not to say that technological effects on labour are purely benign: technology can affect not only the quantity (employment levels) but also the price of labour (wages and their distribution) and possibly the quality of jobs. Indeed, in more recent years, attention has focused on the phenomenon of job polarisation, whereby automation of routine activities seems to have led to the growth of low and high-skilled jobs at the expense of middle-skilled jobs. Estimates of the fraction of jobs at risk of automation vary greatly – ranging from 10% to 60% – and are quite sensitive to assumptions.

We then examine the collaborative economy and start with online platforms and the sharing economy, followed by an analysis of the relationship between digitalisation and employment growth. Box 5 shows that the collaborative economy is still small but is growing rapidly and is spread over several sectors, such as finance, accommodation and transport. In EU countries, the collaborative (or sharing) economy accounted for up to almost 1% of GDP and 3% of employment in 2016, but there was considerable cross-country heterogeneity, with eastern European euro area and EU countries showing some of the higher levels of activity in these areas. Box 6 uses employment as another metric for gauging differences in digitalisation across EU countries, revealing that ICT-related employment shares range from around 22% in Luxembourg (surpassing the United States) – with the United Kingdom, Sweden and Estonia also high at around 17% – down to approximately 7% in Greece, Slovakia and Italy. Furthermore, from a cross-country perspective, digitally intensive sectors make important contributions to employment growth, while countries with higher shares of value added accounted for by digital sectors are associated with relatively lower unemployment rates over the longer term.

We also provide some new evidence on the implications of technological change for the labour market. Box 7 investigates whether the decline in average hours worked in EU countries over recent decades is related to job polarisation. Routine manual jobs – precisely the occupations most negatively affected by employment polarisation from routine biased technical change – have been subject to large declines in hours worked, as have non-routine manual physical occupations, which have also experienced a decline in employment. Overall, this suggests that not only employment but also hours worked have become polarised, and the decline in hours worked exacerbates the impact of polarisation on wage inequality. The subsequent Section 5.3 presents a general equilibrium model perspective on how

automation affects the labour market, examining the interaction of two effects. On the one hand, automation eliminates some tasks and displaces labour; on the other hand, it reinstates labour by creating new tasks and by raising productivity, hence increasing demand for all labour. According to this model-based analysis, while both a standard factor-augmenting total factor productivity (TFP) shock and an automation shock have positive effects on GDP and productivity growth and a short-term downward impact on price inflation, they differ in terms of their employment effects. Although an automation shock initially leads to an employment displacement effect, over time the productivity improvements from the automation process lead to positive employment effects on both high and low-skilled workers, but with higher wage inequality.

Digitalisation has also had a major impact on investment as well as implications for potential output. These issues are covered in Section 6, which covers the supply side. In particular, a defining feature of the rise of digital technologies is the prominent role of intangible capital. This covers items such as software, databases and research and development (R&D) in digital technologies but also includes firm-specific attributes (e.g. human capital, networks, etc.) which are not digital per se but complement investment in digital technologies. According to some estimates, between one-third and two-thirds of digital investment is in intangibles. However, the measurement problem is non-trivial as, for example, the definition of intangibles in Eurostat's national accounts does not include items that are covered by wider definitions, such as staff training, new engineering designs and market research. Broader definitions of intangible items capture, in certain instances, almost twice the investment in intangibles currently identified by national accounts for EU countries. Digitalisation is also likely to reduce tangible investment through several channels: cloud storage and computing, for instance, allow firms to purchase services instead of equipment, while improved matching technologies or more efficient use of capital may incentivise sharing over buying (e.g. car sharing).

This, in turn, may help explain firms' rather sluggish investment in physical capital in the euro area in recent years. Box 8 shows that intangible investment explains up to one-third of the (negative) gap between firm's investment in tangible assets and Tobin's Q (a market-based proxy for firms' investment opportunities), suggesting that the rising share of intangible assets is linked to the weakness in capital investment in tangibles.

Another signature feature of the current phase of digitalisation regarding the supply side is big data, which have a large take-up rate and whose value is growing by more than 20% per year. Estimates by the European Commission suggest that the value of the data economy, which includes data workers and data companies, will increase from €300 billion in 2016 to €739 billion in 2020. Big data are often collected by online platform companies and analysed by data workers. They represent a source of growth for the company that stores and maintains them.

Digitalisation is affecting consumer prices and inflation in a variety of ways. Some of those channels are reviewed in Section 7. Digital products only make up a small share of total private consumption (around 6% in the euro area), and the direct downward impact of the decline in the prices of these products on aggregate inflation is notable but relatively small, with significant differences across the euro area and EU

countries. Overall, the inflation rate for ICT products has contributed negatively to euro area headline inflation – as measured by the Harmonised Index of Consumer Prices (HICP) – by around 0.1 to 0.2 percentage points per year since 2002.

A particularly salient mechanism through which digitalisation can affect consumer prices is through the expansion of e-commerce. E-commerce can provide cost savings as well as increasing price transparency and competition. There is, however, also a possibility that “superstar” internet firms may actually reduce competition and lead to higher markups in the long term. Estimates in this paper suggest that e-commerce – proxied by the percentage of people looking for the prices of goods and services online – has contributed to a decrease in annual non-energy industrial goods inflation in the euro area by 0.06 percentage points on average per year over the period 2006-2018. In comparison, the average annual inflation rate for non-energy industrial goods prices was 0.6% over the same period. In summary, the direct impacts of digitalisation-related products and the indirect impacts of e-commerce are having notable downward effects on inflation. These downward effects can emerge over time and may last for fairly long periods but should be temporary in nature and cease when the diffusion of digitalisation and e-commerce technologies has reached a saturation point.

Box 9 looks at one important mechanism through which digital technologies, and particularly intangible capital, affect the economy owing to their impact on market structure and markups. The increasing importance of intangible capital (data, software, R&D) implies substantial fixed costs but very low marginal costs (as business processes linked to intangible capital can frequently be reproduced costlessly). This can allow rapid increases in the size of a company and the achievement of “scale without mass”. Early movers can have a sizeable advantage and dominate their markets, resulting in “superstar” firms. Hence, digital technologies may have some characteristics which make them conducive to higher market concentration. At the same time, digital technologies may also enhance competition through e-commerce, or by reducing barriers to entry and enabling access to diverse global markets even for small firms. Overall, the evidence seems to be that market power is on the rise, particularly in the United States but less so in the EU, and that technology may be playing a role as markups are rising more rapidly in digitally intensive sectors.⁴ Companies with high market power in general respond less to changes in costs, and hence monetary policy, than perfectly competitive firms. This does not mean, however, that less market power will result in higher pass-through of cost shocks or transmission of monetary policy; this will depend on how the incentives of firms change as market power changes.

1.3 Policy implications

The process of digitalisation is relevant for monetary policy as it may affect productivity and the supply side of the economy. In particular, digitalisation can be

⁴ See, for example, Basu (2019), Syverson (2019) and Berry et al. (2019) for the United States; see Bajgar et al. (2019), Calligaris et al. (2018a), Cavalleri et al. (2019), Diez et al. (2018), Weche and Wambach (2018), Canton and Thum-Thysen (2017) and Deutsche Bundesbank (2017) for Europe.

seen as a supply-side shock which can raise productivity and lower both prices and inflation. However, the timing and extent of these impacts are difficult to quantify and measure. In addition, they may be heterogeneous across countries and should therefore be monitored closely.

The uncertainty surrounding data measurement may increase in the digital era, and make monetary policy even more challenging. Not enough is known yet, for example, about how digitalisation affects the measurement of inflation, particularly regarding the prices of digital services and products. This may also have repercussions for the measurement of the real values of investment, output and productivity (which are derived from their nominal values by appropriate deflators). Some findings suggest that the slowdown in GDP growth and productivity, which started before the financial crisis, may be less pronounced if deflators are computed under different methodologies. At the same time, it should be noted that even if one allows for such mismeasurement, the main conclusion that productivity growth has substantially slowed down is not overturned. In addition, ostensibly “free” products (such as social media where consumers “pay” with their data or by accepting advertising), or the utility gained from activities such as car-sharing, may provide challenges as to how these benefits are measured.

If there are measurement issues or mechanisms related to digitalisation that lead to lower readings of inflation in the short run, then reaching an inflation objective may become more challenging. However, the impact of digitalisation on inflation is not clear-cut, and may differ at short and long horizons. Apart from the possible impact of more flexible (dynamic) pricing, which is likely to occur across all horizons, as well as the estimated downward impacts of digitalisation on prices and inflation in the shorter term, there may be upward pressure on markups and inflation from digitalisation in the medium to long term via increasing concentration.

The transmission of shocks may be different in the era of digitalisation. This may also apply to monetary policy shocks if – in a digital economy – firms are able to change prices more quickly. Meanwhile, changes in market power, related to digitalisation and “superstar firms”, may affect how firms set prices and, in turn, the transmission of monetary policy. Additionally, different adoption rates and usage of digitalisation across the euro area countries may lead to country heterogeneity regarding monetary policy transmission. Which channels prevail, along with the importance of such heterogeneity, is an empirical question that is not easy to answer.

Many of the big data generated in the digital economy are proprietary to firms and are not readily available to central banks for the purposes of analysing, monitoring and forecasting economic developments. Although central banks have access to large amounts of financial and banking data, they may not be able to tap into the potential of some big data that are held by large private sector firms.

Regulation and policies may have to be adapted. Core governance issues such as the rule of law and control of corruption are important foundations for the adoption of digitalisation. Changes to labour, product and financial market regulations may be required in order to fully reap the potential gains from digital technologies and their applications. At the same time, policy changes may be necessary to maintain

inclusiveness and safeguard vulnerable groups who may experience job insecurity and lower earnings. It may become necessary to support alternative options for the financing of intangible investment, which is hard to collateralise, needs expert judgement to be assessed and may be more suited to equity financing than to bank lending.

Labour mobility within the EU can be enhanced by digitalisation via virtual labour flows. In the future, digitalisation may create significantly more growth in virtual labour flows, in addition to traditional physical labour flows, which can enhance inter-regional and international labour mobility across the euro area and EU economies. This could possibly help to alleviate high localised unemployment levels as well as labour market bottlenecks in stronger growing EU economies. It could also help to address demographic issues associated with ageing populations. Particular policy action might be required for this to be feasible for the less skilled and more vulnerable groups in the labour market.

Policies for distribution, competition, innovation and education may have to be aligned. Digitalisation may entail more market concentration among firms, which in turn may entail a more uneven distribution of income and wealth. It may be necessary to put in place further policies to maintain equal opportunities and incentives for innovation for all firms and workers, while supporting those in the labour market particularly affected by the transition to a digital economy. Access to the internet, education and training, along with business models supporting digital skills, tasks and jobs, would seem especially important and would reduce digital exclusion. This may require further policies at the EU and national level.

The Digital Single Market is an important policy strategy, but its implementation could be accelerated and expanded. At the EU level, the aim is to further the Single Market in the digital domain and to facilitate the process of digitalisation across the EU. This can deliver increased choice and lower prices for both consumers and firms, together with scale economies and improved EU competitiveness. However, more investment by the public sector in AI and robotics may be useful, along with faster progress in e-government, while start-ups and investment in intangible capital could be stimulated by greater provision of venture capital (VC), including in conjunction with further advances in the capital markets union.

Digitalisation is indeed “virtually everywhere”, but to differing degrees across the EU countries and across continents. The position of EU countries may have to be strengthened. Not all countries in the EU are near the frontier of dissemination, and adoption of digital technologies, and the firms and workers at the very forefront of the digital revolution are often found outside the EU. This may raise the question as to whether the EU needs a more far-reaching digital policy agenda to overcome second-mover disadvantages, advance closer to the technology frontier and remain competitive in global markets.

2 The degree of digitalisation across EU countries

Prepared by Robert Anderton and Lara Vivian

This section looks at the extent of digitalisation across EU countries and the trends over time. It also draws comparisons with other countries such as the United States where feasible.

For example, we assess country differences in the DESI, which is a composite index of various measures such as connectivity, digital skills, use of internet and digital public services. We also look at the size of the digital economy – measured as the share in value added of digital-related manufactured goods and services - and the degree of robotisation. Overall, we find significant country heterogeneity across the EU in terms of the adoption of digital technologies, while EU countries tend to be falling behind competitors such as the United States and Japan.

Meanwhile, the use of cloud computing has been linked to higher productivity, yet in 2018 only the Netherlands showed high adoption rates of higher-level cloud computing among the larger euro area countries. However, rapidly falling prices are an important feature of cloud computing, making this new technology available to a greater number of smaller firms and facilitating its economy-wide adoption.

Given the increased use of digital technologies during the COVID-19 pandemic, this may lead to an acceleration of digitalisation.

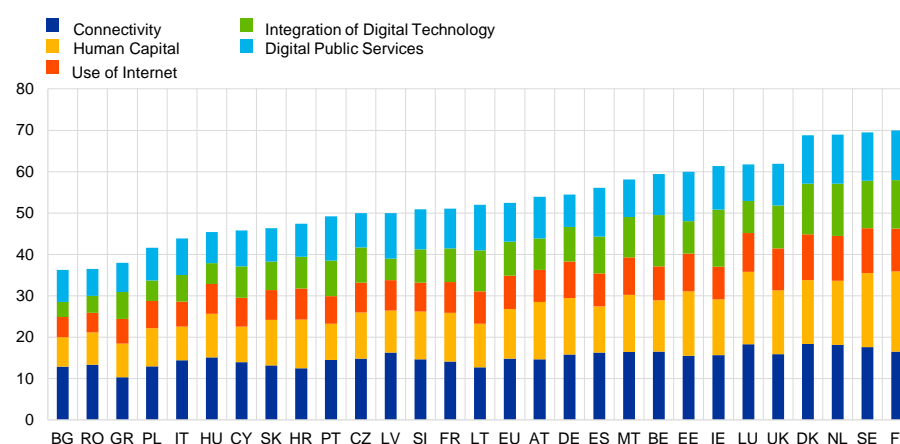
2.1 Dimensions of digitalisation and the size of the digital economy

A composite index can help us to understand the degree of digitalisation from various perspectives. The DESI is a weighted index of five components: connectivity, human capital, use of internet, integration of digital technology and digital public services. Each component corresponds to a category of digitalisation. In turn, each category is a combination of several further sub-categories. Chart 1 shows the DESI scores for each of the five components in 2019. Higher DESI scores indicate higher degrees of digitalisation.⁵

⁵ Chart 1 shows the DESI for 2019. The same weight is assigned to each of the five components of the index.

Chart 1

Digital Economy and Society Index for 2019



Source: Digital Economy and Society Index (DESI), where each component has equal weight.

Details of the five DESI categories of digitalisation are as follows: “connectivity” in the DESI refers to the broadband market developments in the EU, including indicators such as fixed, fast and ultrafast broadband coverage and take-up; “human capital” focuses on internet usage, digital and ICT skills, and science, technology, engineering, and mathematics (STEM) graduates; “use of internet services”, combines citizens’ use of content, communication and online transactions including online banking; and “integration of digital technology” takes into account e-commerce and business digitisation. The term “business digitisation” refers to the adoption of technologies that have been shown to be productivity-enhancing, such as electronic information sharing, social media, e-invoices and cloud computing.⁶ Finally, “digital public services” captures whether governments have adopted systems of pre-filled forms, online service completion, open data, e-health and more.

EU countries are relatively homogeneous in aspects of digitalisation such as connectivity. The 2019 index for the euro area and EU28 is at around 50, ranging from slightly above 70 for the high-digitalisation Nordic countries to around 40 at the lower end for Greece, Romania and Bulgaria. The differences in the level of connectivity among EU countries do not explain the digitalisation gap, suggesting that the diffusion of infrastructure, such as broadband, has reached comparable levels in most countries.

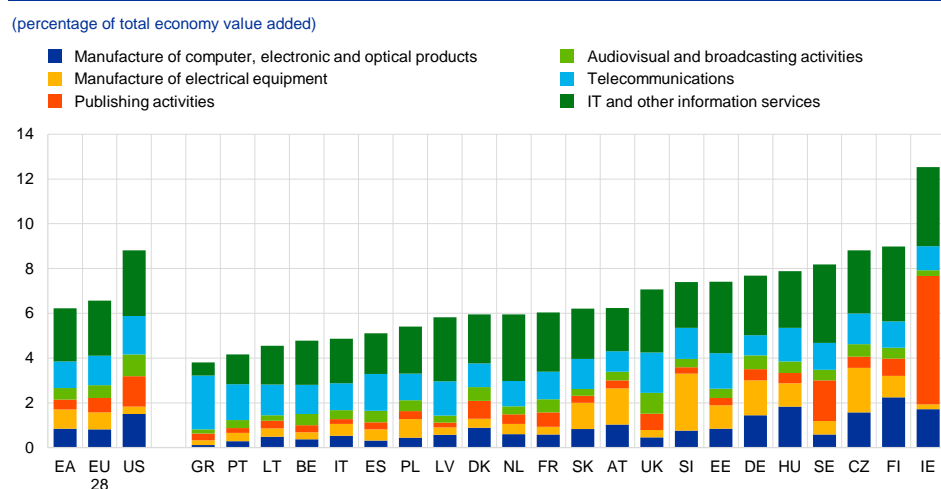
At the same time, cross-country differences in other dimensions persist, and lower levels of human capital relating to digitalisation may account for the cross-country variation of the technology integration component. Finally, the index for digital public services and use of internet ranges from a high value of almost 15 in the Nordics and Estonia to around 8-10 in Romania and Bulgaria, highlighting large cross-country variation in the deployment of digital technologies.

The economy includes several digital activities that span a number of manufacturing and service sectors. The “digital economy” can be defined as mainly

⁶ See Box 1 for an in-depth discussion on cloud computing and its relevance for productivity.

comprising the following industries according to the latest version of Eurostat's statistical classification of economy activities in the European Community (NACE Rev. 2): (a) manufacture of "computer, electronic and optical products" and "electrical equipment" (divisions 26, 27); and (b) the IT service sector "information and communication" (Section J consisting of divisions 58 to 63). Chart 2 uses this classification to show the share of the digital economies' subsectors in total economy value added (in nominal terms) for the EU countries and the United States in 2016 (which is the latest year for which data are available for most countries).

Chart 2
Digital economy subsectors in 2016



Sources: OECD database, ECB staff calculations.
Notes: The data for Ireland refer to 2014. The euro area aggregate excludes Malta, Cyprus, Luxembourg and Ireland, owing to missing data for 2016. NACE codes are as follows: V26: Manufacture of computer, electronic and optical products; V27: Manufacture of electrical equipment; V58: Publishing activities; V59_60: Audiovisual and broadcasting activities; V61: Telecommunications; V62_63: IT and other information services.

The digital economy is larger in the United States than in all EU and euro area countries except for Ireland and Finland.⁷ The digital economy of the United States represents more than 8% of total economy value added, compared with only around 6.5% for the EU28 and just over 6% for the euro area. Thus, the EU digital economies – with the exceptions of the Czech Republic, Ireland and Finland – are notably smaller than that of the United States. The IT service sector alone (industries 58 to 63 in the NACE Rev. 2 classification) contributes around 6% to overall value added in the United States, which is almost equal to the contribution of the whole digital economy in the euro area. Also, despite the US economy in general being service-oriented, its core IT manufacturing sector (industry 26), comprising semiconductor manufacturers, communication equipment and consumer electronic producers, etc., is around twice as large as that of the euro area and even exceeds that of European countries specialised in manufacturing activities, such as Germany.

Within the EU, however, there is considerable heterogeneity with respect to the size and specialisation of countries' digital economies. In the same way as

⁷ The results for Ireland need to be interpreted with care, as the size of the Irish digital economy is linked with the activities and domiciles of global digitalisation-related firms. In other words, globalisation favoured the relocation of intangible assets, in the form of intellectual property, to Ireland, as well as the outsourcing of the manufacturing of products.

indicated by the DESI, Nordic countries seem to have larger digital economies, while Greece and Portugal are among the countries with the smallest. In terms of specialisation, the IT manufacturing subsector (industry 26) makes up around 1.8% of total economy value added in Germany, while the share is around 0.8% in France. However, France has a large publishing industry, while Sweden has the largest (except for Ireland), comprising media companies as well as the software industry. Sweden also has large IT and telecommunications sectors (covering, among other things, telecommunications and internet service providers). One should bear in mind certain caveats when comparing countries and interpreting the digital economy subsectors. For example, some countries may have a high share of value added in the IT manufacturing subsector, but this may sometimes correspond to the outsourcing of computer parts to that country, hence high country shares of value added in the IT manufacturing sector do not necessarily indicate that the country is at the forefront of digitalisation.

2.2 Robots

Robot adoption is another aspect of digitalisation and may signal technological advancement. This section discusses the adoption of industrial robots that are already in use as they are more likely to have an impact on current production and employment. An industrial robot is defined as “an automatically controlled, reprogrammable, and multipurpose [machine]” (Friis, 2017). In other words, industrial robots are fully autonomous machines that do not need a human operator and can be programmed to perform several manual tasks such as welding, painting, assembling, handling materials or packaging (Acemoglu et al., 2017).⁸ Table 1 shows the adoption of robots by the United States, Japan, the euro area and the EU over time.⁹ In order to provide comparable magnitudes across time we follow Acemoglu et al. (2017) and divide the robots in operation by the number of workers, in thousands, for each combination of country, industry and year. We use the information on employment by country and industry provided by the KLEMS dataset.¹⁰

⁸ One caveat to the data regarding the number of robots is that possible changes in robot quality and their sophistication over the sample period are not accounted for, which implies that comparisons over time should be interpreted with caution.

⁹ The euro area is approximated by Austria, Belgium, Finland, France, Germany, Italy, the Netherlands, Portugal and Spain, while the EU aggregate is approximated by the euro area, Czech Republic, Denmark, Hungary, Poland, Sweden and the UK.

¹⁰ Consistently with Acemoglu et al. (2017), we allocate unclassified robots to industries. To do so, we rely on the share of robots by industry obtained using the classified data. In addition, we keep employment fixed at the year 2004. For a detailed explanation of KLEMS data, see Jäger (2016).

Table 1

Robotisation: selected industries for the euro area, the EU, Japan and the United States

(number of robots per thousand workers)

Industry	Aggregate	2004	2006	2008	2010	2012	2014	2017
Manufacturing:								
Food and beverages	EA	2.39	3.57	4.59	5.84	7.07	8.55	10.2
	EU	1.82	2.78	3.57	4.5	5.44	6.63	8.01
	JP	2.36	2.15	2.15	2.32	2.83	3.33	3.93
	US	3.09	3.56	4.25	4.83	5.19	5.76	6.5
Plastic and chemicals	EA	14.21	18.92	20.01	18.84	17.4	19.29	20.72
	EU	11.04	14.86	15.74	15.05	14.37	16.39	17.93
	JP	59.94	59.72	53.52	44.24	38.88	34.25	27.08
	US	5.49	7.59	8.3	8.81	9.77	10.77	11.55
Metal products	EA	5.18	7.76	9.16	9.74	10.95	12.46	15.33
	EU	4.66	6.91	8.11	8.52	9.45	10.77	13.38
	JP	11.61	12.01	12.13	12.8	13.18	14.17	15.97
	US	8.41	10.19	10.57	10.04	9.07	8.83	7.41
Metal machinery	EA	1.15	2.66	3.99	5.51	6.71	8.24	9.22
	EU	0.88	2.26	3.4	4.88	5.94	7.38	8.21
	JP	18.51	16.99	15.79	11.82	9.69	10.48	12.38
	US	0	0	0.2	1.47	2.28	2.47	2.94
Electronics	EA	5.14	5.3	5.26	5.7	5.9	6.43	7.09
	EU	4	4.18	4.15	4.44	4.6	5.03	5.58
	JP	61.53	55.01	47.26	46.99	52.09	50.57	56.79
	US	5.94	11.87	12.42	15.44	16.65	20.05	25.09
Automotive	EA	80.59	92.59	91.95	98.79	100.03	103.14	108.95
	EU	67.41	77.55	77.06	83.48	86.61	91.53	99.57
	JP	183.97	230.76	231.49	214.86	205.63	179	172.53
	US	70.42	83.56	83.69	85.55	95.02	107.66	115.71
Total manufacturing:	EA	10.56	12.41	12.82	13.51	13.8	14.75	16.24
	EU	8.28	9.81	10.17	10.79	11.24	12.26	13.77
	JP	31.93	31.98	29.89	27.5	27.25	25.72	26.67
	US	7.65	9.92	10.25	11.15	12.5	14.4	16.08

Sources: [International Federation of Robots](#) and [KLEMS](#) database, ECB staff calculations.

Notes: EA is composed by the following countries: Austria, Belgium, Finland, France, Germany, Italy, the Netherlands, Portugal and Spain. The EU is composed by: EA, Czech Republic, Denmark, Hungary, Poland, Sweden and the UK. Only selected manufacturing sectors shown, therefore selected sectors do not add up to total manufacturing.

Robots are increasingly common in manufacturing industries, with Japan using the most robots in total manufacturing in 2017 (around 27 robots per thousand workers) compared with the euro area and the United States, which use around 16 robots per thousand workers. In particular, Table 1 shows that the rate of robots per thousand workers in 2017 was the highest in the automotive sector, with rounded figures of 172, 115, 108 and 99 for Japan, the United States, the euro area and the EU respectively. Similarly, the electronics industry – especially in Japan and, to a lesser extent, the United States – adopts a larger number of robots than the euro area and the EU (in 2017, the number of robots per thousand workers in Japan and the United

States was 56 and 25, respectively, while only around 5 and 7 robots were employed in the euro area and in the EU, respectively). Among the four economies, Japan also has the highest rate of robot adoption in metal machinery and plastics and chemicals, while in these industries, the euro area and the EU outstrip the United States. In addition, the euro area and EU lead the United States in robot adoption in metal products and the less robot-intensive food and beverages industry. Most industries have increased their number of robots per thousand workers during the last decade, stimulating academic and policy debates on the possible implications of robotisation for employment and productivity.

The five largest economies of the euro area show different patterns of robot usage, with Germany showing the strongest adoption rates, on a par with those of Japan for total manufacturing (Chart 3).¹¹ In 2017, Germany is roughly level with the leader Japan in the deployment of robots in plastics and chemicals, and metal machinery (although the Netherlands is ahead of Germany in the latter sector) but substantially leads Japan in robot adoption in metal products.¹² Italy has relatively higher rates of robot adoption in low-robotisation industries such as food and beverages, metal products and metal machinery, as well as in plastics and chemicals.

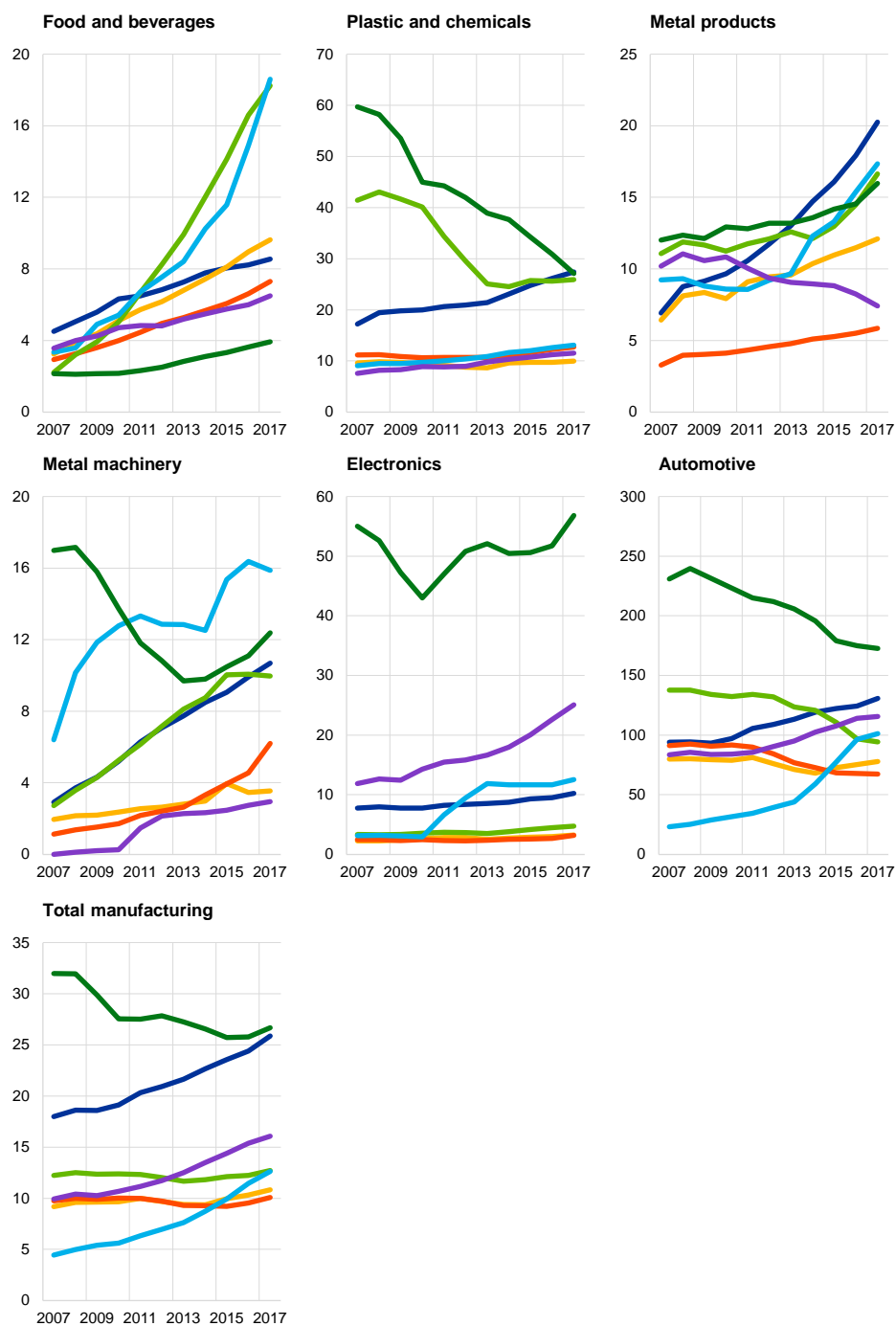
¹¹ The high rates of robot adoption in manufacturing for Germany and Japan is in line with the findings of Acemoglu and Restrepo (2018b), who provide cross-country evidence that adoption of industrial robots increases with population ageing and in industries more amenable to automation.

¹² Scales differ across industries in Chart 3 owing to large differences in robot adoption across industries.

Chart 3

Robotisation: selected industries for the larger euro area countries, Japan and the United States

(number of robots per thousand workers)



Sources: [International Federation of Robots](#) and [KLEMS database](#), ECB staff calculations.

Notes: Only selected manufacturing sectors shown, therefore selected sectors do not add up to total manufacturing.

Box 1

Cloud computing, firms' performance and barriers to adoption

Prepared by Lara Vivian

Cloud computing allows firms and individuals to access computing storage or computing resources through the internet, without having to buy and maintain computing infrastructures.

A definition of cloud computing comes from Mell et al. (2011): "Cloud computing is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management effort of service provider interaction". Three types of cloud exist: private, public and hybrid (Byrne et al., 2018). Irrespective of the type, cloud computing can offer several product classes¹³ and can be separated into the following levels of complexity:

1. low-level cloud computing, i.e. email, office software, storage of files;
2. medium-level cloud computing, i.e. all of the above plus the hosting of the enterprise's database;
3. high-level cloud computing, i.e. accounting, software applications, customer relationship management (CRM) software and computing power.¹⁴

Chart A provides evidence that EU firms are increasingly buying cloud computing products, but that they are switching towards "high" levels of complexity of cloud computing services.

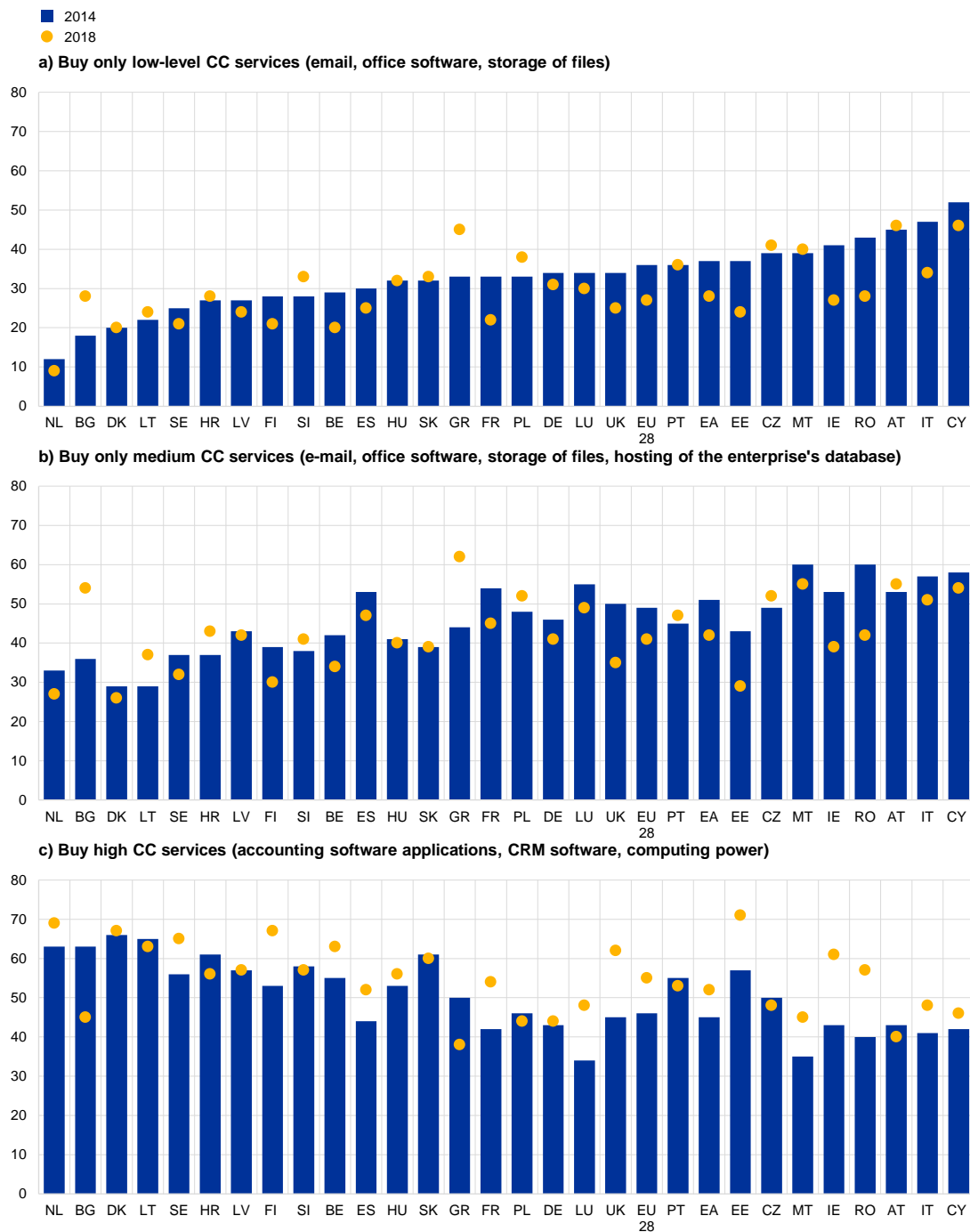
In 2014, slightly less than 40% of enterprises bought low-level cloud computing services in the euro area, while only 30% of them made the same purchase in 2018. Similarly, the share of enterprises buying medium-level cloud computing in the euro area went down from 50% in 2014 to slightly above 40% in 2018. On the other hand, a higher percentage of euro area firms purchased high-level cloud computing in 2018 (52%) than in 2014 (43%), suggesting that firms are increasingly deploying the higher-level potential of cloud computing. However, the rate and the evolution of adoption are fairly heterogeneous across European countries and within the euro area. In the Netherlands and Estonia, for instance, around 70% of firms adopted high-level cloud computing in 2018, while only 45% of firms invested in high-level cloud computing technology in Germany. Furthermore, in countries such as Slovakia, Latvia, Portugal and Austria, the share of firms buying cloud computing, irrespective of its type, is fairly constant over time, suggesting a weaker pass-through of the benefits of higher-level adoption.

¹³ In particular, Byrne et al. (2018) update Mell (2011) and provide definitions of cloud products as follows. (i) Infrastructure as a service (IaaS): provides computer processing, storage, networks and other fundamental computing resources, where the consumer can deploy and run arbitrary software, including operating systems as well as applications. (ii) Platform as a service (PaaS): provides the ability to deploy consumer-created applications created using programming languages, libraries, services and tools. (iii) Function as a service (FaaS) – added by Byrne et al. (2018) to the Mell (2011) definition: provides the capability of deploying functions (code) on a cloud infrastructure. (iv) Software as a service (SaaS): provides the capability of running providers' applications on a cloud infrastructure. The applications are accessible from various client devices through either a thin-client interface (e.g. a web browser) or a program interface. From IaaS to PaaS, the level of abstraction increases, and the level of complexity of the cloud computing passes from low to high.

¹⁴ CRM software enables customer data to be stored and analysed.

Chart A Cloud computing

(percentage of enterprises (2014, 2018))



Source: Eurostat's Digital Economy and Society database.
Note: CC stands for cloud computing here.

Cloud computing is an enabling technology that allows firms to decrease their investment in physical capital while improving their working practices. The adoption of cloud computing, among other technologies, has been shown to increase productivity and the overall scale of the firm through several mechanisms (Andrews et al., 2018). A survey of Chief Financial Officers (CFOs) and

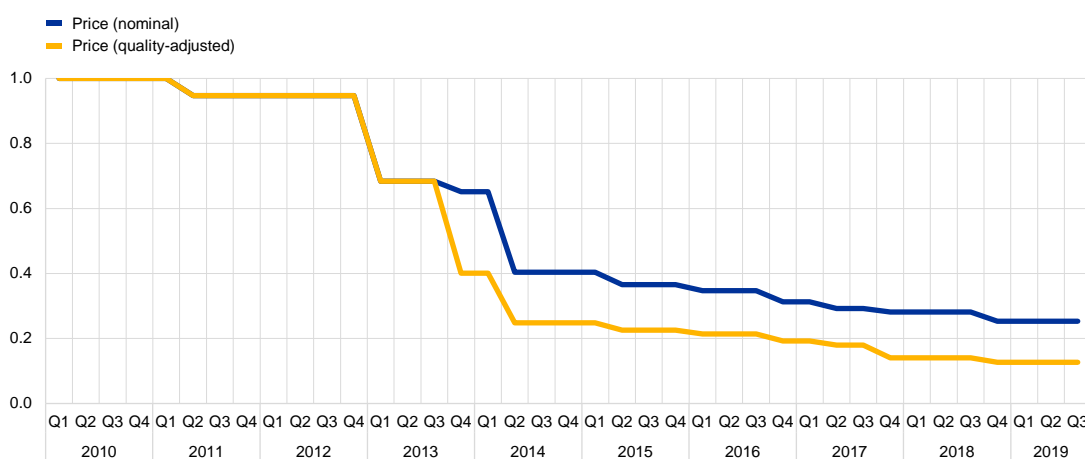
finance executives at a broad range of large US companies carried out by Deloitte in 2012 highlights cost savings, improved worker flexibility and productivity as relevant channels of the benefits of cloud computing. In particular, various one-off fixed costs for the enterprise, such as costs related to hardware, software, backup of data, but also operational costs of IT maintenance and spending, tend to be significantly lower once enterprises switch to the cloud. Furthermore, the possibility of accessing the cloud through the internet improves workers' mobility, while effective collaborations and better handling of version updates tend to be the forces behind the positive impact on workers' productivity. Similarly, a large survey of SMEs and large companies by Deloitte (2018) suggests that more than 300,000 businesses could not operate without cloud computing and that, on average, 5% of users' revenue is cloud-enabled. Cloud computing now gives start-ups and small enterprises access to resources that would have previously required large costly investments in physical capital. As a result, it has reduced some barriers to entry for small firms.

According to some studies, prices of cloud computing may not have been correctly measured. The studies suggest that prices may be significantly lower and volumes of cloud computing services significantly higher than current estimates. Prices for cloud computing services have been falling dramatically over the last ten years. Byrne et al. (2018) show that the price of a selected class of cloud product decreased by 58% between the first quarter of 2010 and the third quarter of 2018. However, when they adjust for quality change,¹⁵ the price reduction is around 80%. Similarly, Coyle and Nguyen (2018) find that quality-adjusting the price index for cloud computing services gives a price drop that is 20 to 27 percentage points larger than for an index based on non-quality-adjusted nominal prices. Chart B shows the unadjusted and quality-adjusted price of this specific set of cloud computing services, which have high processing power and were available over the period from the first quarter of 2010 to the third quarter of 2019,¹⁶ revealing a fall of approximately 90% in quality-adjusted prices of cloud computing over this period. This might have implications for productivity and overall GDP.

Chart B

Price indices for cloud computing services: unadjusted and quality-adjusted

(price index=1 in 2010Q1)



Source: Source: Coyle and Nguyen (2018).

Notes: Prices are computed for the grouped product classes ("large") of Amazon Web Services relating to the operating system Linux. Price index has a value of 1 in base period 2010Q1.

¹⁵ Byrne et al. (2018) account for improved processing power, memory and storage when computing the cloud computing quality-adjusted price index.

¹⁶ Prices refer to the Amazon Web Service operating system Linux.

Nevertheless, several concerns still impede full adoption of cloud computing, with survey results for large firms pointing towards difficulties in hiring and retaining high-skilled ICT staff as a major obstacle to the adoption of technologies such as cloud computing and big data.¹⁷ According to another survey (CFO, 2012), data privacy is the main obstacle to adoption of cloud computing. Similarly, firms attach importance to issues of data security and the location of the server. These concerns are likely to be driven by the lack of a common data privacy regime across countries (Berry and Reisman, 2012). International organisations, such as the European Commission, the European Banking Authority and the Organisation for Economic Co-operation and Development (OECD), work to fill this gap by developing common guidelines in terms of international cooperation on data security issues.¹⁸ A parallel policy agenda is aimed at promoting competition among cloud providers by tackling the issue of difficulties in switching cloud providers. At the moment, moving from one cloud provider to another may not be possible owing to different operating systems or application interfaces which are not interoperable, meaning that firms using cloud services could find themselves dependent on one service provider (this is also known as “lock-in”).¹⁹

The COVID-19 pandemic may result in an acceleration in the take-up of digitalisation. Firms, workers and consumers are rapidly becoming more accustomed to, and familiar with, using digital technologies – such as video conferencing, teleworking or working from home, online banking and online shopping – which may result in an acceleration in digitalisation, with possible implications for labour markets, growth and productivity.

An acceleration in digitalisation in the aftermath of the COVID-19 pandemic could also speed up the process of structural change. Rapid increases in online sales of food, consumer durables, clothes, etc., may have implications for offline sales as well as inflation. Growth in video conferencing and teleworking may reduce international and even local travel, with implications for travel providers and car manufacturers. Greater use of digital technologies may lead to higher investment in complementary intangible capital, while part of the capital stock related to tangibles may become obsolete as the digital economy grows in importance. Such structural change, particularly if it occurs rapidly, may lead to some temporary disruption in the labour market as well as skill mismatch, while geographical labour market mismatch within and across countries could decline as virtual labour flows increase. Such structural change could increase productivity as the economy restructures towards more productive sectors, while an acceleration in digitalisation can potentially increase productivity via more efficient methods of production and various other mechanisms. At the same time, further measurement issues may possibly arise as the digital economy accelerates. Although these possible developments may provide challenges for EU countries, they may also provide opportunities for EU countries to catch up with major competitors in the adoption of digital technologies.

¹⁷ See Box 11 in the Appendix.

¹⁸ See Berry and Reisman (2012) for an exhaustive list; see also information from the [European Commission's on Cloud Computing](#).

¹⁹ See European Commission (2012), and the agenda of the Cloud and Software unit of the European Commission for a description of the European Cloud Partnership (ECP) and its mission in this respect.

3 Effects of digitalisation on key variables

Prepared by Vincent Labhard and Lara Vivian

This section provides an overview of the qualitative impact of digitalisation on key macroeconomic variables based on a collection of estimates from a comprehensive review of the literature. According to that evidence, digitalisation has effects that are similar to those of other supply and technology shocks, at least in sign, tending to raise productivity and activity but not necessarily employment, with the impacts on inflation skewed to the downside.²⁰ Another strand of the literature relating to digitalisation concerns measurement issues, which are a recurring theme throughout this paper. These measurement issues are summarised in a box in this section. The box places a special focus on the measurement of deflators of digital-related products and services. It also looks at the related possible downward bias to the measurement of output.

The section provides a qualitative review of the effects of digitalisation, based on a collection of estimates from a comprehensive review of the literature. In total, the review encompasses 103 studies, which cover all aspects of digitalisation, including both the degree of digitalisation, in terms of the take-up of the various digital technologies (for production and communication), and the effects of digitalisation on key parts of the economy and key variables (such as the supply side/productivity, labour markets and the real and nominal economy).

Table 2 shows the signs of the effect of digitalisation on the economy, including the supply side, labour markets, the real economy and the nominal economy. Although estimates are not strictly comparable, as they are often based on different samples – both along time-series and cross-section (country/country groups) dimensions – this qualitative review of the literature provides a number of interesting insights. First, the area of impact for which the largest number of estimates are available is the supply side (productivity), followed by the labour market (employment) and the real economy (activity). Second, the estimates tend to suggest a positive impact of digitalisation on the supply side and the real economy, and an uncertain impact on labour markets, with the estimates for the impact on prices and inflation skewed to the downside. Moreover, these results are in line with the answers given by a sample of large firms to a survey carried out in 2018 by the ECB which is shown in Box 11 in the Appendix.

²⁰ These impacts are broadly in line with answers given by a sample of large firms to a survey on the impacts on macroeconomic aggregates of digitalisation carried out by the ECB, reported in Box 11 in the Appendix.

Table 2

Qualitative overview of the effects of digitalisation on the economy

A summary of the evidence from the literature

Topic	Variable	Sign of the effect	Explanation
Labour market	Employment	+/-	Exposure to robots seems to decrease employment. The sign of the effect also depends on the level of skill of workers
	Hours	+/-	Adoption of robots decreases hours worked. Unclear for different technologies
	Labour share	+/-	Similarly to their impact on hours, robots have a negative impact on the labour share, while the opposite is true for different technologies
	Tasks	+/-	Positive for non-routine jobs, negative for routine jobs
	Wages	+	Positive overall, although exposure to robots is associated with lower wages
Prices	Prices	-	Negative overall for price levels and positive for price dispersion
Technology adoption	Technology adoption	+	Investing in R&D, broadband and other technologies is positively correlated with innovation
Value added/TFP/ labour productivity	Labour productivity	+	With few exceptions, the adoption of most technologies is associated with higher labour productivity
	TFP	+	With few exceptions, the adoption of most technologies is associated with higher TFP
	Value added	+	The adoption of most technologies is associated with higher value added

Source: References.

Note: The results shown in this table do not distinguish between studies which focus on a particular sector/country and those which focus on the whole economy/several countries; see Table A.2 in the Appendix for a more in-depth review and additional papers.

In addition, there are further interesting insights regarding Table 2. In relation to the supply side, for example, the effect on TFP and labour productivity is somewhat less certain than the effect on value added. Furthermore, the labour market impact of digitalisation is estimated to be more likely to affect hours and employment than to affect wages. Finally, while price inflation is expected to fall as a result of digitalisation, reflecting initially fiercer competition and smaller margins, price dispersion is expected to rise.

In summary, it seems that digitalisation has effects that are similar to those of other supply and technology shocks, at least in sign, tending to raise productivity and activity, but not necessarily employment, with a mild negative effect on inflation. The results should be viewed with caution, as the number of estimates available – presented in the Appendix in Table A.2 – is still not that large in all cases.

Box 2

Some measurement issues and the digital economy

Prepared by Robert Anderton, Gian Marco Pinna and Valerie Jarvis

This box looks at some measurement issues related to digitalisation and how they may affect the wider economy. It begins with a summary of selected articles from the literature regarding how digitalisation may affect the measurement of nominal and real variables. This is followed by a more in-depth review of the implicit deflators of ICT-related products and services and how their measurement may affect GDP in an era of digitalisation, also looking in more detail at deviations in these deflators across the EU countries. Although this Box reports the results of papers which

highlight possible measurement issues related to digitalisation, it does not critically assess their findings: more definitive conclusions must wait for the results of various studies on this issue by researchers and statistical agencies.²¹

The period since the financial crisis has been one of considerable debate around the degree to which slower growth – in GDP, investment, productivity and potential output – may result from measurement issues associated with digitalisation.²² It has been suggested that a significant amount of the decline in headline inflation may be directly traced to digitalisation and digital technologies impacting upon an ever-greater proportion of the consumption basket.²³ At the same, it may well be that the digital (or rather, “big data”) revolution in fact offers additional possibilities with which headline indicators may be measured more accurately.

Price measurement is likely to have been directly affected – with implications for both consumer price indices and deflators. Proponents argue that price changes are likely to be overestimated owing to the underestimation of quality improvements regarding digital products. In addition, many digital consumption products (such as social media, apps, online news, encyclopaedias, music streaming, etc.) are now typically offered as ostensibly “free” products (for which consumers “pay” with their data or by accepting advertisements). “Free” products are not taken into account in consumer price measurement,²⁴ although this type of consumption is a substitute for other types of consumption for which a market price can be observed.²⁵ By making strong assumptions, Reinsdorf and Schreyer (2019) calculate that the maximum plausible overstatement of price changes in OECD countries amount to around -0.7 and -0.6 percentage points in their sample years of 2005 and 2015 respectively.²⁶ Another challenge for measuring prices is presented by the additional possibilities offered for “dynamic/personalised pricing” (price discrimination afforded as a result of sophisticated digital algorithms) and the increasing degrees of customisation enabled by digitalisation.

As regards the real side of the economy, a key area for research to date has been the degree to which possible digitalisation-related measurement issues regarding the output components of GDP and price changes may help to account for the observed slowdown in productivity across advanced economies. Brynjolfsson and McAfee (2014) argue that since official statistics (i) fail to fully capture quality improvements in new ICT goods and services, (ii) ignore the benefits to consumers from freely available products (e.g. digital photos, social media and online encyclopaedias) and (iii) cannot adequately keep up with the rapid changes in prices given the accelerating pace of change in quality and specifications, standard growth accounting

²¹ There are several initiatives from various statistical agencies for measuring the digital economy and addressing possible measurement issues arising from digitalisation. For example: digitalisation is one priority area in the United Nation’s research agenda for the review of the System of National Accounts; Eurostat (2018a) follows a similar approach to the IMF for estimating the size of the digital economy in the European countries in terms of the ICT sector; the G20 addresses the digital economy in its G20 Digital Economy Ministerial Declaration of August 2018; and the OECD has been working in the past couple of years on developing digital satellite accounts.

²² See, for example, ECB (2017) and, for a wider discussion of the challenges for policy makers from statistical uncertainties, see Mersch (2016).

²³ See Section 7, “Digitalisation and inflation”.

²⁴ This is in accordance with the fundamental principle that price statistics refer to transaction prices.

²⁵ Note that the replacement of the consumption of products with positive prices by the consumption of “free” products is eventually reflected in Laspeyres-type consumer price indices only by means of lower expenditure weights given to them when basket weights are updated.

²⁶ They also state that such a correction of over half a percentage point to annual real consumption growth would not be insignificant, but it would moderate only a small fraction of the productivity slowdown. See Reinsdorf and Schreyer (2019).

disaggregations effectively overestimate inflation and thus underestimate increases in output volume growth. Turning more directly to deflators, analysis by the UK Office for National Statistics suggests that if different measurement methodologies were used, the UK national accounts telecommunication services deflator could have fallen by between 35% and 90% over the period 2010-2015, i.e. by much more than the official deflator. This result “also suggests that the real output of telecommunications services in the United Kingdom – and probably other countries – may have been significantly understated during this sample period”.²⁷ For the United States, Federal Reserve staff research suggests that “declines in official prices indexes are increasingly being understated because the quality change in prices for digital goods and services is unaccounted for”.²⁸ This work suggests that “the slowdown in US GDP and productivity growth since 2007 would be less pronounced if the value of consumer digital goods and services were more carefully measured”.²⁹

Problems arise not least due to issues related to measurement of “output”. For example, the emergence of new products without equivalent in the past as well as products with very short life cycles (less than a year). In addition, there are issues relating to co-production by consumers (online travel booking, etc.), along with broader trends towards “servicification” – in both cases reflecting a substitution of formerly physical goods (such as data storage) which are now increasingly replaced by service activities (e.g. cloud computing, digital photos, information gathering, newspapers, encyclopaedias, etc.).³⁰ However, these issues are not unique to digital technologies; arguably, it is the impact of the structural changes which digitalisation brings about that are of greater importance. As far back as 1987, Robert Solow argued that the inability to adequately measure the extent and degree of accelerating technological change on headline growth meant that “you can see the computer age everywhere but in the productivity statistics”.³¹

At the same time, there is now a growing body of work suggesting that, in the longer term, digitalisation is likely to lead to greater measurement opportunities – not least for better understanding price developments in real time (see e.g. OECD, 2015). ECB (2016) notes that digitalisation allows the use of scanner data, which enables the collation of consumer price data not just from a few hundred observations but from many thousands, also enabling a better understanding – in real time – of the seasonality of purchasing patterns. Ahmad and Schreyer (2016a,b) note that digitalisation “provides new data sources and data-gathering techniques, including scanner data and web-scraping, which provide capacity to collect large samples of prices at high frequency – weekly or even daily. With a higher frequency of price collection, the turnover of models between periods of price collection is reduced, making it easier to match models between consecutive periods, and so improve the ability to control for quality change”. They note further that such methods are likely to be able to help reduce the possible extent of “new product bias” (whereby prices of newly introduced variants decline more rapidly in the period immediately following their introduction, which is not taken into account in a consumer price index when the product is incorporated with a significant delay).

More recent studies examining the post financial crisis slowdown in GDP and productivity growth such as Cette and de Pommerol (2018)³² look at how the positive effects of ICT

²⁷ See Abdirahman, Coyle, Heys and Stewart (2017).

²⁸ See Byrne and Corrado (2019).

²⁹ See G7 Central Bank Digitalisation Working Group (2019).

³⁰ See, for instance, ECB (2016), Coyle (2015) and Varian (2016).

³¹ See Solow (1987).

³² See Cette and de Pommerol (2018).

diffusion on growth have faded away in the past 15 years or so and ask whether this drop could be partly explained by an underestimation of the fall in ICT prices. Using alternative ICT price indices (for instance as in Byrne and Corrado, 2016) suggests that gains in technological performance have been higher than captured in national accounts and that the contribution of ICT to growth in the period 2004-15 is closer to the higher growth between 1974 and 1995. Nevertheless, even in this case, GDP growth remains well below the levels seen in the period 1995-2004. Meanwhile, Syverson (2017) suggests that mismeasurement problems have so far not become more problematic over time. Ahmad et al. (2017) use a methodology that is described further below and conclude that “even if suspected mismeasurement is occurring, it is not of sufficient scale, at least for now, to significantly depress measured GDP growth or multi-factor productivity growth, nor to explain the recent, near-global slowdown in productivity and GDP growth”. However, their upper bound estimates of measurement error based on strong assumptions “point to upward revisions [to GDP growth] of around 0.2% per annum in most economies” for the period 2010-2015.

In more detail, Ahmad et al. (2017) find substantial cross-country differences in price indices for three ICT categories: (a) investment in computer hardware and telecommunications equipment, (b) investment in computer software and databases and (c) consumption of communication services. The differences in the price dynamics for these products could be challenged by suggesting that price changes for products that are internationally traded can be expected to be similar across countries. Ahmad et al. (2017) carry out their analysis in two steps: first, they correct for potential mismeasurement of the above ICT price indices for individual countries by taking into account the deviation of price dynamics vis-à-vis the other countries in the sample, thereby obtaining estimates of possible upper and lower bound ICT price indices for each country;³³ second, they calculate the impact on the growth rate of real GDP of replacing the actual ICT price with a reference country price index using the method proposed by Schreyer (2002)³⁴ and compute three possible impacts on GDP growth using different scenario assumptions: (i) the impact of the price adjustment only flows through to final demand, (ii) the impact of the price adjustment only flows through to imported intermediate products and (iii) the impact of the price adjustment flows through both imports and final demand.

Chart A shows the calculated impacts on real GDP of potential mismeasurement of the prices of the above ICT products and services for the three scenarios assumed by Ahmad et al. (2017). There are a broad range of impacts, with some scenarios generally finding that real GDP growth would have been higher for some countries after taking potential price mismeasurement into account, while other scenarios suggest real GDP growth could have been lower. More generally, for the countries considered, these experiments with minimum deflators for ICT equipment, software and communications services indicate that measurement errors in GDP growth could be in a range of up to 0.2 percentage points per year. Scenarios for some countries suggest that GDP could have been significantly higher: for example, Belgium’s average GDP growth rate could have been 0.4 percentage points higher than its actual average GDP growth of 1% for each year over the period 2010-2015 (i.e. GDP growth of 1.4% per year instead of 1% per year).³⁵

³³ For example, for ICT equipment in a given country *i*, the authors add to country *i*’s index for non-ICT, non-residential investment the deviation between the ICT equipment index and the non-ICT, non-residential investment index in the reference country, i.e. the country in which the price index increased/declined the most relative to the non-ICT investment price over the observation period.

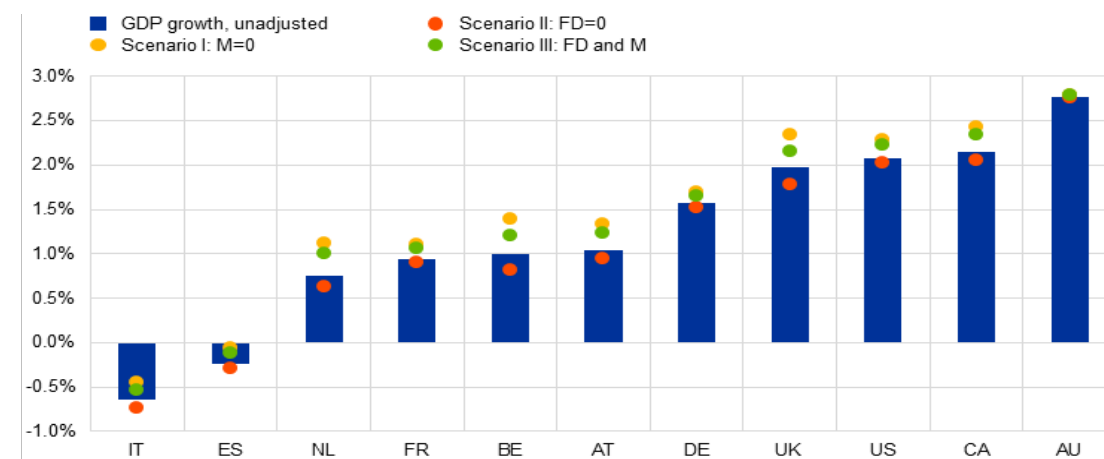
³⁴ This methodology consists of evaluating a “multiplier” by which price index adjustments of ICT and communication products would carry over to measured GDP growth rates.

³⁵ These findings should be interpreted with caution as they are based on strong assumptions.

Chart A

GDP growth: estimated impact of using alternative measures of prices for ICT assets and communication products and services (2010-2015)

(percentages, y-axis: average annual growth)



Source: Ahmad et al. (2017).

Notes: M=imports; FD=final demand. The estimates are calculated by the authors using "lower bound" prices as defined in Annex 1 of Ahmad et al. (2017). The impact of the alternative price measurement in the different scenarios is as follows: in scenario (i), it only flows through to final demand, with imports unchanged; in scenario (ii), it only flows through to imported intermediate products, with final demand unchanged; in scenario (iii), it flows through to both imports and final demand. Latest observation: 2015 or latest year available.

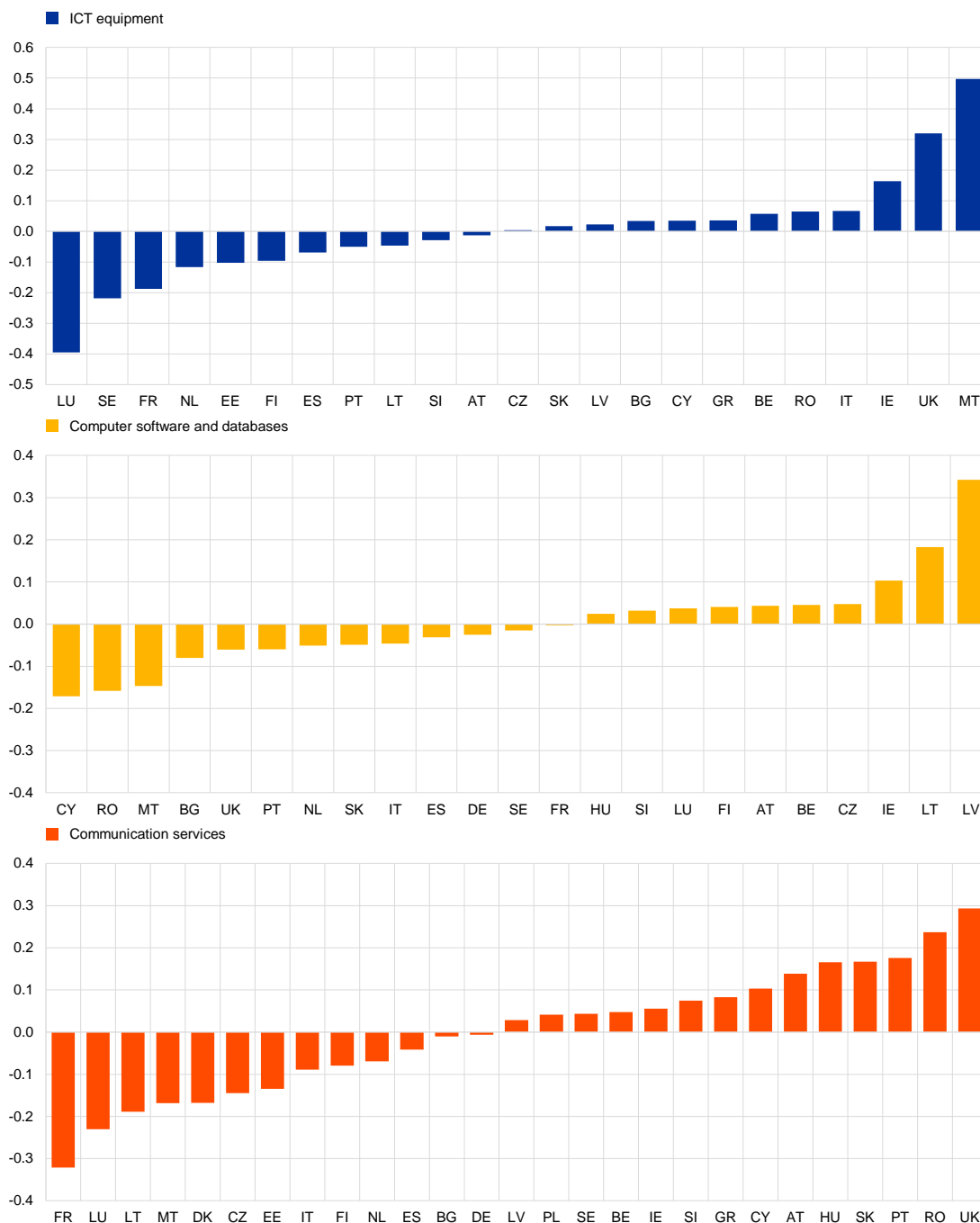
Using the same categories of deflators examined as in Ahmad et al. (2017), we find some considerable cross-country heterogeneity for these deflators across the EU countries, i.e. for investment in ICT equipment and computer software and databases, as well as for deflators for consumption of communication services (Chart B). Although the depicted divergences in ICT deflators across the EU countries do not imply the existence of mismeasurement, they could be used as upper and lower bounds that indicate the possible scale of the potential mismeasurement of GDP growth caused by potential mismeasurement of deflators. The implications of this cross-country heterogeneity in deflators and HICP for telecommunications is that, if one follows the same methodology as Ahmad et al. (2017), then one may find indications of possible measurement uncertainty of real GDP across some EU countries.

Overall, this Box has focussed on papers which highlight possible measurement issues related to digitalisation. However, this issue is being investigated across various ongoing workstreams in the statistical and research communities, underlining the need for further work. More definitive conclusions must wait for the results of various studies on this issue by researchers and statistical agencies.

Chart B

Deflators for investment in ICT assets, computer software and databases and consumption of communication services (index, year = 2010)

(2010-2017, deviation from the mean)



Sources: Eurostat (national accounts) and the ECB staff calculations.

Notes: The chart shows each country's deviation from the mean deflator value across all considered countries. Latest observation: 2017. For ICT equipment, latest available data for Spain, Romania, Latvia and Portugal are from 2016. For computer software and databases, latest available data for Cyprus, Spain, Ireland, Latvia, Portugal, Romania and Sweden are from 2016.

4 Productivity

Prepared by Filippos Petroulakis

A major effect of digitalisation is the change in production processes through the adoption of digital technologies in industry. Despite the promise of remarkable productivity growth through technological progress, the past two decades have been accompanied by relatively low productivity growth. A number of stylised facts about the productivity slowdown have emerged: rising productivity dispersion, with frontier firms growing faster than other firms, lower business dynamism, and high resource misallocation. These facts possibly underline bottlenecks in technology diffusion, rigidities due to financing or other frictions that affect firm decisions, which constrain productivity growth. These may be at least partially related to the nature of ICT itself, which, contrary to traditional physical technologies, requires a complex combination of specialised labour, new production processes and managerial capital, posing a challenge to incumbent firms. Nevertheless, the growing consensus seems to be that the productivity gains of the ongoing second stage of the digital revolution, primarily driven by advances in AI, will eventually be realised; like the steam engine or electricity, such GPTs require a high enough stock of specialised physical, human and managerial capital to be fully operational, and hence suffer from implementation lags. This section includes a detailed discussion of the challenges to productivity growth in the digital era, including the role of complementary assets, specialised finance, particularly for intangible assets, and the role of policy, along with important structural changes due to the rising share of the services sectors in the economy. A box analyses the productivity distribution for firms in the digital and non-digital sectors across the four largest euro area countries, focusing on productivity differences across sectors and revealing non-negligible churning at the top of the productivity distribution for both sectors, with incumbent productivity leaders slowly losing their leadership status and new leaders arising over time. Another box looks at how policy may influence technology and shows that better institutions and governance – proxied by indicators such as the effective “rule of law” and “control of corruption” – have a positive impact on the rate of adoption of digital technology.

4.1 Productivity slowdown

The fourth industrial revolution is unfolding alongside a protracted productivity slowdown across advanced economies. The euro area started to slow significantly in the mid-to-late 1990s, well before other advanced economies (Table 3), but the slowdown eventually became widespread even before the crisis. The slowdown was driven primarily by lower growth in TFP in the pre-crisis era but in later years also by lower capital deepening (capital per unit of labour), a result of a pronounced investment slump during the recovery.

Table 3**Productivity growth across advanced economies**

(percentage of annual average)

Labour productivity

	EA	US	JP	UK	CA	AU
1980s	2.1	1.6	3.9	2.5	1.1	0.9
1991-1995	2.7	1.3	2.0	2.7	2.1	1.6
1996-2000	1.3	2.3	2.2	2.3	2.3	1.9
2001-2005	1.0	2.7	1.5	2.1	1.9	1.2
2006-2010	0.8	1.5	0.7	0.4	1.2	0.6
2011-2016	0.6	0.4	1.0	0.3	1.6	1.0

Total factor productivity

	EA	US	JP	UK	CA	AU
1980s	1.4	1.2	2.6	2.3	0.6	0.2
1991-1995	1.5	1.0	0.5	1.5	1.6	0.8
1996-2000	0.9	2.0	1.0	1.7	1.7	1.8
2001-2005	0.3	1.8	0.9	1.6	1.3	0.7
2006-2010	0.2	0.6	0.3	-0.2	0.2	-0.2
2011-2016	0.3	0.5	0.9	0.4	0.7	0.4

Source: Banque de France Long-Term Productivity Database (Bergeaud et al., 2018).

Note: JP=Japan, CA=Canada, AU=Australia.

It may seem paradoxical that an era of such rapid technological progress is not accompanied by great productivity improvements. In fact, the slowdown is most

pronounced in the sectors which are the most intensive users of ICT, a finding that, among others, lends credence to the view that we are still in the installation phase of ICT (van Ark, 2016). This section will show that this may not be all that surprising given the special challenges facing any new type of technology and also given certain particularities related to ICT and to the service economy in general. The section will also examine the role of institutional factors and some of the challenges to the measurement of growth.

Productivity growth is comprised of four channels: growth of existing firms, resource reallocation (capital and labour) from less to more productive firms, entry of new firms and exit of old ones. The channels interact with each other. In

particular, reallocation interacts with within-firm growth: reallocation raises aggregate productivity directly, as resources move to more productive uses, but also indirectly, as the increased availability of resources allows these firms to expand further.

Evidence has confirmed the prediction of canonical models of firm dynamics (Hopenhayn, 1992), where reallocation is critical for productivity growth. Decker et al. (2016) show that muted reallocation accounts for a major part of the slowdown.

A number of key stylised facts on the slowdown are emerging. First, there is an increase in the dispersion of productivity between frontier and laggard firms (Andrews et al., 2016), suggesting that, contrary to the techno-pessimism hypothesis of Gordon (2012), the pace of growth of the technological frontier has not abated and is driven by

the frontier firms of the fastest-growing sectors.³⁶ Second, there has been an increase in the misallocation of resources, particularly in southern Europe in the pre-crisis era and especially for capital (Gopinath et al., 2017). This means that capital was not flowing to the most productive firms but to the least liquidity-constrained firms, a phenomenon that has not materially reversed during the crisis or the recovery (Gamberoni et al., 2016 and Masuch et al., 2018). Third, there has been a pronounced decline in business dynamism, particularly in the rate of creation of new businesses. This is a robust finding for the United States (Decker et al., 2018) and has also been observed for some European countries (Criscuolo et al., 2014), although clear-cut conclusions are difficult owing to data limitations.^{37,38}

A host of inefficiencies and rigidities hinder entry and reallocation. These include high barriers to entry that protect the rents of incumbents, an unfriendly business environment in the form of large costs of red tape and administrative procedures, insufficient access to credit for new ventures and an absence of specialised finance. Rigidities in the exit margin are also important.³⁹ Weak firms may inefficiently stay in the market through insolvency frameworks that prevent their restructuring or resolution, weak banks that want to avoid recognising losses, or political pressure. This acts like an implicit tax on healthy incumbent firms, and can have substantial negative effects on productivity growth (Adalet McGowan et al., 2018; Andrews and Petroulakis, 2019).

4.2 Productivity and ICT

The slowdown in productivity growth started much earlier in the euro area. By the mid-1990s (Table 3), the euro area was experiencing a substantial slowdown compared with earlier years, but also relative to other advanced economies, some of which even accelerated. A consensus explanation for the pre-crisis slowdown relative to the United States (van Ark et al., 2008; Timmer et al., 2011) was the inability of European economies to reap the benefits of the ICT revolution, particularly in market services. In the United States, following rapid advances in semiconductors, the mid-1990s saw a surge in innovations in ICT, a large increase in TFP growth in ICT-producing industries and a large increase in capital deepening, which was due in turn to a surge in ICT-related investments and, eventually, higher TFP in ICT-using sectors (Jorgenson et al., 2008).⁴⁰

By contrast, European economies were late in developing or even using these new technologies. Indeed, the contribution of the knowledge economy (labour quality, ICT capital and TFP) to labour productivity was 1.1% in the period 1995-2004

³⁶ See CompNet, 6th edition.

³⁷ For evidence on the importance of firm dynamism for TFP growth in the EU, see Anderton et al., 2019.

³⁸ The United States has also experienced a decline in labour market dynamism, with a steep reduction in the job-finding and separation rates since the 1990s. This is not the case for the euro area: while labour markets remain much less dynamic than in the United States, the trend seems unchanged (Cavalleri et al., 2019).

³⁹ See Anderton et al. (2019), who find that competition-enhancing product market regulation can increase firm entry and exit in the EU, which in turn boosts productivity growth.

⁴⁰ Later research (Decker et al., 2018) argues that were it not for the boom in the high tech sector in the late 1990s and early 2000s, dynamism would have declined even earlier.

in a sample of European countries and 2.6% in the United States over the same period, while the contribution of non-ICT capital was almost identical (0.5% and 0.4%, respectively).⁴¹

One explanation for this is the inability of firms to take advantage of the opportunities that ICT provides, which are different from those offered by older technologies. Physical capital in the form of factory machines and equipment was traditionally complementary to any type of labour, so the mere accumulation of such capital for a given amount of labour (capital deepening) was sufficient to generate growth through embodied and disembodied technical change (De Long and Summers, 1992). By contrast, ICT capital requires skilled labour, an adaptation and rethinking of organisational processes and other relevant changes, which poses challenges to existing firms.⁴² As such, ICT capital is complementary to a more complex set of other inputs, and synthesising them efficiently can generate higher productivity returns from ICT investment (Bresnahan et al., 2002) – much higher than what is expected from a Solow-Swan model (Brynjolfsson and Hitt, 2002).

Differences in management practices have emerged as a key explanation of why some countries are better at exploiting ICT. The complex relationship of ICT capital to other inputs means that it requires more sophisticated management. Bloom et al. (2012) show that UK establishments owned by US firms are more productive owing to higher ICT-related productivity. They argue that this is due to the different organisational structures of US firms, which are more flexible and decentralised (a more common feature of frontier firms, according to Acemoglu et al. (2017)). They provide evidence of large cross-country variation in labour reward and human resource management.⁴³

The importance of management practices can be useful in understanding developments in specific countries (Chart 4). Pellegrino and Zingales (2017) argue that lack of meritocracy is an important factor driving differences in TFP growth in ICT-intensive sectors. Lack of meritocracy is associated with poor management and governance structures, preferential treatment of family members over professional managers and the prevalence of small firms. Poor management may be more problematic in relation to ICT capital for the additional reason that, owing to the higher pace of technological change, the dispersion of firm-specific shocks may have risen (Decker et al., 2018), which would amplify the importance of agile and flexible management. Calligaris et al. (2018b) show that misallocation is higher in sectors where R&D intensity has changed most. Chart 5 (replicated from Schmitz and Schivardi, 2018) shows the raw correlation of average annual productivity growth net of non-ICT capital deepening and management scores for a range of advanced economies, before and after 1995, when productivity growth in the United States took off as a result of ICT technologies. Pre-1995, the correlation is essentially zero:

⁴¹ See van Ark et al. (2008). See also ECB (2017).

⁴² As aptly put by Bresnahan et al. (2002): “Firms do not simply plug in computers or telecommunications equipment and achieve service quality or efficiency gains.”

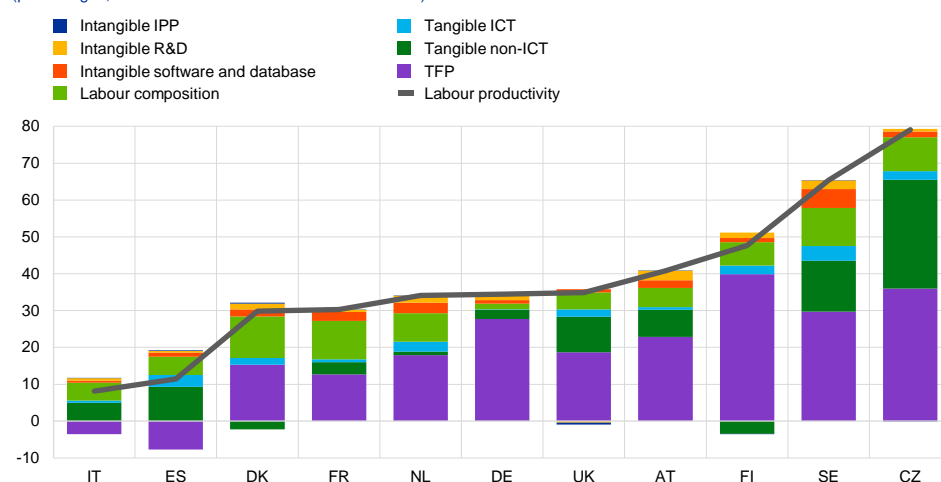
⁴³ Even within the United States, Bloom et al. (2019) find enormous differences in management practices. 40% of the variation in management practices is across plants within firms and can account for 20% of the productivity dispersion across plants, which is similar to the effect of R&D and twice as much as the effect of ICT.

management quality was not a particularly important factor determining productivity (within the relatively selected group of advanced economies). In contrast, in the 1995-2008 period, the correlation turned positive and high: countries whose firms had adopted good management practices achieved much higher rates of productivity growth than others. In fact, some of the worst performers of the ICT era, such as Portugal, Italy and Spain, performed as well as or better than the average in the previous era.

Chart 4
Productivity growth decomposition, 1996-2016

Contributions to labour productivity growth

(percentages; cumulative contributions from 1996 to 2016)



Source: EU KLEMS. Replicated from Pellegrino and Zingales (2017).

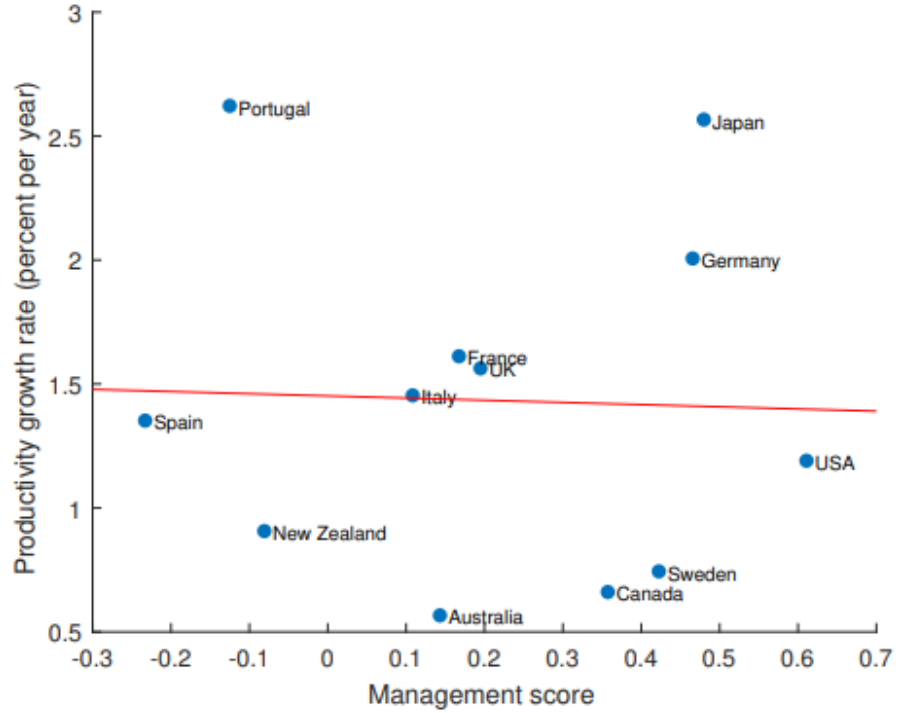
A corollary of the meritocratic hypothesis is that failure to exploit ICT was not the result of financial or other frictions preventing investment. One would then expect that, all else being equal, countries with non-meritocratic practices would have a higher non-ICT capital deepening *contribution* (not just the level) to productivity growth compared with the contributions from ICT capital or TFP: unsophisticated management would rely on “brute force” capital accumulation that is not TFP-enhancing, instead of more complex and sophisticated projects with higher returns. Eichengreen et al. (2017) make a similar argument and show that, for the 1950-2007 period across medium and high-income countries, high investment rates are indeed correlated with the probability of a TFP slump. Indeed Chart 4 shows that slow-growing countries had a higher growth contribution from non-ICT capital deepening and little from TFP, the largest driver for the faster-growing countries.⁴⁴ This is consistent with the idea that intense factor accumulation, probably the key to rapid growth in previous decades (as seen with the “Asian tigers”) is no longer a sufficient growth strategy.

⁴⁴ The exceptions here are Czech Republic, Slovenia and Ireland. The first two were transitioning economies at the time, for which the dynamics were quite different, as they were still industrialising. Ireland, in turn, presents measurement problems for capital owing to the large presence of multinationals.

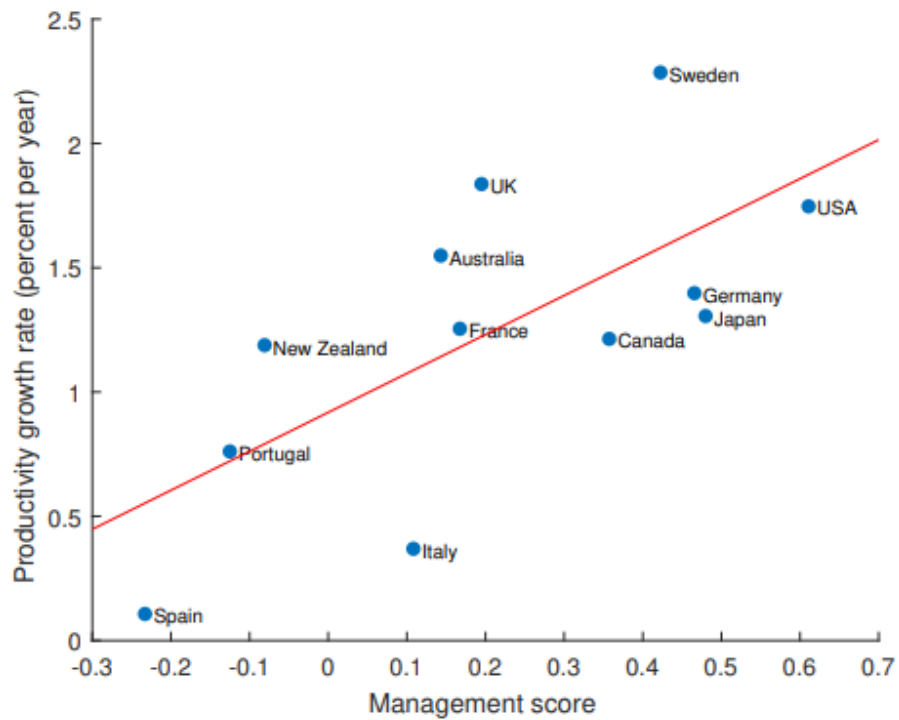
Chart 5

Productivity growth and management score

a) Productivity growth and management quality, 1985-1995



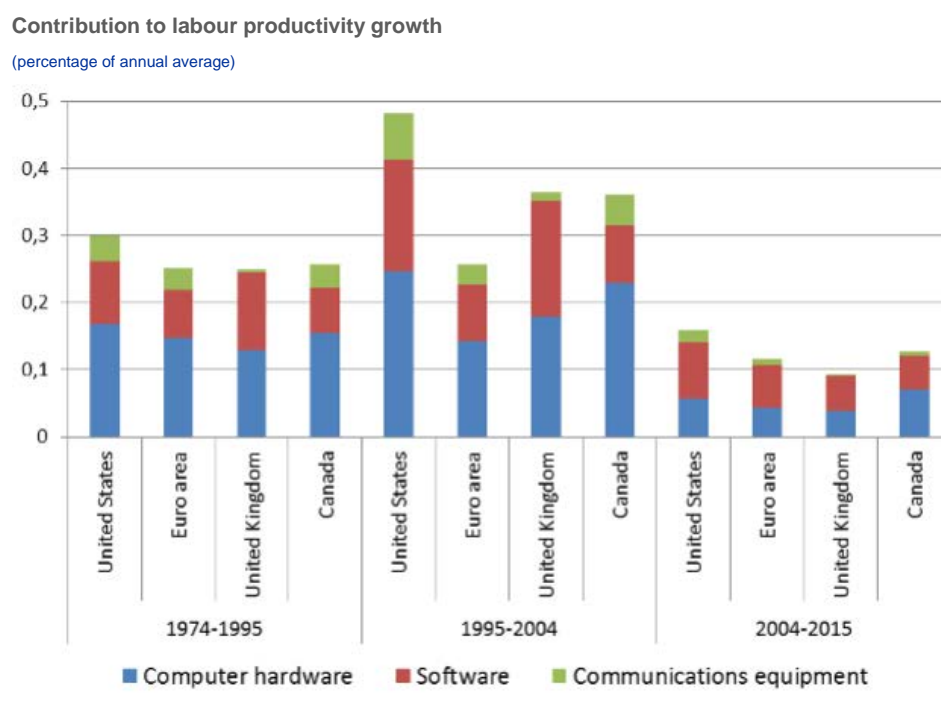
b) Productivity growth and management, 1995-2008



Notes: Replicated from Schmitz and Schivardi (2018). Schmitz and Schivardi (2018) estimate management scores using the World Management Survey (WMS), where senior managers are interviewed by telephone on their management practices. Each answer is ranked on a scale of 1 and 5 (from worse to best), and management scores are then defined at the firm level as the average of the scores for the single questions, standardised to have a zero mean and a standard deviation of 1 across the sample. For further details, see Schmitz and Schivardi (2018).

There is evidence that the ICT contribution to productivity growth has declined across advanced economies. Chart 6 (Cette and de Pommerol, 2018) shows the ICT capital contributions to labour productivity growth for the United States, the euro area, the United Kingdom and Canada from 1974 to 2015. The ICT capital contribution is further broken down into three categories: hardware, software, and telecommunications equipment. While the euro area performed substantially worse relative to its peers in terms of productivity growth in the 1995-2004 period,⁴⁵ over the past decade, productivity gains from ICT capital have been muted throughout. While some have suggested that the 1995-2004 gains were anomalous and the current period has seen a return to normal growth, the gains since 2005 have been much lower even than in the period before 1995.

Chart 6
Productivity contributions of ICT capital by region and type



Source: Cette and de Pommerol (2018).

4.3 Challenges for a GPT technology

The current period of technological change – often dubbed “the fourth industrial revolution” (World Economic Forum, 2016) – is in fact made up of a wide spectrum of technologies spanning computer science, nanotechnology, biotechnology, energy and other fields. A common view is that the most encompassing and important of all as regards its effects on what we conventionally call economic growth is AI, and more specifically machine learning (ML). Similarly to the previous period, it is primarily based on digital innovations, but it differs in its pace,

⁴⁵ These estimates come from different sources relative to Table 3 and Chart 5, so absolute magnitudes are not directly comparable. However, relative magnitudes are consistent across data sources.

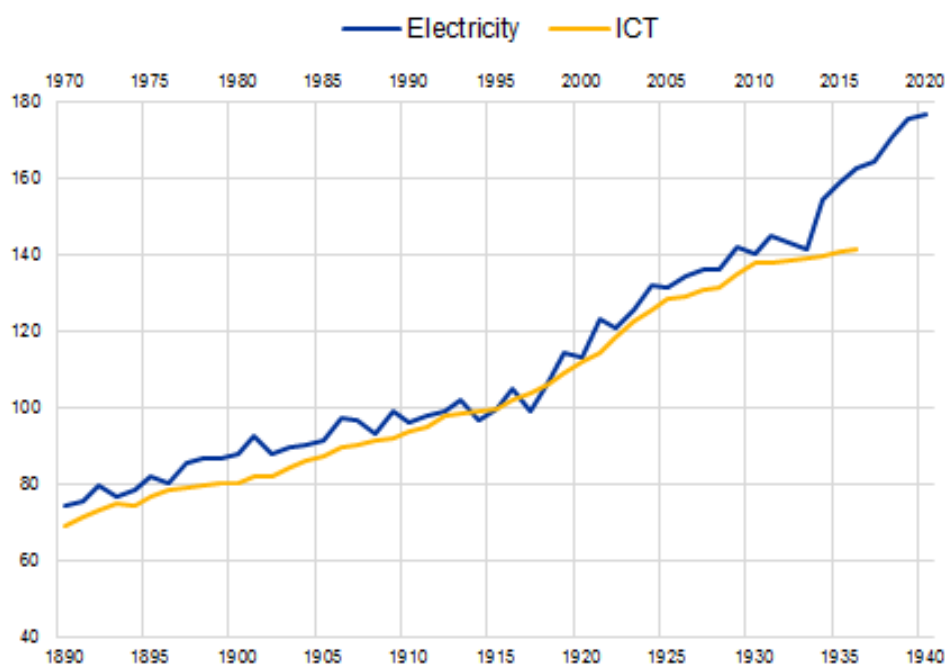
scope and potential systemic impact (World Economic Forum, 2016). Both periods are considered examples of GPTs.

Chart 7

Productivity growth from two General Purpose Technologies

Labour productivity in the United States

(1915=100 for electricity, 1995=100 for ICT)



Sources: Banque de France Long-Term Productivity Database (Bergeaud et al., 2016) and Kendrick (1961). Reproduced from Brynjolfsson et al. (2019).

GPTs are technologies that are paradigm-shifting in terms of how they affect both firms and households and that are important enough to have aggregate impacts (Jovanovic and Rousseau, 2005). Typical examples are the steam and internal combustion engines, electricity and ICT, as well as earlier technologies such as the wheel and agriculture. Bresnahan and Trajtenberg (1995) identified three distinguishing features of GPTs: (i) pervasiveness, (ii) inherent potential for technical improvement and (iii) innovation complementarities – GPTs lead to the creation of complementary innovations. It is the combined effect of these three qualities that makes GPTs unique and leads to their singular productivity effects. Bresnahan and Trajtenberg (1995) argue that electricity became pervasive once its production became efficient enough for its installation and usage cost to be sufficiently low; once that happened, a myriad of innovations leveraged electricity to bring about previously unimagined growth through the more efficient production of existing goods and services and the creation of new products. Higher incomes further increased demand for electricity and the peripheral products that used electricity, eventually bringing about further reductions in the cost of provision and so forth, in a virtuous circle of innovation and growth. A similar pattern of falling cost characterised ICT: Nordhaus (2007) estimated that by 2006, the real cost of computational power relative to labour input had fallen by a factor of at least 2 trillion.

Historically, it has taken a long time for GPT technologies to have substantial effects on productivity (Chart 7). Brynjolfsson et al. (2019) and Jovanovic and Rousseau (2005) point out some interesting regularities of GPTs as regards their productivity effects in the United States. Focusing on ICT and portable power, they document a compressed S-shaped pattern for each technology: a very slow initial phase, followed by an acceleration and then a plateau. In both cases, the initial phase lasts for almost 30 years, and the acceleration by 10-15 years. The behaviour at the plateau phase is interesting in light of the recent slowdown, but it is less clear, as the ICT phase is still running its course. For electricity, there is a further acceleration after the plateau (in the 1930s), but of course a number of extraneous factors could be involved.⁴⁶

Implementation lags can be very important for GPTs. It is intuitively clear that adapting production processes to a completely new technology can be a very long process. Investment in physical capital is lumpy, given high adjustment costs, while the production of technology itself becomes more efficient through time. Jorgenson et al. (2008) argue that improvements in semiconductor production (and corresponding price reductions) can explain why it took almost four decades from the introduction of commercial computers to substantial ICT-related productivity growth. Skilled workers may also be hard to come by, especially before the new technology has become sufficiently widespread that a large enough scholarly base has been created, so that the technology can be taught at universities on a mass scale.⁴⁷ Production processes also have to be adapted to cater to and leverage the new technology, and managerial practices have to be updated. In short, a critical mass of physical, human, organisational and managerial capital needs to be accumulated for the productivity benefits to be reaped. In addition, complementary capital from peripheral innovations (roads for cars, internet for ICT) needs to be accumulated, which also takes time.

The delay in productivity growth from the fourth industrial revolution has called into question how we measure productivity.⁴⁸ While the productivity paradox is not much of a paradox from a historical perspective, the particular nature of the current technological revolution has made the mismeasurement hypothesis salient, owing primarily to (i) the increasing role of intangible capital, which is much harder to capture; and (ii) the presumed increase in consumer surplus due to advances in leisure technology. Some researchers have addressed this issue for the United States and have argued that the slowdown is not merely the result of accounting.⁴⁹ Ahmad et al. (2017) consider the effect of mismeasuring ICT deflators on growth for a number of European countries and also find that the mismeasurement is modest and not likely to much change our view of the slowdown. Brynjolfsson et al. (2018) make a more

⁴⁶ Such a comparison is not easy for Europe, which suffered a major war during the electrification phase.

⁴⁷ Since 2000, the number of scientific papers on AI has grown at a rate almost double that of computer science in general, and almost triple relative to all papers. At Tsinghua University, the leading Chinese university in AI, involvement in relevant courses has increased 16-fold since 2010 (Shoham et al., 2018).

⁴⁸ Some measurement issues are further discussed in Section 6, "Supply side", and in Box 2.

⁴⁹ Byrne et al. (2016) point out that measurement issues precede the slowdown, and argue that any increase in consumer surplus falls far short of the "missing output" due to the slowdown, a conclusion shared by Syverson (2017) and Nakamura and Soloveichik (2017). More fundamental is quality improvement bias: inflation is imputed from surviving products, understating growth if low quality products disappear; Aghion et al. (2019) find a non-trivial but constant effect of this bias on growth, so it cannot explain the slowdown. Groshen et al. (2017), from the perspective of the measurement specialist, reach a similar conclusion.

nuanced argument: these complementary innovations are often intangible (datasets and algorithms, firm-specific human capital, new processes) and hence poorly measured but are also used in the production of other goods. As official data may partially miss these investments, TFP will be underestimated initially, when the growth rate of this new investment and its return is high, and will be overestimated later, when enough capital has been accumulated.⁵⁰

4.4 Productivity growth in the digital era

Productivity growth in the digital era is more complex than in previous periods.

For embodied technical change, the various complementarities characterising new technologies imply that the mere accumulation of production factors is not enough to increase TFP. Similarly, in the case of disembodied technical change (arguably rising in importance) the production and adoption of ideas (which may also include intangible assets) also requires a deeper level of sophistication than previous technologies. Over and above considering how digitalisation affects productivity, the specific determinants of adoption of these technologies are crucial. Given the well-documented dispersion in productivity, it is likely that differences in diffusion are critical.

Adoption of new technologies has been shown to be strongly influenced by the availability of complementary assets, such as human and managerial capital.

These complementarities are well known (Bresnahan et al., 2002; Bloom et al., 2012). Firms will adopt new technologies if their workers possess the necessary skills to utilise them and incorporate them into the production process. Existing workers will be able to acquire such skills through relevant training, which requires that firms have managers who recognise the need to provide such training and that these managers are able to recruit skilled workers from outside the firm. Sophisticated management is also needed to initiate the organisational change required to incorporate the new technologies into the workings of the firm. This interplay between technologies and firm capabilities determine both the adoption of the technologies and their effects. Some technologies may also be adoption factors themselves, as they provide critical infrastructure. Broadband internet is considered to be such a technology, as it is a necessary input to be able to exploit other technologies.⁵¹

Another technology that has received a great deal of attention recently is that of industrial robots. Acemoglu and Restrepo (2018b) show that differences in ageing explain a substantial part of the variation in cross-country adoption and exports of industrial robots, partially accounting for the fact that Germany and Japan in some industries employ more robots per workers than the United States. They show that the

⁵⁰ Back-of-the-envelope calculations suggest that, for recent years, the undermeasurement of AI may be substantial enough to account for a large part of “lost output” from low productivity growth compared with two decades ago, and hence we may be entering a severe undermeasurement phase. As AI investments have only lately become substantial, this mechanism cannot account for the early year of the slowdown.

⁵¹ Andrews et al. (2018) show that broadband access is highly correlated with adoption of a set of digital technologies. Fabling and Grimes (2016) find causal effects of broadband on productivity only for firms jointly implementing organisational changes, stressing the complementary nature of adoption.

purported adverse effect of ageing on productivity may be moderated by the incentives to adopt robots.⁵² See Section 5.1 for further discussion.

On the financial side, it is commonly argued that intangible assets are hard to collateralise. This means that assets such as training and databases are harder to borrow against compared with tangible assets. As such, firms have a harder time financing these investments, which may have a direct impact on productivity, but may also be less able to adopt technologies complementary to these assets.⁵³ Moreover, diverse financing sources are crucial for financing the complex investments of the digital era. Traditional intermediaries, such as local banks, often lack the sophistication necessary to evaluate risky projects involving innovative ideas based on complex technologies, while small firms lack internal funds and reputation so that they cannot signal their quality to investors (Hall and Lerner, 2010). Specialised financing, in the form of VC or private equity is then crucial for financing such investments, and there is ample evidence that developed VC markets spur growth and innovations (see e.g. Samila and Sorenson (2011) and Andrews et al., 2014).

Technology adoption can be also affected by policy. Even if firms have the capabilities to exploit these technologies, they will only adopt them if doing so is profitable; low competition may lower such profits.⁵⁴ Andrews et al. (2016) show that the gap between laggard and frontier firms is higher for industries that have been less affected by competitive reforms (such as retail compared with telecoms). This could be simply due to the diffusion of ideas in the affected sectors (which raises the gains to be made by adopting innovations) or incentives to improve management quality (Bloom and Van Reenen, 2007). Reforms in upstream services sectors could also spill over to downstream industries, which now face a more competitive pool of sellers and hence have larger gains to make by adopting innovations. At the same time, given that firms need to be able to attract skilled workers and respond to changing needs, rigid employment protection legislation (EPL) may make it harder for firms to attract these workers and adopt new technologies. Andrews et al. (2018) provide evidence that higher EPL is associated with lower adoption of a set of digital technologies for sectors characterised by a high technological need for employee turnover. Cette et al. (2016) show that higher EPL leads to (i) positive effects for non-ICT physical capital intensity and the share of high-skilled employment and (ii) negative effects for R&D capital intensity and the share of low-skilled employment. As such, EPL implies a high cost of low-skilled labour, which is substituted by non-ICT capital.⁵⁵ Box 3 further explores the role of policy for technology adoption with a focus on how institutions and governance may be related to the take-up of digitalisation.

⁵² Note that the positive effect of ageing on exports of robots and other automation technologies (a home-market effect) is potentially an additional positive domestic spillover of ageing.

⁵³ There is in fact suggestive evidence (Duval et al., 2020) that financially vulnerable firms, which experienced a larger productivity hit after the 2008 shock compared with firms having strong balance sheets, had significantly lower intangible investments and patent applications than less indebted firms. At the same time, conventionally measured intangible investment suffered a much smaller hit on aggregate during the crisis, so this is an unresolved issue (see Section 6.1).

⁵⁴ While there is a lot of empirical work on how competition affects innovation at the firm level (see Aghion, 2017), there is less evidence on the effects of competition on adoption of outside innovations.

⁵⁵ See also Box 3, "Governance and institutions".

Box 3

Digitalisation: interactions with institutions and governance

Prepared by Claudio Baccianti, Vincent Labhard and Jonne Lehtimäki

This box provides evidence on how the process of digitalisation may be related to institutions and governance. The focus is on the evidence over a longer period, as the progress of both digitalisation and of institutions and governance may not be fast and so may not be accurately measurable from one year to the next. In addition, it is likely that relationships between these variables may only be captured using a relatively longer sample period.

The empirical measures of digitalisation are taken from the World Bank Development Indicators (WDI) given their relatively long sample periods.⁵⁶ Those measures include the number of individuals using the internet and the number of fixed broadband subscriptions.⁵⁷

The data on institutions and governance are from the Worldwide Governance Indicators (WGI), also compiled by the World Bank.⁵⁸ In this box, the institutional environment is considered to be captured by the three indicators “voice and accountability”, “political stability and absence of violence” and “government effectiveness”. The governance aspect is considered to be captured by the three indicators “regulatory quality”, “rule of law” and “control of corruption”.

The institutional environment and governance aspects are important for market functioning. Institutions play a role by providing equal opportunities to market participants, e.g. in terms of access to information, by defining the framework for transactions on the market, the participants, etc., and by providing options for enforcement. Governance plays a role by creating accountability to stakeholders, etc. Like institutions, governance has been shown to affect the performance of the economy, especially in terms of growth.

In very general terms, institutions and governance have been shown to affect the performance of the economy, especially in terms of growth.⁵⁹ If institutions and governance are strong, then economic performance tends to be strong, and vice versa. The growth-enhancing impact of institutions and governance may stem from the positive effects they have on investment in new technologies, of which digitalisation is one example.

In an environment that protects investments in and returns from new technologies, economic agents are likely to engage faster and to a greater extent with new technologies and the investment opportunities they bring. Accordingly, it may be the case that progress in digitalisation is

⁵⁶ The WDI are a collection of (internationally comparable) statistics on a number of themes. Those themes include (i) poverty and inequality, (ii) people, (iii) the environment, (iv) the economy, (v) states and markets and (vi) global links. The WDI are available for 264 countries/territories or country groupings, for the period 1960-2018. More information is available at [The World Bank](#).

⁵⁷ To the extent possible, the results in this section were cross-checked against (and found to be similar to) other measures of digitalisation. Those other measures include notably the data from the European Commission's Digital Economy and Society Index (DESI) already used in Section 2.

⁵⁸ Those data are described in Kaufmann et al. (2007) and Kaufmann et al. (2010). The WGI are a set of survey-based indicators, available for 229 countries/territories, for the period 1996-2018 and for six aspects of governance. The six aspects of governance are (i) voice and accountability, (ii) political stability and absence of violence, (iii) government effectiveness, (iv) regulatory quality, (v) rule of law and (vi) control of corruption. More information is available at [The World Bank](#).

⁵⁹ See Masuch et al. (2018), who document the evidence on institutional and governance factors and their impacts on the euro area countries.

held back if the returns to investing in digitalisation cannot be fully realised because institutions (and governance) are weak, i.e. there is little accountability, security or government effectiveness.⁶⁰

At the same time, the spread of digital technologies may also have repercussions on institutions and governance. For example, greater digitalisation may make access to information easier and thereby foster greater transparency, which puts pressure on institutions in turn to be more transparent and to strive for better governance. A high degree of digitalisation may also mean that there are more digital traces that make it easier to scrutinise the performance of institutions and their governance.

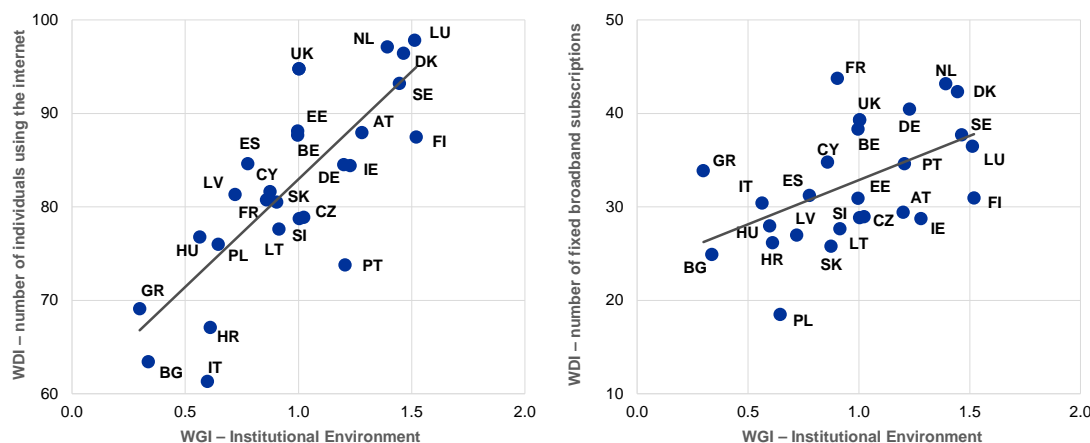
The prima facie evidence is provided in Chart A (for institutions) and B (for governance).

These charts show that a higher number of individuals using the internet (or fixed broadband subscriptions) tends to be associated with a higher quality of institutions and governance. In general, the correlation between the degree of digitalisation and institutions or governance is relatively strong.

Chart A

Digitalisation and institutions across the EU28 in 2018

(individuals using the internet: percentage of population, institutional environment: between 0 and 2.5)



Sources: World Bank, ECB staff calculations.

Notes: The line is a fitted linear regression line. It shows how the institutional environment on the horizontal axis, measured by the indicators "voice and accountability", "political stability and absence of violence" and "government effectiveness" from the WGI (World Governance Indicators) might map into the degree of digitalisation on the vertical axis, measured alternatively by the indicators "access to the internet" (left-hand panel) and "broadband subscriptions" (right-hand panel), taken from the WDI (World Development Indicators).

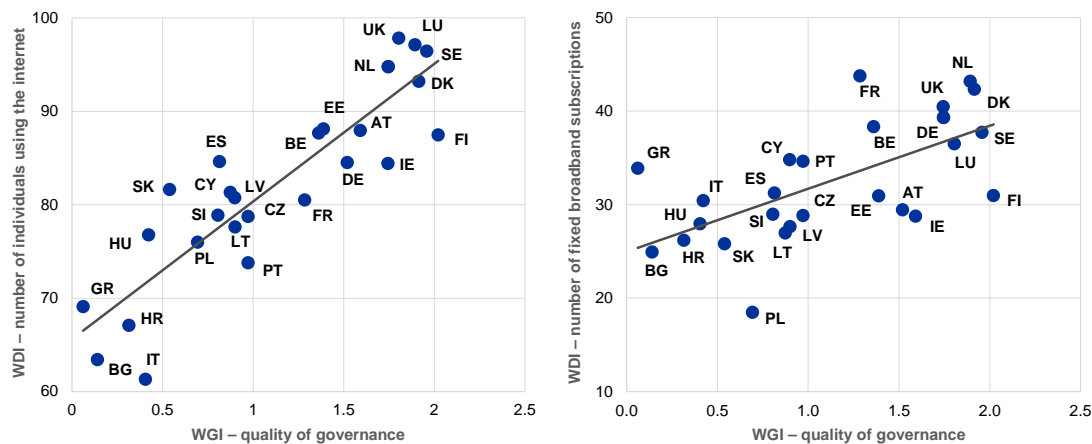
There is also evidence for possible clusters of countries with respect to digitalisation and quality of institutions. The clusters of countries sharing specific features tend to be similar in both charts. Some of the Nordic countries, Luxembourg, the Netherlands and the United Kingdom score particularly highly, while some eastern European countries have particularly low scores (such as Bulgaria, Croatia and Hungary). However, some euro area countries also have low scores (for example Greece and Italy).

⁶⁰ See also Section 2, "The degree of digitalisation across EU countries", and the list of enablers of digitalisation, as well as Box 10, "Trust and digital technologies", in the Appendix.

Chart B

Digitalisation and governance across the EU28 in 2018

(individuals using the internet: percentage of population, quality of governance: between 0 and 2.5)



Sources: Eurostat, World Bank, ECB staff calculations.

Notes: The line is a fitted linear regression line. It shows how the quality of governance on the horizontal axis, measured by the indicators "regulatory quality", "rule of law" and "control of corruption" from the WGI (World Governance Indicators) might map into the degree of digitalisation on the vertical axis, measured alternatively by the indicators "access to the internet" (left-hand panel) and "broadband subscriptions" (right-hand panel), taken from the WDI (World Development Indicators).

As in the case of digitalisation and institutions, there is also evidence pointing to country clusters in the case of digitalisation and governance. Moreover, the clusters tend to be broadly similar in both cases. The results are shown in Chart A, with some Nordic countries displaying high scores and some eastern European and other southern European countries receiving lower scores.

The remainder of this box reports quantitative evidence suggesting a possible relationship between digitalisation on the one hand, and institutions and governance on the other. The analysis builds on the epidemic model of technology diffusion, in which the growth rate of the technology diffusion is an increasing function of the number of individuals who have yet to adopt the new technology. In this model, the diffusion rate picks up in the early stages of diffusion and slows down as the technology adoption approaches the long-term saturation level. As a result, this model yields a non-linear, S-shaped process of technology adoption over time.⁶¹

The chosen model is quite intuitive for the process of digitalisation. It reflects obstacles in the initial phases of technology adoption that need to be overcome before the majority of agents join in, and at an increasing rate, until the composition of agents is such that they are less and less likely (or take more and more time) to adopt the new technology. In the empirical implementation of this model, the speed of internet diffusion and the steady-state adoption rate are both allowed to depend on institutions and governance as well as other structural country characteristics.⁶²

Digitalisation is proxied by the number of individuals using the internet (in percentage of population), as used in Chart A and Chart B. This measure of digitalisation tracks the proportion of individuals in the total population who have used the internet in the last three months from any location or device. It is available from the WDI dataset of the World Bank. This measure of digitalisation has the advantage of being available across most EU countries and, importantly, for the

⁶¹ See, for example, Geroski (2000) and the references therein.

⁶² This model of technology diffusion is similar to a model of economic convergence in which the growth in real GDP per capita is a function of its initial level and a set of growth determinants.

period 1994-2017, and hence is one of the few aggregate ICT indicators with a sufficiently long time span, which is important for properly estimating the technology diffusion curve.⁶³

The measures for the quality of governance and institutions are from the World Bank's WGI.

For governance, they include “regulatory quality”, “rule of law”, “control of corruption” and the corresponding aggregate, while for institutions they include “voice and accountability”, “political stability and absence of violence” and “government effectiveness”. Control variables are the logarithm of real GDP per capita from the European Commission and the human capital stock from the Penn World Tables. The former variable captures income effects in the diffusion process, whereas the latter controls for the role of education.

The results suggest that higher income increases the adoption of digitalisation and that digitalisation might be faster and greater when institutions and governance are of higher quality.⁶⁴

As shown in Table A, higher GDP per capita seems to be associated with higher adoption of digitalisation. Institutions and governance overall (the variable “WGI Total”) have a statistically significant positive impact on both on the rate of adoption of digital technology as well as the long-run level of digital adoption.⁶⁵ The effect on the rate of adoption is captured by the coefficients on the product of adoption rate and the WGI indicator (listed under “interaction terms”), while the effect on the long-run level of digital adoption is captured by the coefficient on the lagged WGI indicator (listed under “other terms”).⁶⁶

This suggests that good institutions and governance support the process of digitalisation.

This may be because good institutions and governance contribute positively to investment in digital infrastructures by public and private agents, or are important as framework conditions supporting the diffusion of internet use in the economy. As also shown in Table A, the results are broadly similar for the overall indicator (WGI Total) that measures institutions and governance jointly, as well as some of the measures capturing specific aspects of institutions or governance, such as the “effectiveness of government” or “rule of law” indicators.

⁶³ There are not many indicators of digitalisation that go back such a long way with the necessary country coverage, which also precludes an extensive sensitivity analysis. For the alternative indicators with a similar sample, which are not as close proxies of the degree of digitalisation, the results are broadly comparable but not quite as significant.

⁶⁴ The countries missing from the EU28 are Greece, Luxembourg, Malta and Romania.

⁶⁵ The overall fit of the diffusion model is also quite good.

⁶⁶ For the lagged and interaction terms, a negative sign means a positive effect on the rate of digital adoption; for the other terms, a positive coefficient means a positive effect on the long-term level of digital adoption.

Table A**The link between quality of institutions and digitalisation****Evidence from the number of individuals using the internet (in percentage of population)**

Dependent variable: Δ log Individuals Using the Internet (IUI), % of population	(1)	(2)	(3)	(4)	(5)	(6)
Lagged level						
log Individuals (t-1)	-0.207*** (0.0297)	-0.208*** (0.0315)	-0.207*** (0.0302)	-0.167*** (0.0286)	-0.180*** (0.0307)	-0.166*** (0.0352)
Other terms						
Human Capital Stock	0.0585 (0.107)	-0.0305 (0.101)	0.0558 (0.100)	0.00418 (0.112)	-0.0289 (0.0984)	0.0219 (0.106)
log GDP per capita PPP (t-1)	0.114* (0.0590)	0.157* (0.0783)	0.129** (0.0608)	0.138** (0.0623)	0.170** (0.0729)	0.133** (0.0620)
WGI Total (t-1)	0.161*** (0.0553)			0.230*** (0.0583)		
WGI Rule of Law (t-1)		0.0306 (0.0591)			0.106* (0.0535)	
WGI Governance (t-1)			0.169*** (0.0479)			0.266*** (0.0711)
Interaction terms						
Individuals / WGI Total (t-1)				-0.0453** (0.0166)		
Individuals / WGI Rule of Law (t-1)					-0.0341*** (0.0113)	
Individuals / WGI Governance (t-1)						-0.0449** (0.0196)
Constant						
Constant	0.188 (0.351)	0.486 (0.328)	0.151 (0.327)	0.254 (0.362)	0.408 (0.329)	0.170 (0.342)
Statistics						
Observations	431	431	431	431	431	431
R-squared	0.751	0.745	0.754	0.761	0.756	0.761
Number of countries	24	24	24	24	24	24

Sources: ECB staff calculations, based on data from the European Commission (GDP per capita), Penn World Tables (human capital stock) and the World Bank (WDI, WGI).

Notes: Fixed effects model. Country-clustered standard errors in parentheses (** p<0.01, * p<0.05, * p<0.1).

The rise in services may imply structural impediments to productivity growth.

A salient structural shift over the last few decades in advanced economies is the service sector's increasing share in value added and employment. This is a direct result of productivity growth in manufacturing but is also due to the rise in living standards, as services are income elastic (see Section 5). Empirically, services are well known to be characterised by slower productivity growth than manufacturing (Baumol, 1967), so the rise in services imposes a challenge to aggregate productivity growth. Services possess distinctive features that are detrimental to productivity growth. They are typically less tradable than manufacturing, making them less contestable and harder to scale up, and are harder to automate (see Section 5). They are also less standardised and suffer more from informational asymmetries than manufacturing, so they allow for a lower level of selection. At the same time, digital technologies may help address some of these issues, both through the application of AI technologies to bring automation in services and through the rise in online platforms, which increase contestability. See Sorbe et al. (2018) for a comprehensive overview.

Box 4

Productivity leaders (and laggards) in digital and non-digital sectors

Prepared by Vasco Botelho, Filippos Petroulakis and Romano Vincenzo Tarsia

The advent of rich firm-level datasets over recent years has revolutionised economists' understanding of the micro drivers of aggregate performance. A robust stylised fact is that there are large productivity differences between firms even within narrowly defined sectors (Syverson, 2004), which is considered as evidence that factors of production are not allocated efficiently (Hsieh

and Klenow, 2009, Bartelsman et al., 2013). Andrews et al. (2016) further document rising dispersion of productivity between top “frontier” firms (“leaders”) and all other firms (“laggards”) across OECD countries. They argue that the pace of technology diffusion has slowed down in the last two decades. The slowdown in productivity growth is also related to a decline in business dynamism and labour market fluidity (Davis and Haltiwanger, 2014; Anderton et al., 2019), which can be the result of a reduction in the responsiveness of firms to idiosyncratic productivity shocks, an interpretation consistent with a common increase in adjustment frictions at the firm level (Decker et al., 2018).

A largely unexplored issue, however, relates to the persistence of productivity leadership across countries and sectors. Put another way, are today’s productivity leaders also tomorrow’s leaders? While many studies have found productivity to be highly persistent, suggesting that some firms are consistently more successful than others in running their businesses (Syverson, 2011), there is evidence that this persistence is not sufficiently high for the boundary between frontier and laggard firms to remain impermeable to macroeconomic shocks and to structural changes in market conditions (Decker et al., 2018). The “churning” of productivity rankings has mostly received attention in the business cycle literature, as there is evidence that it is a countercyclical phenomenon.⁶⁷ Conversely, the focus here is on the secular and structural features of the economy.

This box provides suggestive evidence on the churning in the firm-level labour productivity distribution for the four largest euro area countries, with a focus on comparing the digital and non-digital sectors. To do so, it explores firm-level information available in Orbis, the largest commercially available cross-country database of firm-level balance sheet data for the euro area.⁶⁸ The underlying interest here is in providing a characterisation of the heterogeneous dynamics of labour productivity, defined as turnover (or gross output) per employee.⁶⁹ The sample is further partitioned into two supersectors⁷⁰ – digital and non-digital – with the intent of isolating the industries mostly associated with the digital economy. The sample for the euro area countries comprises more than 2.6 million firm-year observations during the 2006-2016 period (implying an average of roughly 241.1 thousand firm observations per year) and representing broadly 19.6 million employees per year. The digital sector encompasses 6.2% of the total number of firms and 8.6% of the total number of employees, with the average firm in the digital sector being around 40% larger than the average firm in the rest of the economy.

⁶⁷ Bloom et al. (2018) show that firms change productivity rankings more frequently in recessions, a fact they interpret as evidence of uncertainty-induced turbulence. Yu (2016), shows that churning may be associated with a low industry-level employment growth.

⁶⁸ The Orbis database was harmonised for the EA19 countries following the standard approach advocated by Kalemli-Ozcan et al. (2019). However, the main analysis focuses mostly on the four largest euro area countries (Germany, France, Italy and Spain) during the period 2006-2016. As is conventional for such studies, the focus is on the market economy. Therefore, the final sample excludes firms in the following sectors: agriculture, forestry and fishing; mining and quarrying; finance, insurance activities and real estate activities (FIRE); public administration and defence; education; human health and social work activities; arts, entertainment and recreation; and other service activities.

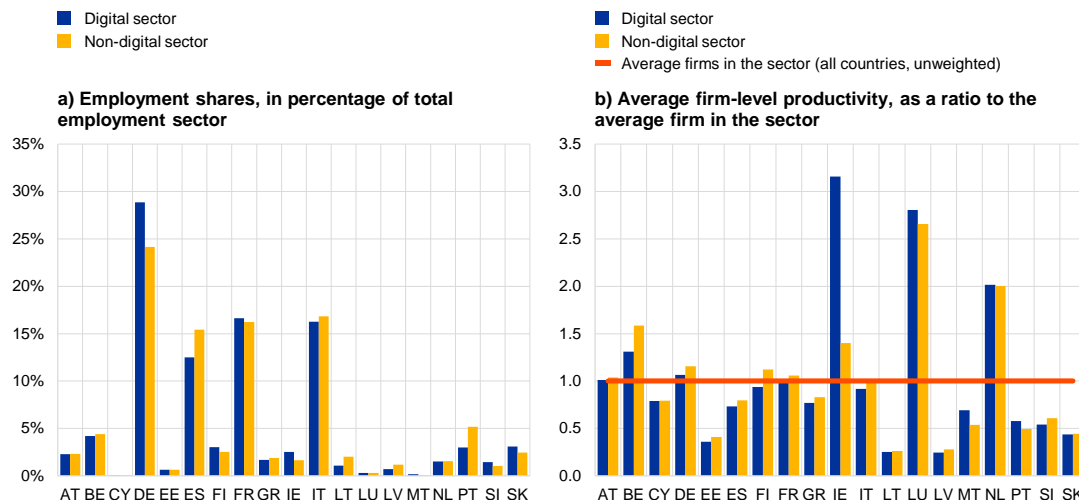
⁶⁹ This definition for labour productivity is comparable conceptually to gross output produced at the firm level per employee. Turnover (or total operating revenues) includes net sales, other operating revenues and stock variations, while employment is measured as the number of full-time employees. A robustness analysis of the results in this box, using production measures based on value added measures at the firm level and on the use of state-of-the-art productivity estimation methodologies to calculate total factor productivity (e.g. Wooldridge, 2009), is left for future work.

⁷⁰ The digital sector is comprised of the high-tech manufacturing (manufacture of computer, electronic and optical products and electrical equipment) and ICT services (publishing, audiovisual and broadcasting, telecommunications, IT and other information services) sectors. While, typically, the cluster of analysis for firm-level exercises is a sector, firms across different sectors can share similar characteristics. Although labour turnover occurs primarily within sectors (Bartelsman et al., 2009), certain occupations (e.g. IT engineers) are highly mobile across different sectors. As such, most of the analysis takes place at the level of the super-sector (i.e. digital vs non-digital).

Chart A

Employment shares and productivity: firms in the digital and non-digital sectors in the euro area

(2006-2016)



Sources: Orbis Europe (Bureau van Dijk) and ECB staff calculations.

Notes: The employment shares are calculated as the ratio of the number of employees in each country to the total (unweighted) number of employees in the EA19 sample. Average firm-level productivity is measured as the real gross operating revenues per employee, in thousands of 2010 EUR per person, for firms with at least ten employees in any given year between 2006 and 2016. The digital sector comprises the manufacture of computer, electronic and optical products (C26), the manufacture of electrical equipment (C27), publishing activities (J58), audiovisual and broadcasting activities (J59, J60), telecommunications (J61), and IT and other information services (J62, J63). The non-digital sectors comprise the remaining manufacturing industries (C11-C25, C28-C33); utilities (D, E); construction (F); and market services (G-I, M-N). The average firm in each sector is constructed as an unweighted average across all EA19 countries for the relevant sectors of economic activity.

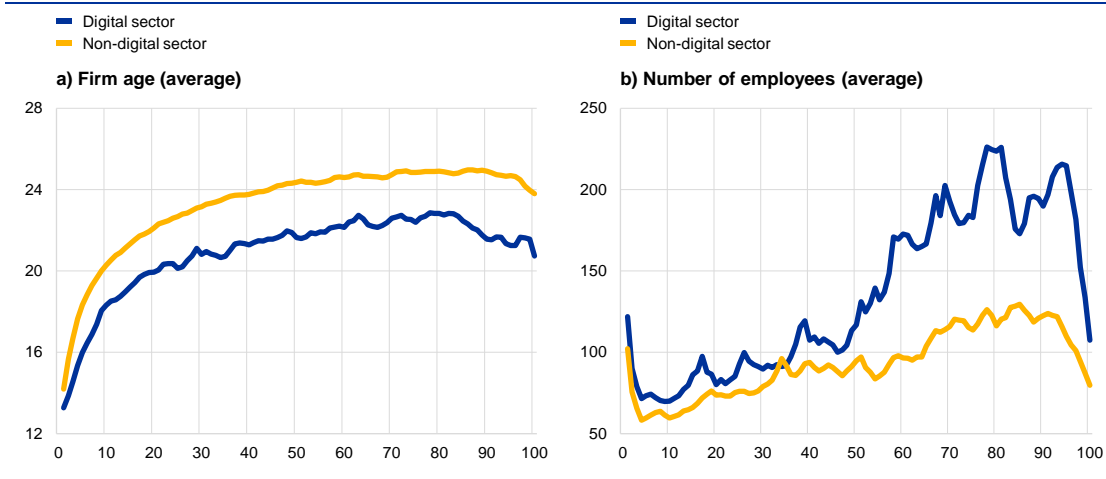
There is some cross-country heterogeneity in labour productivity for both the digital and non-digital sector, with limited within-country heterogeneity across sectors. The left-hand panel of Chart A shows the employment of each country as a share of total euro area employment for the digital and non-digital sectors across the euro area. The sample is broadly able to replicate the cross-country distribution of employees at the aggregate level, with the combined employment share of the four largest euro area countries (Germany, Spain, France and Italy) – referred to as the EA4 – representing 72.4% of the total number of employees for the euro area, very close to the 75.5% employment share measured using aggregate national accounts data for the same period.⁷¹ The right-hand panel of Chart A looks into the cross-country differences in labour productivity separately for the digital and non-digital economy. Average labour productivity is quite heterogeneous among the four largest euro area countries, slightly above the EA19 average in Germany and France, around the EA19 average for Italy and lower than the EA19 average for Spain.⁷² The remaining analysis focuses on EA4 firms, which provide the most representative group in the entire EA19 sample.

⁷¹ The EA4 countries comprise Germany, France, Italy and Spain. The left-hand panel of Chart A reveals larger employment share biases for smaller countries, and in particular the under-representation of the Netherlands and the over-representation of Portugal, Belgium and Slovakia in the EA19.

⁷² Average labour productivity for the euro area, in both sectors, is prone to an upward bias due to the presence of multinational enterprises (MNEs) in the Netherlands, Ireland, and Luxembourg.

Chart B

Firm age, average employment and productivity distribution for digital and non-digital firms (Germany, France, Italy and Spain)



Sources: Orbis Europe (Bureau van Dijk) and ECB staff calculations.
Notes: See Chart A for details of sample construction. Sample consists of firms in Germany, France, Italy and Spain.

Firms are ranked in terms of their labour productivity to assess the existence of churning in the productivity distribution and, consequently, the persistence in productivity leadership.⁷³

Digital firms are younger than non-digital firms (Chart B). The left-hand panel of Chart B shows the average firm age in the digital and non-digital sectors for the year 2016. In particular, it reveals that more (less) productive firms are on average older (younger) than their peers in both the digital and non-digital sectors. Overall, there seems to be an increasing quadratic relationship between the firm's age and its respective productivity ranking for both the digital and non-digital sectors,⁷⁴ while firms in the non-digital sector are on average older than their counterparts in the digital sector for all percentiles in the productivity distribution.

Digital firms are larger than non-digital firms across the productivity distribution, and the size gap increases for high-productivity firms in both sectors (Chart B). The right-hand panel of Chart B shows the average firm size for firms in each percentile of the productivity distribution, for firms in the digital and non-digital sectors and for the year 2016. The main underlying message is that more productive firms are on average larger than their less productive counterparts. While the average firm in the digital sector is larger than the average firm in the rest of the economy, this difference is mostly accounted for by the large relative size of highly productive digital firms, while lower-productivity firms are roughly of the same size in both the digital and non-digital sectors.

While the majority of digital firms are less productive than their non-digital counterparts, frontier firms in the digital sector are considerably more productive than frontier firms in the non-digital sector (Chart C). The majority of digital firms, up to the 90th percentile in the productivity distribution for firms in both sectors, record an average productivity around 6% lower than the average productivity of their non-digital counterparts at each point in the productivity distribution. On

⁷³ The productivity ranking is constructed for each of the three-digit industry, country and year cells. That is, firms in a specific three-digit industry, for a given country and for a given year, are ranked in terms of their labour productivity and assigned to a percentile on the productivity distribution of their respective cell, denoting these firms' relative productivity relative to their peers. These rankings are assigned to all EA4 firms in the dataset between 2006 and 2016, allowing for comparability of churning in the productivity distribution and leadership persistence across different industries, countries and time periods.

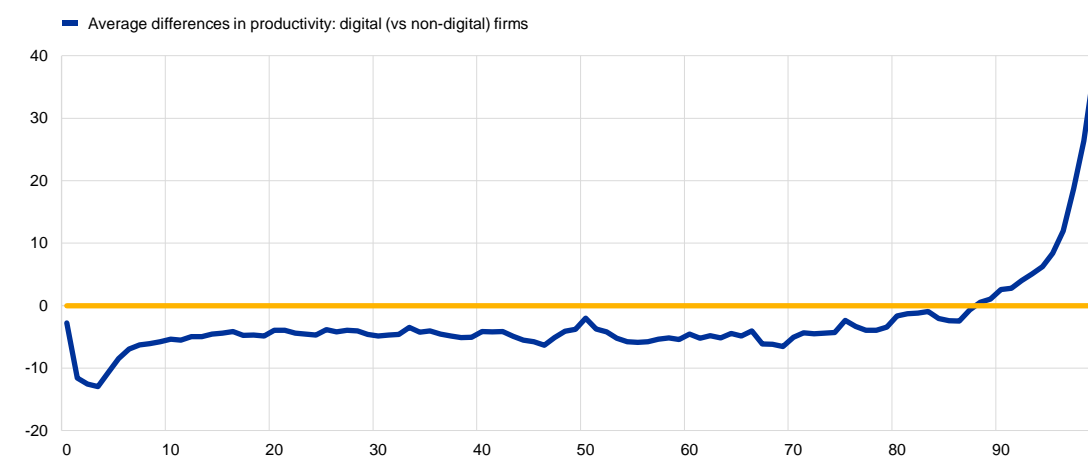
⁷⁴ This finding is similar to those of Haltiwanger et al. (1999), Power (2006) and Haltiwanger et al. (2017).

the other hand, the top-10% firms in the digital sector are 11% more productive than their non-digital counterparts. The difference in the average productivity between digital and non-digital firms increases at the very top of the productivity distribution, with top-5% (and top-1%) firms in the digital sector being 19% (and 37%) more productive than their non-digital counterparts.

Chart C

Average productivity differences between digital and non-digital firms in the productivity distribution (Germany, France, Italy and Spain)

(y-axis: average difference in the productivity level, percentages; x-axis: productivity ranking, in percentiles)



Sources: Orbis Europe (Bureau van Dijk) and ECB staff calculations.

Notes: See Chart A for details of sample construction. Sample consists of firms in Germany, France, Italy and Spain.

Overall, digital firms are younger, larger (especially above the median of the productivity distribution) and less productive than their non-digital counterparts except at the very top. To some extent, this is surprising. Traditional service industries, which comprise the bulk (roughly 60%) of the non-digital sector, have always exhibited lower productivity, as they are less competitive, less susceptible to automation, and operate at a small scale (Sorbe et al., 2018). This may also explain the smaller average size of the non-digital firms. As such, one would expect digital firms to dominate right across the distribution. Instead, they are more productive only at the very top, which suggests that, relative to the non-digital sector, productivity is more dispersed. This could imply that the importance of “getting it right” is greater for the digital sector, which may result from the higher importance of experimentation, innovation, tacit knowledge and intangible assets, and from the skilled labour and management needed to synthesise these inputs into the production process.

There is non-negligible churning at the top of the productivity distribution, with incumbent leaders slowly losing their leadership status and new leaders arising over time. The left-hand panel of Chart D focuses on the future average productivity ranking over time for firms that were among the top 1% highest-productivity firms in any given year between 2006 and 2015. The right-hand panel of Chart D looks instead at the past average productivity of firms that are among the top 1% most productive firms in any given year between 2007 and 2016.⁷⁵ The main underlying

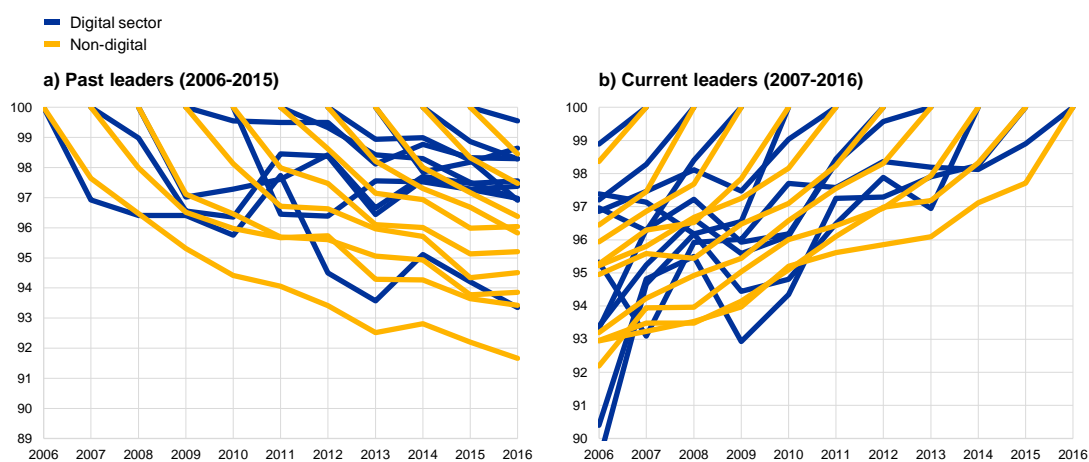
⁷⁵ Firms considered in Chart Da for each year T between 2007 and 2016 are the productivity leaders of 2006 and remain in the sample in year T for each year T. Conversely, the firms considered in Chart Db for each year T between 2006 and 2015 are the firms that are productivity leaders in 2016 and are in the sample in year T for each year T. While this description is applicable to all past productivity leaders between 2006 and 2015 (Chart Da) and all current productivity leaders between 2007 and 2016 (Chart Db), the focus on the past productivity leaders in 2006 and current productivity leaders in 2016 is aimed at anchoring the description of the each time series in Chart D, for the digital and non-digital sectors, to a concrete example.

message is that productivity leadership persistence seems to be high for both sectors, with the average leader remaining among the top 10% of firms for productivity even after a decade comprising a significant recession period. At the same time, there is also non-negligible churning every year at the top of the productivity distribution, with the average leader consistently decreasing its productivity ranking over time. This means that even though leaders remain highly productive, the frontier is not static, but is instead quite porous.

Chart D

Productivity leadership persistence: average productivity ranking over time (Germany, France, Italy and Spain)

(y-axis: productivity ranking)



Sources: Orbis Europe (Bureau van Dijk) and ECB staff calculations.
Note: See Chart A for details of sample construction.

While incumbent leaders are more likely to remain leaders in the digital sector than in the non-digital sector (Chart Da), the rise of new leaders seems to be broadly similar across sectors (Chart Db). The evidence suggests that productivity leadership persistence may be slightly more accentuated in the digital sector than in the non-digital sectors, with incumbent digital sector leaders losing on average less than 4 percentiles in their productivity ranking, and non-digital sector leaders losing less than 8 percentiles in their productivity ranking, between 2006 and 2016. An important fact to consider is that the average leader cohort in the non-digital sector loses around 2 points in its productivity ranking in the first year after being a leader, while the average leader cohort in the digital sector only loses around 1 point in its productivity ranking for the same time span. New leadership creation is however more similar across sectors, with new leaders arising every year among the set of frontier firms. Cohorts of new leaders improve their productivity ranking by around 8 to 10 points between 2006 and 2016 in both the digital and non-digital sectors. There is somewhat less leadership persistence when the creation of new leaders is considered, in contrast to the productivity developments for incumbent leaders, but the average new market leader arises mostly from past frontier firms. This would suggest that few firms manage to crack the frontier. The bulk of today's leaders (but not all) were already highly productive in previous years.

While the churning in the productivity distribution is similar for both the digital and non-digital sectors, the productivity leadership persistence is higher for the digital sector. The production of digital sector services is a relatively new market for firms to invest in and seems more characterised by winner-takes-all dynamics, as well as possibly higher market concentration, than the other sectors of the economy, with the digital sector frontier firms being considerably more

productive than their non-digital sector counterparts. In addition, digital sector leaders are more likely to remain leaders once they are part of the technological frontier in the sector. Finally, it is worth noting that product and labour market reforms aimed at reducing entry barriers and labour market rigidities and at increasing the degree of competition in the economy could be beneficial for creating the necessary framework conditions to spur innovation, technological diffusion and economic growth through the rise of new leaders and through the birth of new firms, similarly to the main messages in Anderton et al. (2019).

5 Labour markets

Prepared by Filippos Petroulakis

Technological anxiety is part and parcel of technological change. Of course, we know that the dawn of the industrial age ushered in an era of remarkable improvement in incomes and standard of living across industrialised countries, to an extent unfathomable hitherto, and that a strong concept in economics is that technology does not threaten labour as a whole. At the same time, digitalisation has had significant effects on the labour market by automating tasks previously associated with skilled jobs, but also creating others, while possibly having significant effects on income distribution and the labour share.

This section first considers the historical effects of technological change on labour markets, highlighting the fact that different types of technological change can have different effects. It then focuses on the more recent period and discusses the phenomenon of job polarisation, whereby automation of routine activities seems to have led to the growth of low and high-skilled jobs, at the expense of middle-skilled jobs. It considers what drives the path of technology and other competing explanations for observed outcomes, and looks at distributional issues, including using a dynamic stochastic general equilibrium (DSGE) framework to compare the likely impacts of an automation shock compared with a standard TFP shock. The final subsection focuses on the future of labour and particularly on the role of AI. The section includes three boxes. Box 5 looks at online platforms and finds that they only accounted for about 3% of employment in 2016 but are growing rapidly, with considerable cross-country heterogeneity across the EU. Box 6 reveals that ICT-related employment shares range from around 22% to 7% across the euro area countries. Furthermore, digitally intensive sectors make important contributions to employment growth, while countries with higher shares of value added accounted for by digital sectors are usually associated with lower unemployment rates. Box 7 examines whether changes in average hours worked have been an exacerbating or mitigating factor regarding job polarisation in Europe.

5.1 Skill-biased and routine-biased technical change

While it seems to be a commonplace that technology tends to complement highly skilled individuals, this has not always been the case.⁷⁶ Indeed, most models that economists use to analyse the relationship between technology and labour feature some bias in the way in which technology affects workers of different skills (Goos, 2018). In fact, the first wave of rapid productivity growth, starting around the early 1800s in the textile industries of Northern England⁷⁷, was *unskill-biased*, as

⁷⁶ As is standard in economics, we assume a one-to-one mapping of wages to skills. As such, highly-skilled individuals are assumed to be those with the requisite education, training, experience etc. to be employed in highly compensated occupations.

⁷⁷ A conventional starting point for rapid productivity growth is 1820 (Baldwin, 2016). Note that the basic technology was introduced several decades prior, highlighting the substantial lags facing GPTs.

the machines replaced skilled artisans with unskilled workers who were migrating to the cities (Acemoglu, 2002). For the entire 19th century, the main production technologies, from the first factories (which improved the division of labour) up to the assembly line, did not complement skilled labour (Goldin and Katz, 1998).

Technology became complementary to high-skilled individuals in the early 20th century. Goldin and Katz (1998) posit that several contemporaneous innovations were “black-box” technologies, where raw material was processed to produce a final good, with little human input, except for skilled machinists and attendant mechanics. This process continued later on: Goldin and Katz show that by the mid-20th century, manufacturing industries which benefited from such innovations employed better educated blue-collar workers and had higher capital intensity.

The relative earnings of skilled workers for much of the 20th century seemed to follow the relative supply of skills. This led Katz and Murphy (1992) to argue for skill-biased technological change (SBTC), the idea that technology raises the relative value of the marginal product of high-skilled relative to low-skilled workers, thus raising their relative demand and wage.⁷⁸ Changes in the skill premium are then driven by changes in relative skill supplies, as dictated by a simple supply-demand framework.

From the early 1990s, labour markets in advanced economies started to polarise. Concurrently with the rise in employment and wage premiums for high skills, there was also a substantial increase in the employment share of low skills, albeit not always necessarily with rising wages. The increase in employment at the tails therefore implied a reduction in the middle, giving rise to job polarisation, a phenomenon identified in virtually all advanced economies (Autor et al., 2006; Goos et al., 2009). This presented a challenge for SBTC, whose abstraction from the content of jobs (tasks) implied a one-to-one mapping of skill and jobs (Acemoglu and Autor, 2011). The principal explanation for polarisation is that the rise of automation has in fact given rise to routine-biased technological change (RBTC); jobs characterised by a high content of routine and repetitive tasks (bank tellers, machine operators, office clerks) can eventually be performed more efficiently by machines or computers.⁷⁹

Automation tends to favour skills found at both high and low wages. On the one hand, jobs that require complex analytical skills with a certain level of abstraction (and hence limited automation potential) or a high level of interpersonal communication are naturally complemented by such technologies, both because it allows individuals to specialise away from routine tasks and be more productive in their core tasks and because these technologies raise the productivity of core tasks (as predicted by SBTC). On the other hand, automation has not yet affected non-routine manual jobs, typically requiring little to no specialised education but with a large content of tasks that require intuition, discretion, flexibility, adaptability or interpersonal interaction, which are also hard to automate; this category encompasses a very broad array of jobs mostly found in the service sector, such as cleaning, maintenance, personal care,

⁷⁸ This is based on Tinbergen's (1974) famous hypothesis of a race between education and technology, where the race is between an increase in supply of skills and technical change. This simple supply-demand framework can explain why returns to skill can rise even when the supply of skill rises.

⁷⁹ It should be noted that “routine” does not imply trivial or mundane; instead the task at hand involves a high enough element of repetition that it can be readily codified for an unintelligent machine to repeat it.

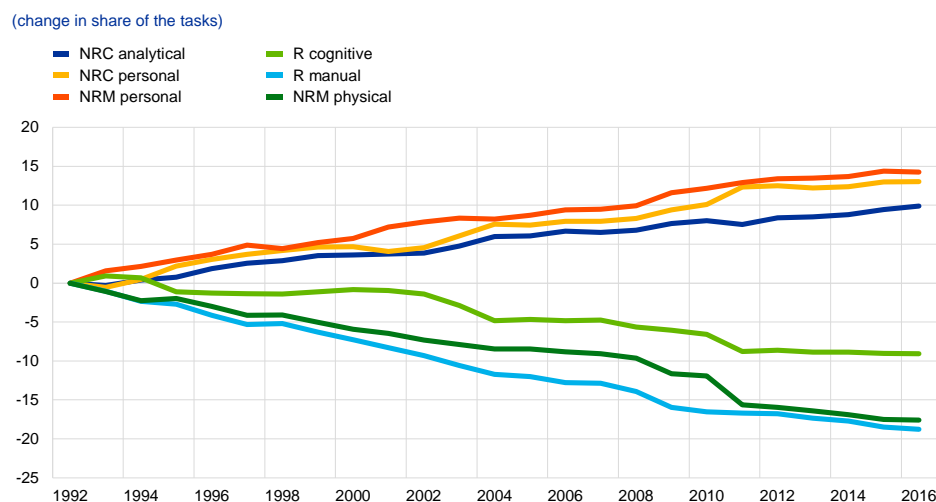
security and food services. Since demand for these goods tends to be income elastic and price inelastic (so low productivity growth in these sectors will not harm demand), aggregate growth has raised demand for such workers (Goos et al., forthcoming).

According to Autor (2015), the main reason why automation has not managed to replace manual service occupations is Polanyi’s paradox. Attributed to Karl Polanyi (1966), it says that “we know more than we can tell”. Humans are better at describing skills they developed to solve specific problems (like mathematics or logic) than skills they evolved (intuition, judgment, sensorimotor skills). We have managed to write into code how to do complex arithmetic and run simulations impossible for the smartest humans to accomplish, yet teaching a computer something as commonplace to a child as identifying a chair can be a daunting task (Autor, 2015).

The theoretical foundation underlying RBTC is the task framework of Autor et al. (2003), which views jobs as collections of different tasks, some of which are more automatable than others. In this framework, technological change does not raise labour productivity directly; rather, it automates some tasks and creates new ones, destroying some existing jobs and creating new ones in the process. RBTC posits that goods are produced by a collection of imperfectly substitutable tasks performed by differently skilled individuals and capital (Acemoglu and Autor, 2011). Sorting of workers to tasks leads to a task-skill assignment according to complexity; since digital capital has a comparative advantage in middling tasks (routine-intensive and codifiable), middle-skill workers shift away from these tasks (Goos, 2018).

Chart 8

Evolution of the task content of the mean job in selected European Countries (EU15)



Source: Dias da Silva et al. (2019).

Notes: Each line shows the task content of the mean job. NRC=non-routine cognitive; NRM=non-routine manual, R=routine. Sample normalised to 0 in 1992. EU15 comprises Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden and the United Kingdom.

A graphical exposition of the evolution of job polarisation by task content is shown in Chart 8 (reproduced from Dias da Silva et al., 2019). The chart uses the finer task representation of Acemoglu and Autor (2011). Non-routine cognitive tasks are split into analytical and personal (mathematicians and managers), routine tasks are split into cognitive and manual (clerks and machine operators), and non-routine

manual tasks are split into physical and personal (cleaners and waiters). The chart considers the evolution of the task content of the mean job, and shows the sharp reduction in its routine content and a corresponding increase in its non-routine cognitive content. Results are split for non-routine manual tasks, as the non-routine manual physical content of the mean job has diminished substantially. The picture emerging from this chart is consistent with the view of polarisation as accompanied by changing allocation of skills across occupations (Acemoglu and Autor, 2011).

The precise nature of the effects on labour depends on the equilibrium interaction of technology, skill supply and consumer demand. As workers abandon middling tasks for low and high-skilled tasks, then the effects on employment and wages in these groups will depend on the relative comparative advantages of the middling workers in these tasks. It is presumably easier for middle-skill workers to perform low-skill than high-skill tasks.⁸⁰ These are also determined by the degree of task substitutability between digital capital and unskilled labour relative to consumption complementarities (Goos et al., forthcoming).⁸¹

A leading example of a modern automation technology with high potential to displace labour is that of industrial robots. Robots are currently primarily used to perform repetitive tasks in manufacturing and hence present a prominent example of routine task replacement. Graetz and Michaels (2018) show that robots raise TFP and labour productivity in Europe, with no significant effects on employment, except for a small shift in favour of high-skilled workers. Acemoglu and Restrepo (2017) show that local labour markets in the United States which were relatively more exposed to robots experienced broader negative effects on employment and wages, which may point to another difference between the effects of modern technology on labour in the United States and Europe. Dauth et al. (2018) use worker-level data for Germany. They find no overall effect on local employment and no displacement effect on incumbent workers in robot adopting industries; instead, incumbent workers switch occupations, while new entrants shift to other sectors. However, they do find evidence of lower labour share and polarised earnings growth from robot exposure (with negative effects for low and middle skills). Acemoglu and Restrepo (2018b) provide cross-country evidence that adoption of industrial robots is increasing with population ageing, especially in industries more reliant on younger workers and more amenable to automation; the latter experience higher productivity gains and lower labour shares. At the same time, automation in response to ageing may raise industry productivity despite the negative direct effect of ageing. Another key aspect of digitalisation and

⁸⁰ Indeed, Autor (2015) notes that college attendance for men in the United States has remained flat since the 1970s, despite the rise in the skills premium.

⁸¹ For instance, Akerman et al. (2015) show that broadband internet improves the outcomes and productivity of skilled workers, but unskilled workers fare worse than before. They find suggestive evidence that broadband internet complements skilled workers in executing non-routine abstract tasks and substitute unskilled workers in performing routine tasks. Lordan and Neumark (2018) provide evidence that workers more substitutable by machines fare worse after an increase in the minimum wage – especially in the case of older workers – while job opportunities for higher-skilled workers improve. At the same time, consumer preferences matter: demand for goods and services produced by abstract labour appear to be price and income elastic, while those (primarily services) produced by low-skilled workers are price inelastic but income elastic (Autor, 2015). Overall, these forces lead to higher employment at the poles, but not necessarily wages, although at times wages at the bottom may also rise relatively (Autor and Dorn, 2013). Goos et al. (2014) argue that similar effects have attenuated the employment fall in middling industries.

labour markets is the rise of the gig economy and online platforms, which is examined in Box 5 below.

Box 5

Employment, customers' welfare and policy challenges of the platform economy

Prepared by Lara Vivian

Internet-enabled platforms have led to the emergence of collaborative or sharing economies where the supply and demand side of the market can trade under the supervision of the platform operator, bearing minimal intermediate costs of matching. According to recent estimates, the size of these platforms has rapidly increased over time, but their contribution to the economy remains relatively small. They account for up to 1% of GDP and 3% of employment across the EU countries but with considerable cross-country heterogeneity and unclear implications for the economy (European Commission, 2018). The first challenge lies in their definition, as online platforms tend to be heterogeneous in a number of aspects, including their nature – commercial or non-commercial, the services or goods provided, the technology adopted and the compensation of the workers. Nevertheless, the different elements of the collaborative economy share common features: (i) the business transaction takes place between three parties – the service provider, the online platform and the customer; (ii) service providers offer access to their goods, service or resources on a temporary basis; (iii) the goods, services or resources offered by the service provider are otherwise unused; and (iv) the goods, services and resources are offered with or without compensation (i.e. for profit or non-profit/sharing) (Derojeda et al., 2013).

The sharing economy is spread over several areas, and a study from the European Commission (2018) concentrates on four of them: (i) finance, (ii) accommodation, (iii) online skills and (iv) transport. The collaborative economy in the financial sector allows the coordination of investors and borrowers without the additional cost of an intermediary as well as the organisation of the collective financing of projects (crowdfunding). Similarly, the on-demand provision of online skills is fairly heterogeneous. A recent survey conducted by Berg et al. (2018) on a large set of countries shows that common tasks performed by collaborative economy workers include transcription, data collection and, in some instances, training in AI. However, skills exchanged can also include teaching and the provision of expertise in different fields such as translation services. Finally, the sharing economy in the accommodation and transport sectors allows the supply side of the market to compensate for the underutilisation of a good or service – usually a room in an apartment (or house) for accommodation or a car for transport – while decreasing the rental price.

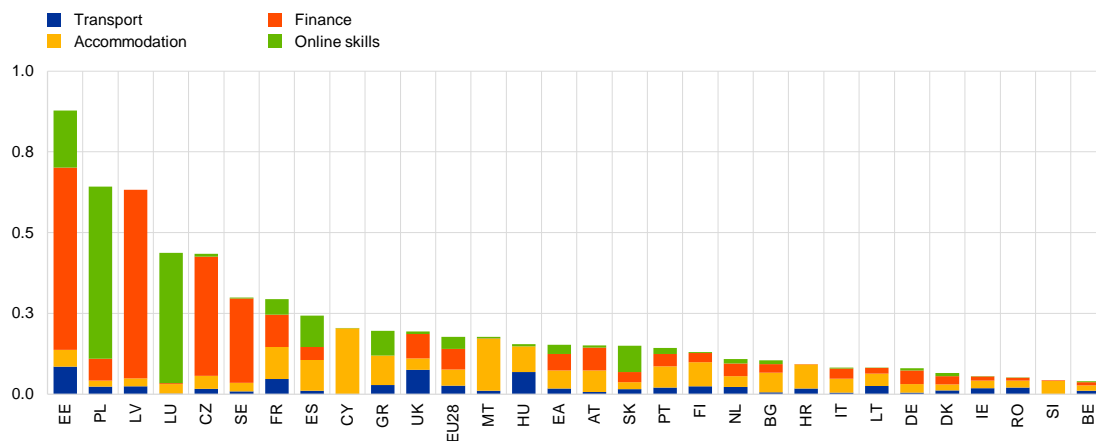
Although the collaborative economy is not a new phenomenon, its size is increasing over time. A recent study estimates that the collaborative economy accounted for around 0.2% of EU28 GDP in 2016.⁸² However, its size differs substantially across the individual countries. Chart A uses data from EC (2018) and shows that the collaborative economy ranges from 0.04% of GDP in Belgium to up to 0.9% of GDP in Estonia. The figure for the euro area is 0.15%, marginally lower than that for the EU28, confirming the gap in the relative importance of the sharing economy between eastern and southern continental European countries. In absolute terms, France has the largest sharing economy in the EU, amounting to around €6.6 billion in 2016, followed by the United Kingdom, Poland and Spain.

⁸² European Commission (2018)

Chart A

Size of the collaborative economy

(percentage of GDP (2016))



Source: European Commission (2018).

Only a small fraction of the platforms operating in the EU originate from different markets (mainly from the United States), yet big international platforms accounted for up to 40% or €10 billion of the total EU28 collaborative economy revenue in 2016, with Airbnb alone accounting for almost half of this international platform revenue (€4.5 billion). The sharing economy is spread similarly across sectors in the EU28 and the euro area, and in countries like France, Germany, Belgium and Portugal (although finance and accommodation tend to be somewhat larger). However, in Estonia, Latvia, Sweden and the Czech Republic, for instance, most of the revenues from the collaborative economy are generated by financial sector platforms, while in Poland and Luxembourg, the sharing economy is almost entirely concentrated in the online skills sector. By contrast, platforms are found almost exclusively in the accommodation sector in Cyprus and Slovenia.

Workers and employers are typically framed as independent contractors, with the platform acting as an intermediary. In this respect, platforms function as labour market intermediation: they decrease matching costs by, for instance, facilitating searches, distributing information and centralising coordination.⁸³ In order to evaluate the overall impact of the “sharing economy” on the economy we need to consider the actors: platforms and competing businesses, workers and consumers.

Perser (2010) provides evidence that online platforms and markets tend to be a significant source of innovation and competition, mainly by lowering the barriers to starting and operating small businesses. Nevertheless, while increasing competition may lead the least productive firms to leave the market, there is also a risk of large disparities in market shares between big players and the others. The evidence points towards increased efficiency and employment, although direct competitors are shown to suffer from the increased competition (Cramer

⁸³ See Autor (2008) for a discussion on the role of labour market intermediaries in the economy. In addition, platform intermediaries significantly benefited from recent technological advances, such as the mass adoption of smartphones and the falling cost and rising capabilities of the internet (Horton and Zeckhauser, 2016).

and Krueger, 2016; Zervas et al., 2017).⁸⁴ However, policy questions arise on how to promote fair competition regarding the platform economy in order to avoid the possible emergence of dominant platforms, possibly by monitoring and revising taxation, mergers and acquisitions but also by implementing regulation on platform costs.

Similarly to the revenues of the sharing economy, platform employment is increasing rapidly and amounted to 0.15% of overall EU28 employment in 2016, with the United Kingdom recording the highest share at 3% (European Commission, 2018).⁸⁵ With the exception of ad hoc surveys, defining platform work and identifying platform workers is itself non-trivial.⁸⁶ Among other shortcomings, data seldom allow a distinction to be made between (i) full-time and occasional platform workers in surveys; and (ii) types of platforms, e.g. Uber, Foodora, etc. Nevertheless, most studies share similar findings: the majority of the workers are male, young and educated and work few hours. Most of the workers are satisfied with job flexibility, although a significant percentage report that they would like to work longer.⁸⁷ As regards labour earnings, it is unclear whether platform workers earn less per hour on average than their counterparts in traditional employment, making comparisons with standard workers difficult. Similarly, in the large majority of cases, social protection and contributions are often not included in platform compensations, with possible implications regarding the quality of the job and overall well-being of workers.⁸⁸ Berg et al. (2018) also raise the question of the possible implications for the economy of skill mismatch, skill upgrading and underemployment of the workforce.

Finally, while customers may benefit from the lower costs of the sharing economy, effectively assessing quality and searching on online markets may require higher expertise and effort. Ranking systems are often useful, but they also risk falling into the trap of the “superstar model”, meaning that highly rated options are likely to stay so because they tend to show first in the sorting of the website. One-sided ratings can also be a source of bias in the rating system itself: while they influence the decision of the potential customer, they seldom disclose information on the reliability of the rating source (Martens, 2016). Similarly to licensed taxi drivers, platform providers may not be subject to as many rules and regulations as standard providers, which creates an uneven playing field in terms of competition between the two sets of providers.⁸⁹

⁸⁴ Cramer and Krueger (2016) find evidence that Uber drivers have a higher capacity utilisation rate than traditional taxi drivers, as they drive a higher percentage of miles accompanied by a passenger, which is possibly explained by a more efficient and faster driver-passenger matching technology and inefficient regulations regarding traditional taxi drivers. Similarly, Texan “economy” hotels and hotels not catering to business travellers have been shown to be negatively affected by the emergence of Airbnb (Zervas et al., 2017). The study conducted by Zervas et al. (2017) finds that Airbnb significantly changed travellers’ consumption patterns and that direct competitors’ revenues decreased by about 5% (which has possible implications for structural change and employment).

⁸⁵ For additional estimates on the platform economy in developed economies, see, for instance, Boeri et al. (2018) and Pesole et al. (2018). See Berg et al. (2018) for a coverage of 75 countries around the world.

⁸⁶ Pesole et al. (2018), for instance, focus on platform workers who provide labour services through digital platforms.

⁸⁷ Berg et al. (2018) show that 88% of their sample would like to work longer, while this share is reported to be around 30% in Boeri et al. (2018).

⁸⁸ For a detailed discussion on employment and working conditions of platform workers in selected EU countries, see De Groen et al. (2018).

⁸⁹ Baker (2015) points out that traditional providers must ensure that services and products meet minimum standards of both quality and safety (e.g. fire alarms in hotels), which may not be required by platform providers, implying a welfare loss for the consumer. Similarly, at the moment, there is no way to ensure that platforms do not discriminate between users (Baker, 2015). Discrimination may arise against both the worker and the customer and can be either direct or indirect. Direct discrimination can manifest through refusing a ride or refusing to rent an apartment for instance, whereas indirect selection can arise whenever a certain service or good is not made accessible to diverse groups of users, such as disabled customers.

5.2 Technical and structural change, demand, and the labour share

A crucial issue is why technology has evolved the way it has. The literature on directed change posits that, since R&D is a profit maximising activity, it will favour the factor of production that will earn the highest profits for the technology creators. Profits earned will be higher (i) the more abundant each factor is and (ii) the more productively the factor uses the relevant technology, in relative terms. And while an increase in the relative supply of a factor tends to reduce its earnings, the endogeneity of technology implies that technology production will adjust in favour of the more abundant factor. It is also possible that, with high enough substitutability across factors, relative factor returns rise in relative abundance. Acemoglu (2002a) uses this framework to account for a number of relevant patterns. For instance, it can explain the rise in unemployment and the labour share in Europe in the 1970s as being the result of a cost-push shock (Blanchard, 1997). It can likewise explain the further increase in unemployment but subsequent reduction in the labour share in the 1980s once labour-saving technologies were created.

Recent work has also considered the role of other factors in explaining polarisation above and beyond technology on its own. Bárány and Siegel (2018) document that polarisation in the United States started in the 1950s, long before ICT played a meaningful role. They propose a structural change explanation linked to the shift from manufacturing to services: as long as the goods produced by all sectors are complementary, then productivity growth in manufacturing will also raise demand for services. Labour demand will rise in services and workers will sort to these sectors according to their comparative advantage, raising relative wages in these sectors. Comin et al. (2019) argue for a demand-driven explanation. They document that income elastic sectors are more intensive in high and low-skill occupations than inelastic sectors. As such, as aggregate income grows and income elastic sectors expand, so will demand for labour employed in those sectors, giving rise to polarisation. Bessen (2019) highlights another role for demand. He shows that employment increased in manufacturing sectors (textiles, metals, automobiles) for decades despite rapid productivity growth. Low initial consumption of these goods meant that demand was highly price elastic, so lower prices raised demand and hence employment. Once demand became satiated it also became price inelastic, and own-industry effects of productivity on employment turned negative. This is a cautionary tale for employment in currently rapidly expanding industries.

In addition to its long-term effects, technology may also affect labour along the cycle. Indeed, there is evidence that employment recoveries in the United States have been substantially slower after recessions since 1990 than previously (Gali et al., 2012). Jaimovic and Siu (2020) argue that routine jobs may be permanently destroyed during recoveries, and the delayed transition of displaced workers into other jobs can explain the slow recovery. If that is the case, technology may have further adverse effects on workers, given the well-documented persistence of recessions on future

earnings (see, for instance, Wee, 2016). Graetz and Michaels (2017), however, do not find such evidence in other advanced economies.

Overall, while technology has had substantial distributional effects on labour, it has not had a negative impact on aggregate employment in advanced economies. Productivity increases in some sectors, particularly manufacturing (and agriculture in earlier times), reduce own-sector employment if demand cannot increase by enough. However, aggregate employment rises in productivity, as higher consumption mitigates this effect by raising employment in other sectors and relocating workers to tertiary services (Autor and Salomons, 2017), as well as through local spillovers (Gregory et al., 2016). The relationship between digitalisation and employment is examined in further detail in Box 6 below, with a general finding that digitalisation generally tends to be positively associated with employment.

Box 6

Digitalisation and EU labour markets: a comparative approach

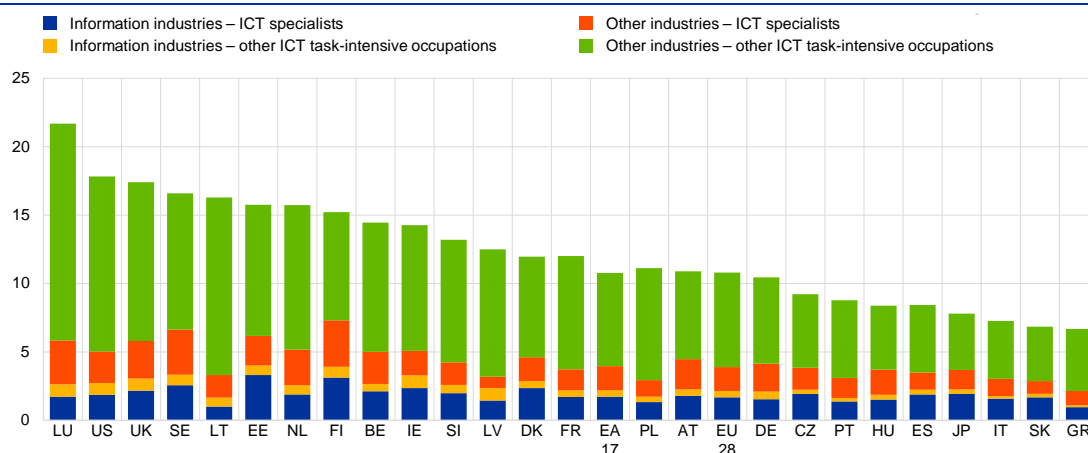
Prepared by Valerie Jarvis

Another metric for gauging the degree of digitalisation across EU countries is the extent to which employment is related to digital activities. This box shows a considerable degree of heterogeneity in digital employment across EU countries. It also traces the evolution of skill development in digital employment across three of the leading European countries in which the digital sector appears relatively large in terms of employment. In addition, it offers insights into the degree to which higher shares of digital employment are typically associated with higher total employment across countries, effectively debunking fears among many that higher degrees of digitalisation may be associated more with job destruction than with job creation.

Measuring the reach of the digital economy is not straightforward, but three EU countries – Estonia, Sweden and the United Kingdom – top the employment charts across a wide range of metrics. While there is no standard definition of digital employment, Chart A takes a relatively wide definition of ICT-dependent employment, which includes all those working in ICT-intensive occupations, whether or not they are employed directly in ICT sectors, as well as those employed in broader ICT task-intensive occupations. It demonstrates both the high degree of cross-country heterogeneity in the shares of total employment accounted for by ICT-intensive occupations and the difficulty of comparing the shares of ICT-dependent employment across countries, given the strong demand for ICT specialists across industries far outside the ICT-producing sectors. The high degree of cross-country heterogeneity is immediately apparent, with the range of total ICT-dependent employment ranging from around 22% in Luxembourg (surpassing even that of the United States) to around 7% in Greece, Slovakia and Italy. While barely reaching 11% in the euro area and the EU, this broader definition of ICT-dependent employment encompasses around half as many workers again in Sweden, the United Kingdom and Estonia (at roughly 17% of total employment) – countries where the shares are relatively similar to those seen in the United States. While some variation is, of course, a natural reflection of differences in patterns of specialisation across countries, the ratio of the differences between the highest and lowest in employment – some 3:1 – is striking. Moreover, while the rankings may differ markedly depending on the metric used, three European countries – Sweden, Estonia and the United Kingdom – typically outperform many of their neighbours, regardless of the metric used.

Chart A

ICT-dependent employment as a share of total employment



Source: OECD (2019).
 Note: The EA17 is the EA19 minus Cyprus and Malta.

Table A ranks countries according to a range of ICT employment measures, though these too reflect marked differences in the sectoral specialisations of the respective countries.

Referring back to the digitalisation measures described earlier in this paper, Chart 2 shows that the contributions from the IT services and telecommunication sectors of Estonia, Sweden and the United Kingdom appear larger than in most European countries on comparisons of total value added, while the proportions of enterprises using high-level cloud computing in these three countries are also well above the EU and euro area averages (see Chart A in Box 1). However, these three countries also possess a number of idiosyncratic factors which underlie their higher employment shares – including a heavy representation for Sweden and the United Kingdom in audio-visual and broadcasting services (given the United Kingdom’s important position in global broadcasting and advertising activities, together with the strong performance of Sweden in the development of consumer-oriented media applications such as Skype and Spotify). In addition, the United Kingdom’s strong performance in fintech, business consultancy services and e-commerce platforms (such as Asos) add to its demand for ICT specialists from well outside the narrow ICT sector, while Estonia’s pre-eminence in developing digital public “e-government” services is well known.⁹⁰ To some extent, these more advanced outcomes may offer insights into future skill needs for other EU countries hoping to increase their own digital sectors.

Table A
 Top six ICT-dependent “employment leaders” under various metrics

Rank	Total ICT-dependent employment	Share of ICT specialists in ICT and other industries	Share of employment from information industries and ICT specialist in other industries
1	LU	FI	FI
2	US	SE	SE
3	UK	EE	EE
4	SE	LU	LU
5	LT	UK	UK
6	EE	NL	NL

⁹⁰ See: [UK teams up with Estonia to develop digital public services.](#)

Source: OECD (2019).

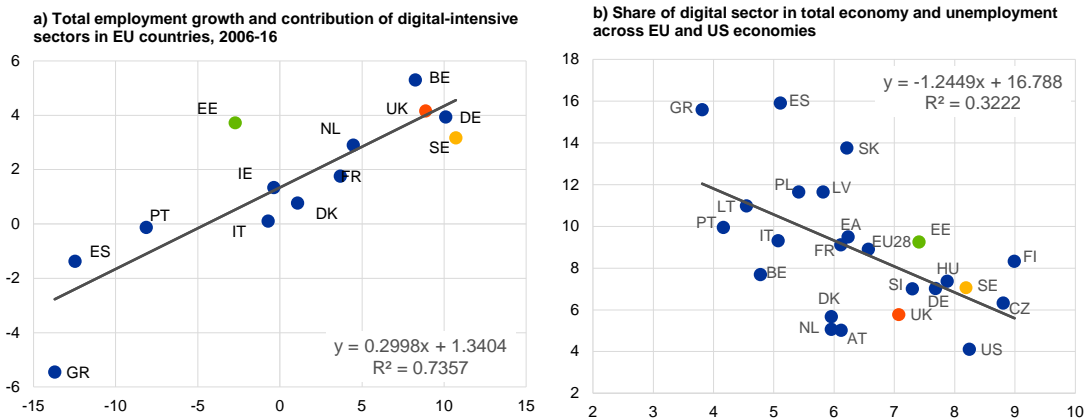
Sectors with higher digital intensity made substantial contributions to employment growth across advanced economies during the decade from 2006 to 2016 (Chart B). Looking at the relationship between total employment growth and the contribution of the digital-intensive sectors for the EU12 countries (with the addition of Sweden and Estonia), Chart Ba suggests a strong contribution from the latter over the decade 2006-16 in the EU. Again, the more strongly digitally dependent countries, i.e. Sweden, the United Kingdom and Estonia, appear to have been among the strongest performers in terms of the employment contribution of the digital-intensive sectors, outperforming many other EU economies.⁹¹

Moreover, there is some evidence to suggest that a higher share of value-added from the digital economy tends to correspond with lower unemployment rates. Chart Bb shows the digital sectors as a share of total value added against the average unemployment rate for the period 2000-18 for the EU economies, alongside the United States by way of broader comparison. These suggest a broadly negative correlation, whereby those economies with larger digital sectors tend to have exhibited lower levels of unemployment over the past decades.⁹² Once again, Sweden and the United Kingdom appear to be among the strongest performers, with unemployment rates close to the bottom of the distribution and higher shares of value added from digital sectors. Although the chart does not imply causation, it seems to offer some evidence contrary to the notion that a higher degree of digitalisation would lead to higher unemployment at the aggregate economy level. Of course, digitalisation can lead to job displacement and cases of job disruption, whereby some workers lose jobs and find it difficult to get back into employment for prolonged periods, but digitalisation also generates new jobs and tasks (as shown in Section 5).

Chart B

Digitalisation, employment growth and unemployment

(left-panel: x-axis: percentage growth in total employment; y-axis: employment contribution of digital-intensive-sectors; right-panel: x-axis: digital sector as percentage of the whole economy value added; y-axis: average annual unemployment rate 2000-18)



Sources: (a) OECD (2019), (b) Eurostat and BLS (US).

Notes: (a) Country coverage reflects data availability; (b) annualised monthly series.

⁹¹ Note that Luxembourg (not shown due to limitations of the scale) showed the strongest performance, recording employment growth of 31.8% between 2006 and 2016, with almost 60% of this employment growth coming from the more digital-intensive sectors.

⁹² While the correlation is relatively weak, the elasticity implied by a simple regression of the average unemployment rate on the DESI indicator and a constant (i.e. replicating Chart Bb) is extremely strong at -0.8.

This box suggests that policymakers should step up efforts to embrace the growth potential from digitalisation. Structural change is part of the dynamic economic process, with digitalisation often at the forefront of policy-makers' considerations, given fears that growing reliance on digital technologies may lead to greater displacement of workers by machines. The evidence from this box suggests that higher shares of value added contributed by the digital sectors are not associated with higher unemployment at the level of the aggregate economy and that the reverse may be true. In addition, digital-intensive sectors have typically made a strong contribution to employment growth. Cross-country heterogeneity remains considerable. Learning from the trends of those countries at the forefront of the digital transformation may hold many lessons for others still in the catch-up phase. Further investigation as to the policy prerequisites with which to achieve this would include more detailed understanding of the types of high-quality skills best suited for the development of the digital sectors and seems urgently warranted.

How can labour markets still generate enough jobs after two centuries of incredible labour-saving technological advances? Acemoglu and Restrepo (2018c), (2019a) argue that technology has a “reinstatement effect”, which creates new tasks as it destroys others. Assuming directed technical change, labour abundance as a result of task replacement leads to the endogenous creation of other labour-intensive tasks. The mechanisation of agriculture may have led to a collapse of labour in that sector, but contemporaneous technologies created a very large range of tasks in manufacturing and services; automation of routine tasks in manufacturing and some services as a result of ICT advances created new tasks even within the same service industries. They argue for a reinterpretation of the relationship between technology and labour as a “race between automation and new labour-intensive tasks”, which reinstates labour and increases productivity.

The benign effect of technology on aggregate employment had led economists to assume that the labour share, the fraction of income paid to workers, is largely constant. This view has recently been challenged, as several advanced economies have experienced a fall in the labour share (Karabarbounis and Neiman, 2013). This issue goes above and beyond the wage discrepancies between different workers, as it relates to the income share of labour as a whole, relative to capital. Autor and Salomons (2018) indeed find that although productivity growth reduces the labour share in growing industries, just as it does employment, the positive effect on other industries (via input-output linkages and aggregate demand effects) is not strong enough to counterbalance the negative effect in growth industries, leading to an overall reduction in the labour share. They also show that such an effect did not exist in the 1970s, but productivity growth became labour-displacing thereafter, with the effect becoming strong in the 2000s. This probably reflects, to some extent, technology-driven increases in market shares for capital-intensive “superstar” firms (Autor et al., 2017b – see also Box 9, “Digitalisation, competition and market power”) – and not only within-firm changes in task allocation between capital and labour. Against the background of digitalisation and the changing nature of tasks and growing labour market polarisation, Box 7 below examines whether developments in hours worked across EU countries may have added to labour market polarisation on the employment side.

Box 7

Hours polarisation?

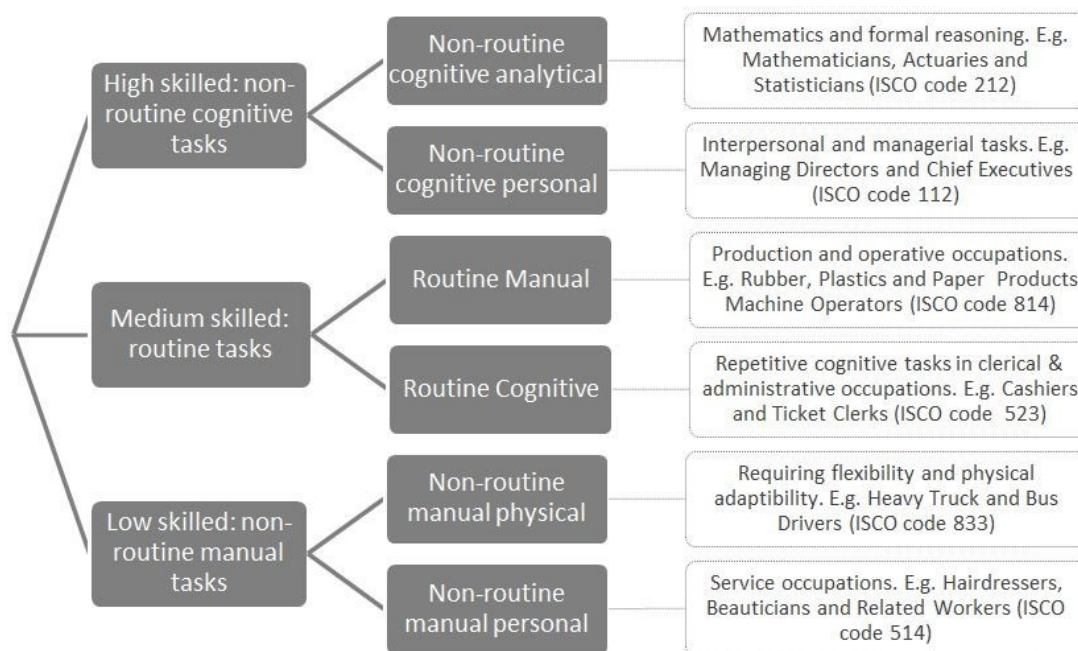
Prepared by Antonio Dias Da Silva and Filippos Petroulakis

Technological progress influences the type of jobs and thus affects the distribution of job options for different individuals. In recent years, the effect of technology on the distribution of job offers has been characterised by polarisation of employment across the occupation skill distribution. Low and high-skill occupations have seen their share of employment increase, while middle-skill occupations have seen a substantial decline in their employment share. A common hypothesis of the polarisation literature is that the rapidly declining price of computers facilitated the replacement of routine tasks by technology (Autor et al., 2003). At the same time, technology complemented analytical tasks and the rise of personal services supported employment creation at the bottom. This is the hypothesis of routine biased technical change.

The employment polarisation patterns are well documented for European countries, the United States and other large economies. Previous analyses on job polarisation have been carried out with regard to employment (both headcount and total hours). This box analyses instead the relationship between employment polarisation and hours per worker. It summarises recent ECB work (Dias da Silva et al., 2019), based on micro-data from Eurostat⁹³, which aims to answer the following question: have average hours per worker been a mitigating or an exacerbating factor of job polarisation? The analysis relies on occupation skill indices developed by Acemoglu and Autor (2011). These indices are based on the Occupational Information Network (O*NET). The occupation skill indices structure and an example for each skill task are shown in Figure A.

Figure A

Occupation skill indices



Sources: Dias Da Silva et al. (2019), based on Acemoglu and Autor (2011).

⁹³ Specifically, the analysis uses microdata on employment from the EU Labour Force Survey (LFS) and wage data from the EU Statistics on Income and Living Conditions.

The empirical model is designed to explain the data in a flexible way. It fits hours per worker, Y , for worker i in industry k in country c at time t to an intercept, the index value of the worker's occupation (as in Figure A), I_i , a linear time trend and an interaction between the index in question and the trend.⁹⁴ For convenience, the continuous index measure is converted into a dummy variable equalling one if the occupation has a high index score, above the 66th percentile for occupations in each year, and zero if it has a low score. The coefficient α_1 accounts for level differences between different occupations that occur regardless of any trends, while α_2 controls for the aggregate trend. The main coefficient of interest is α_3 , which captures the extent to which hours for occupations in a given index trend in a way that differs from the aggregate. Given the overall aggregate negative trend in hours worked, a positive value for α_3 is evidence that occupations with high values of the index in question have exhibited a milder decline, while the opposite applies for a negative value.

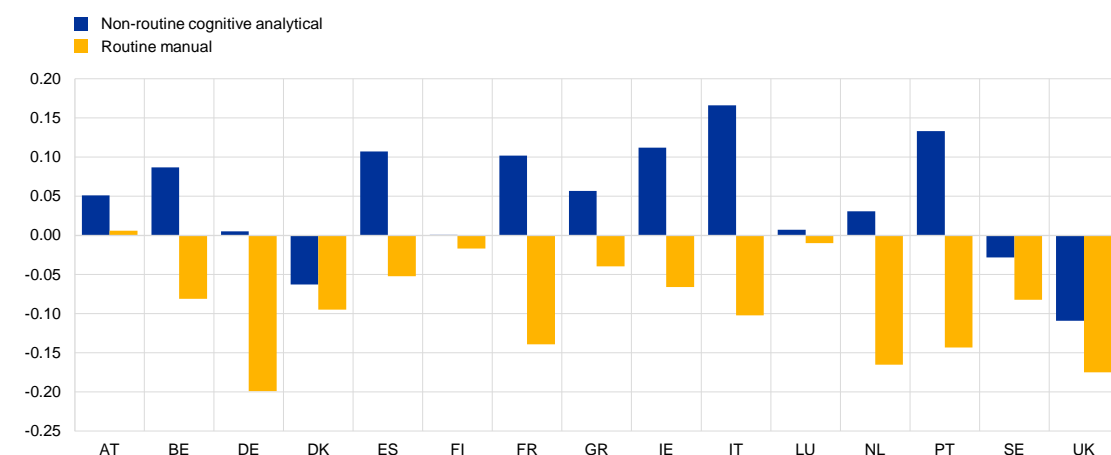
$$Y_{ikct} = \alpha_0 + \alpha_1 I_i + \alpha_2 t + \alpha_3 I_i * t + \beta X_{ict} + c_c + c_k + \epsilon_{ikct}$$

The results show that the level and, more importantly, the trend in hours per worker vary considerably across each occupation task index. We find large declines in hours worked in routine manual jobs – precisely the occupations most negatively affected by employment polarisation from routine-biased technical change. We also find a lower decline in hours per worker for non-routine cognitive analytical jobs, which are growing through polarisation. At the same time, hours per worker declined significantly more than average for non-routine manual physical occupations, a decline not compensated for by an increase in hours per worker in non-routine manual personal jobs. As a result, hours per worker exacerbate employment polarisation patterns at the top and the middle of the occupation skill indices, while they mitigate them at the bottom. The first two results for individual countries are shown in Chart A, which plots the respective estimated α_3 coefficients for each country.

Chart A

Change in hours per worker in non-routine cognitive analytical and routine manual jobs, relative to the average worker

(y-axis: coefficient estimate of interaction term)



Sources: EU LFS and ECB staff calculations.

Note: All results are statistically significant with the exceptions of those for Germany, Finland and Luxembourg for non-routine analytical tasks.

The hours per worker patterns across occupation task indices remain robust to estimation across age, gender and education groups, although the intensity varies and some patterns

⁹⁴ Additional covariates include country and industry fixed effects, demographics (gender, age, education) and firm size.

emerge. For example, the decline in hours per worker in non-routine manual physical jobs and routine manual jobs is stronger for women. Likewise, the decline in hours per worker in non-routine manual jobs is driven by the highly educated. The decline in hours per worker occurs mostly within sector. The increase in part-time work seems important, but it is likely to be itself a consequence of the decline in hours per worker, as classification into full-time and part-time is self-reported.

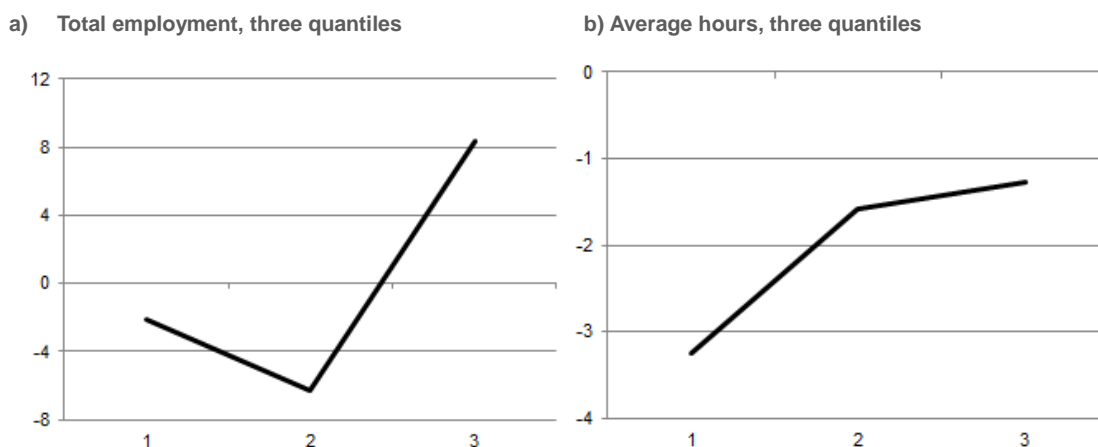
Using a wage ranking of occupations instead of the occupation task indices, the decline in hours per worker is monotonically related to wages. The results obtained for employment changes using a wage ranking is a U-shaped curve, in line with the empirical literature (Chart B). However, when the wage rank is divided into six quantiles (instead of three), the bottom quantile also experiences employment losses, albeit smaller than those in the middle. Hours per worker instead appear to be monotonically negatively related to wages: using three quantiles of the wage ranking of occupations, a sharper decline occurs in the bottom quantile, with a milder decline in the middle and almost no decline at the top; using six quantiles for the wage ranking of occupations, an inverse U-shaped pattern is observed for most of the distribution, but with a lower decrease in hours per worker in the top quantile. Thus, while employment gains are characterised by a U-shaped pattern, the decline in hours per worker is characterised by an inverse L-shaped pattern.

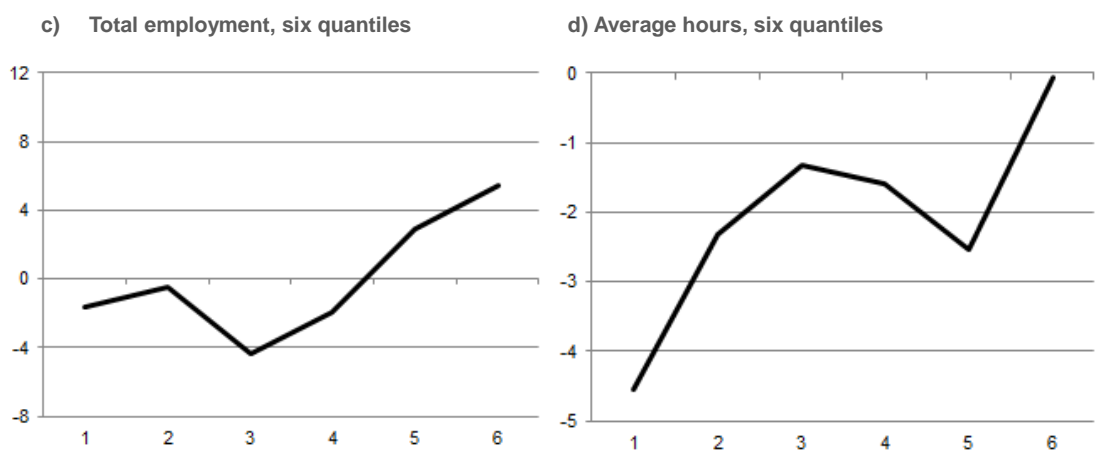
Overall, the above results suggest that patterns in hours per worker exacerbate the impact of polarisation on wage inequality. Highly skilled workers increased their fraction of employment and worked relatively more hours, medium skill workers saw a decline in the share of employment and a decline in hours per worker and low-skilled workers saw a substantial decrease in hours per worker. The analysis based on the wage ranking of occupations makes this point even clearer: hours per worker declined significantly more in low-paying occupations.

Chart B

Changes in employment and hours per worker by wage quantile

(y-axis: % change from 1992 to 2010)





Sources: EU LFS and ECB staff calculations.

5.3 A general equilibrium perspective of how automation affects the labour market

Prepared by Agostino Consolo

Technological changes in terms of the degree of automation in production and the widespread diffusion of digitalisation for businesses and consumers may have important effects on the functioning of the economy and on the transmission of exogenous shocks.

From a monetary policy perspective, technological innovations may affect the goods and services price formation mechanism as well as the functioning of the labour market and real economy. In general, the macroeconomic literature has widely considered the role of technological changes, especially on growth, productivity and labour market outcomes. Canova et al. (2010) provide a comprehensive overview of the effects of neutral and investment-specific technology shocks in the economy. The former type of shock refers to exogenous changes in TFP. The investment-specific technology shock, instead, is defined as directly affecting the price of investment, especially on ICT capital. That is, higher efficiency in producing capital goods leads to stronger investment patterns in machinery and equipment, which is complemented by higher economic growth and stronger labour demand. Automation shocks differ from this set of standard technology shocks. Both neutral and investment-specific shocks would provide similar outcomes across low and high-skilled workers.⁹⁵ Automation shocks, instead, lead to skill-biased technical changes.⁹⁶ The productivity differential between low and high-skilled workers provides support for a stronger labour demand of high-skill jobs. In addition, as suggested by theoretical models and empirical work, the degree of complementarity increases between high-skilled jobs and capital, while the opposite tends to happen with low-skilled jobs (Violante, 2016). As a consequence of

⁹⁵ See Violante (2016).

⁹⁶ Automation shock may also lead to routine-biased technological changes as analysed in Autor and Dorn (2009) and Goos et al. (2014), but this box focuses only on the effects across skills and not on the amount of job displacement or polarisation depending on the degree of routinisable occupations.

the effects on labour demand and wages, an automation shock can generate different employment responses within the skill distribution.⁹⁷

This section provides an overview of some results from a DSGE model based on Abritti and Consolo (2019) regarding the effect of automation shocks on key macroeconomic variables. In this model, automation is defined as the share of worker tasks in the production function which can be performed by capital (machines or robots) and high-skilled labour. According to Acemoglu and Restrepo (2018a) there are two main effects from the automation process. A productivity channel stemming from the complementarity between high-skilled workers and capital, which generates positive effects on aggregate employment, and a displacement channel related to the substitutability between low-skilled workers and the increase in capital accumulation (especially ICT capital). From a monetary policy perspective, it is thus important to discover how these two channels work in a general equilibrium model and how other endogenous macroeconomic variables are affected by the automation process and the change in skill composition in the economy.

5.3.1 Model overview

The model features an endogenous TFP process à la Anzoátegui et al. (2018), in which the R&D sector endogenously shifts out the TFP frontier. The endogenous TFP process is driven by the accumulation of intangible capital, which is supported by the R&D process of creating new patents. The rest of the production function is specified in terms of tasks following the work by Zeira (1998), Acemoglu and Restrepo (2018c) and Aghion et al. (2017). Each task can be performed by a combination of labour and capital. Some of these tasks can be automated and, for instance, produced by high-skilled workers and capital, while the non-automated tasks also require a contribution from low-skilled labour. The production function thus allows for different degrees of complementarity and substitutability among capital and the two types of labour input. Following Acemoglu and Restrepo (2018c), the baseline DSGE model is calibrated so that low-skilled workers show a certain degree of substitutability with capital, while high-skilled workers display complementarity in production. The model features search and matching frictions with two segmented markets for the low and high-skilled workers.⁹⁸ The model assumes that the supply of low and high-skilled workers is exogenously fixed and depends on the distribution of skills in the labour supply. The skill-specific labour demand, instead, crucially depends on the degree of complementarity of these two types of skills in the aggregate production function and on the efficiency of the job matching process.⁹⁹ As productivity levels are

⁹⁷ This section and the work in Abritti and Consolo (2019) focus on two types of skills. A strand of the literature on labour market skills has highlighted the importance of polarisation. The polarisation of the labour market cannot be addressed in this framework, as the model would need to account for three types of skills. Here, it is implicitly assumed that medium-skilled workers are lumped together with low-skilled workers.

⁹⁸ The model does not account for an endogenous human capital process. Hence, the share of each type of worker does not change during the business cycle. The steady-state equilibrium can, instead, be affected by different shares of low and high-skilled workers.

⁹⁹ The simulation exercise presented in this section assumes similar matching functions for low and high-skilled workers. Hence, labour demand is not affected by differences in the matching process across skill type but by the task-based production function.

endogenously different across types, the matching process provides an additional mechanism affecting the job creation margin, real wages and equilibrium outcomes.

5.3.2 The macroeconomic impact of an automation shock

The DSGE model described above can be analysed along several dimensions.

In this subsection, the focus is on the role of technology shocks and, more specifically, on neutral TFP and automation shocks. The DSGE model features two types of technology shocks. The endogenous TFP process usually creates a complementarity between technology and other production inputs.¹⁰⁰ Also in the context of factor-specific technological change such as investment-specific shocks or labour augmented technical change, technology generates a positive co-movement among labour and the other factors of production, under reasonable parameter restrictions. In a task-based production function, technological changes driven by the automation of certain production tasks may instead lead to different employment changes depending on the displacement or productivity effects.¹⁰¹

Chart 9 compares the effects of a standard TFP shock with an automation shock. Both have positive effects on GDP and productivity growth. The efficiency gains lead to lower marginal costs and a reduction in the inflation rate in both cases (panel b). At the same time, nominal wage dynamics are dominated by higher real wages and productivity, which more than compensate for the fall in inflation. A key difference between TFP and automation shocks lies in the response of employment. An automation shock which increases the amount of automated capital in the production process leads to an employment displacement effect that is a function of the degree of substitutability between capital and labour. The automation shock generates a skill-biased technical change which negatively affects the employment rate of low-skilled workers in the initial phase (panels c and f). As the job separation margin is exogenous and constant, the mechanism works via the job finding rates. The productivity of the match of low-skilled workers is lower, and this negatively affects the probability of being hired back following an adverse shock. Over the medium and long term, the productivity gains of automation, coupled with the endogenous R&D process, lead to positive employment effects for both types of workers. Nevertheless, the high to low-skilled worker share remains higher because of the increase in automation and the complementarity of automated capital with high-skilled workers. Similarly, an automation shock delivers a positive response of the wage premium between high and low-skilled worker wages in line with the skill-biased technical change literature.¹⁰² Overall, the automation shock – compared with a standard technology shock – delivers a change in the skill composition of workers and their respective wages. In the current calibration, these effects tend to have a stronger impact on inflation, wages and employment as shown in Chart 9, but they are

¹⁰⁰ This may also depend on the degree of price rigidity embedded in the model. With a high degree of price rigidity, a technology shock can lead to displacement effects. Nevertheless, the reduction in employment happens proportionally across the skill distribution.

¹⁰¹ The model is calibrated around a symmetric steady state in which both low and high-skilled workers have the same deep parameters (outside options in terms of replacement rate, wage bargaining power, etc.).

¹⁰² For simplicity, the current version of the model features the same matching function for both low and high-skilled unemployment.

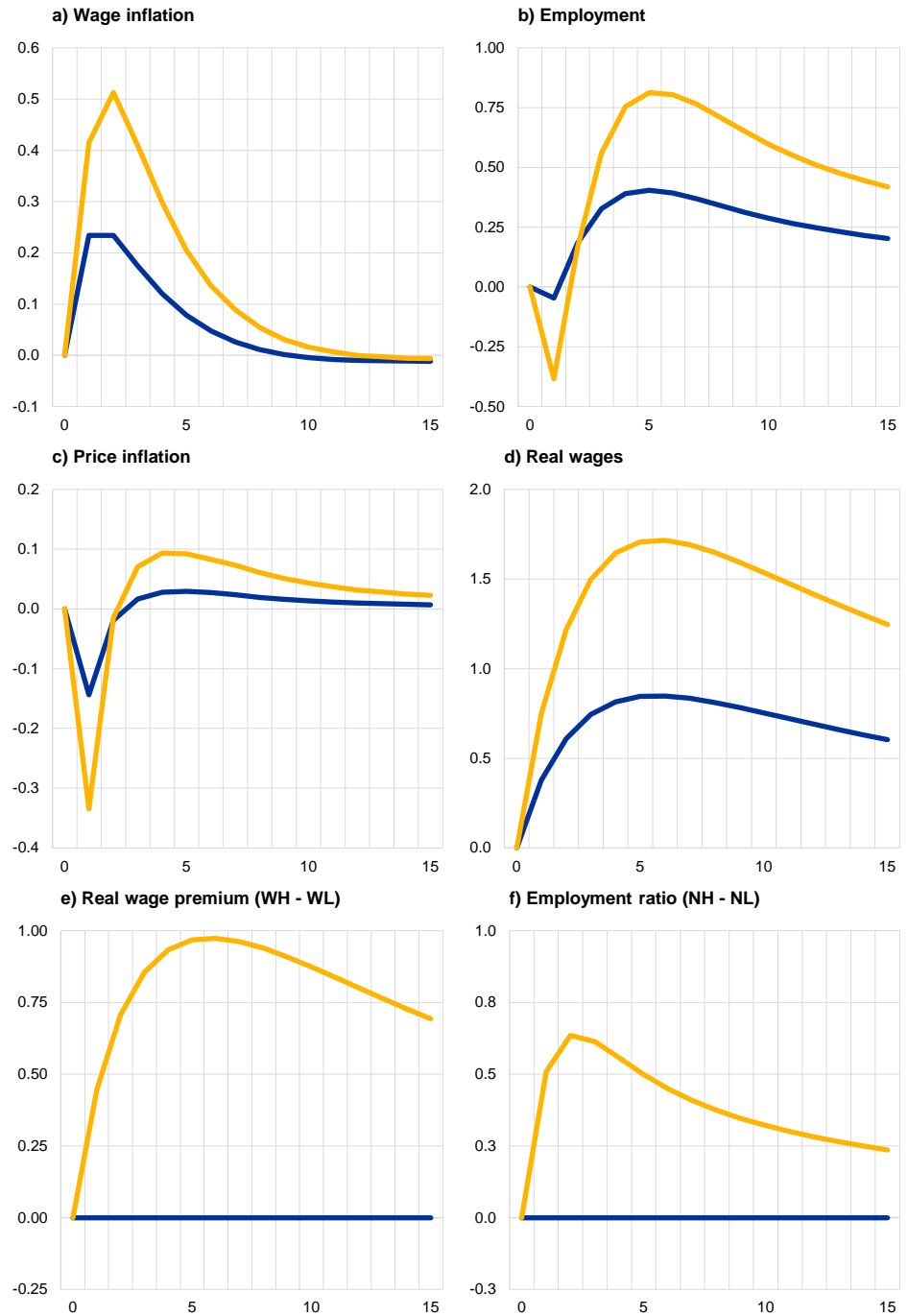
expected to die out as long as the low-skilled workers start benefiting from the higher overall growth rate of the economy in the medium and longer term.

Chart 9

The impact of TFP (neutral) and automation (skill-biased) shocks

(percentage change from steady state)

■ TFP shock
■ Automation shock



5.4 What is the future of labour?

Prepared by **Filippos Petroulakis**

The emergence of AI as the key engine of technological change during the fourth industrial revolution has given new credence to technological anxiety.

While, as detailed above, technology has historically had a net positive effect on job creation (initially driven by within-industry gains and more recently by gains in slow-growing sectors), it has been argued that AI could possibly upend this historical relationship by allowing the automation of an ever-increasing range of tasks.

It is therefore important to understand exactly what AI algorithms do. As argued by Agrawal et al. (2018a), (2018b), (2019), AI algorithms (especially ML) excel in *prediction*: they read massive amounts of data and determine the best course of action in each state of the world. In addition to replacing humans in prediction tasks, they may lead to the automation of decision tasks if the automation of prediction increases returns to capital (e.g. self-driving cars). In contrast, they may enhance returns to labour in tasks when automating decisions raises labour productivity (e.g. real-time imaging in surgeries) or create new tasks that were previously impossible owing to high uncertainty.

Because they lack judgment, machines require a controlled environment to properly function, and algorithms can exhibit overfitting. Despite advances in automation in some environments, such as warehouses, other environments are more difficult to automate. One example is transportation: self-driving cars require detailed maps, but also the ability to react to obstacles or unexpected changes, in which case they revert to a human (Autor, 2015). In contrast, there already are self-driving long-haul trucks serving the mining industry in the Australian outback, where the low population density provides for a more controlled environment than city roads.¹⁰³ Moreover, prediction algorithms run the risk of overfitting, i.e. they fit the data too well and give poor out-of-sample predictions. While there are well-known methods to correct for noisy or unimportant data, a more subtle problem is that, because they are based on past data, prediction algorithms may be affected by human biases. In hiring algorithms, the machine may simply reinforce previous biases of humans found in the training data.¹⁰⁴ Algorithms may also be less flexible than humans or provide poor prediction for rare events.

While this discussion is speculative, some recent theoretical work may shed light on how events can possibly unfold, and provide some guidance on how policy can be designed to protect labour. Acemoglu and Restrepo (2018c), (2019a) stress that a crucial distinction between human labour and factors of production that previous technological innovations rendered obsolete (e.g. horses), is that the former have a comparative advantage in mastering new and complex tasks. As such, even if some current tasks are continuously automated, as long as sufficient labour-complementary new tasks are being created, employment and the labour

¹⁰³ This shift was also induced by automated rig technologies, which made mining in remote areas more profitable (Economist, 2017).

¹⁰⁴ Some recent experiments are more positive. Cowgill (2018) argues that if, in addition to biases, human decisions are sufficiently noisy then machine decisions may correct some of the bias.

share can remain stable, in line with historical patterns.¹⁰⁵ In their set-up, the key requirement for that to happen is that the long-run rental rate of capital is not too low relative to wages. In that case, even periods of rapid automation will be followed by periods of low automation, as market forces respond to the lower cost of labour-intensive production.¹⁰⁶ At the same time, forces that increase the effective stock of capital are akin to capital-augmenting growth and hence are positive for labour.

Automation will tend to reduce labour demand when its productivity effects are low, when it does not result in higher capital accumulation, and when it does not lead to the creation of enough new tasks. Acemoglu and Restrepo point out that, by definition, automation always reduces the labour share; its effect is mitigated by (i) higher productivity, which raises demand for labour in other tasks; and (ii) the creation of new tasks.¹⁰⁷ This is depicted in Chart 10. Tasks from $N-1$ to l are completed by machines, the rest by humans. Automation (bottom panel) reduces the range of tasks done by labour (relative to the top panel) and *replaces* labour. An increase in N increases the range of tasks done by humans and *reinstates* labour (middle panel). Higher productivity raises demand for goods produced by all tasks and in turn increases demand for labour. As such, if AI is geared towards replacing tasks where machines are marginally more efficient than humans or if few new tasks are created, effects on labour will be worse. Ironically, as the authors point out, it is not the “brilliant” technologies that are a risk to humans, but the “so-so” technologies, whose productivity effects are too small to make up for their displacement effects; the automated call centre is a typical example.

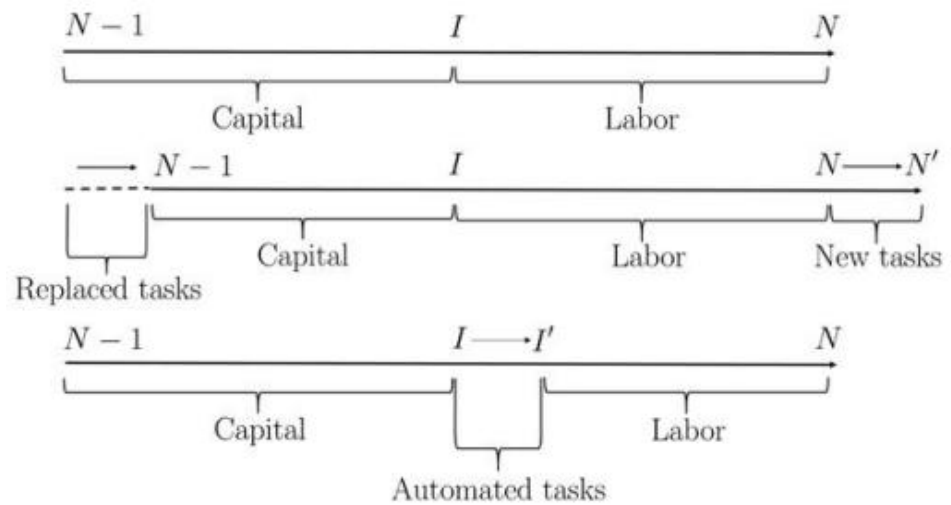
¹⁰⁵ Employment growth from occupations with new job titles (relative to old occupations) has accounted by almost half of the employment growth in the United States from 1980 to 2007 (Acemoglu and Restrepo, 2018c).

¹⁰⁶ Karahan et al. (2015) show that the decline in the start-up rate in the United States over the past few decades is at least partially explained by the slower growth of the labour force, due in turn to lower population growth. This may imply indirect evidence that entrepreneurial activity is indeed responsive to labour abundance.

¹⁰⁷ In that sense, the effect of automation is distinct from capital-augmenting technological progress (CATP), where the effect on labour depends on factor substitutability. Acemoglu and Restrepo (2018c) show that, under reasonable parameters values, CATP raises the labour share, a result at odds with the evidence.

Chart 10

Automation and task allocation between capital and labour



Source: Acemoglu and Restrepo (2019a).

Notes: The top panel shows a range of tasks carried out by capital and labour, the middle panel shows the effect of introducing new tasks to the top panel, and the bottom panel shows the effect of automation.

On the one hand, the relative abundance of labour may lead to the endogenous creation of labour-intensive tasks. Similarly, public policy interventions that raise the attractiveness of labour (removing the premium on non-human capital embedded in the tax code, improving skills matching) are possible and can interact with market incentives to create more socially desirable automation.

Furthermore, as automation moves into new territories, the low-hanging fruit is likely to be gone. AI will have to advance to tasks where labour possesses a distinct advantage or to perfect existing automation technologies where labour has already been displaced, resulting in technological improvements that are more enhancing and deepening than displacing. AI could delve into industries that have been little affected by automation, and whose low productivity growth is a drag on aggregate growth, such as education and healthcare. As these are sectors where human interaction is a key input, it is more likely that the reinstatement effect will dominate.¹⁰⁸ At the other end, directed technical change implies that there will be little incentive to automate tasks with the largest relative abundance of labour and no tangible productivity gains from automation, providing a lower bound on human displacement. Examples are jobs requiring little training, such as cleaning or waitressing, but also more skilled jobs such as hairdressing and in-person care. In such cases, the productivity effect is largely a result of consumer preferences, as consumers place a premium on human interaction.¹⁰⁹

On the other hand, these same factors underline the need to strengthen the positive forces in order to avoid a grim future for labour. The chronic weakness of productivity growth could partly be explained by the lag in the adoption and

¹⁰⁸ Teaching is one activity which Baumol (1967) singled out as unlikely to benefit from productivity growth.

¹⁰⁹ Consumer preferences may also help explain why relatively standard innovations (such as automated check-out counters or self-service coffee shops) coexist with traditional technologies.

implementation of new technologies. The same factors that constrain productivity growth may then also imply a human cost, in that the displacement effect of technology may precede its positive effects, partly because of a direct effect on productivity growth but also because of a delayed reinstatement effect (Acemoglu and Restrepo, 2019b). As such, policies that improve labour reallocation and increase the skill supply are particularly important. Moreover, the particular nature of innovation, which involves large externalities, a high element of spillover and substantial fixed costs, raises the risk that the “wrong kind of AI” may be provided by market forces alone, particularly owing to the rising dominance in innovation of large commercial actors with a singular focus on automation (Acemoglu and Restrepo, 2019a). Autor and Salomons (2019) express scepticism over whether a reinstatement effect is currently under way, showing that new jobs tend to be strongly polarised. In addition to a growing share of frontier jobs complemented by technology, they document an increase in in-person services to wealthy urban workers (e.g. yoga instructors) as well as jobs in occupations with nearly automated tasks that have a residual human component (e.g. warehouse workers).

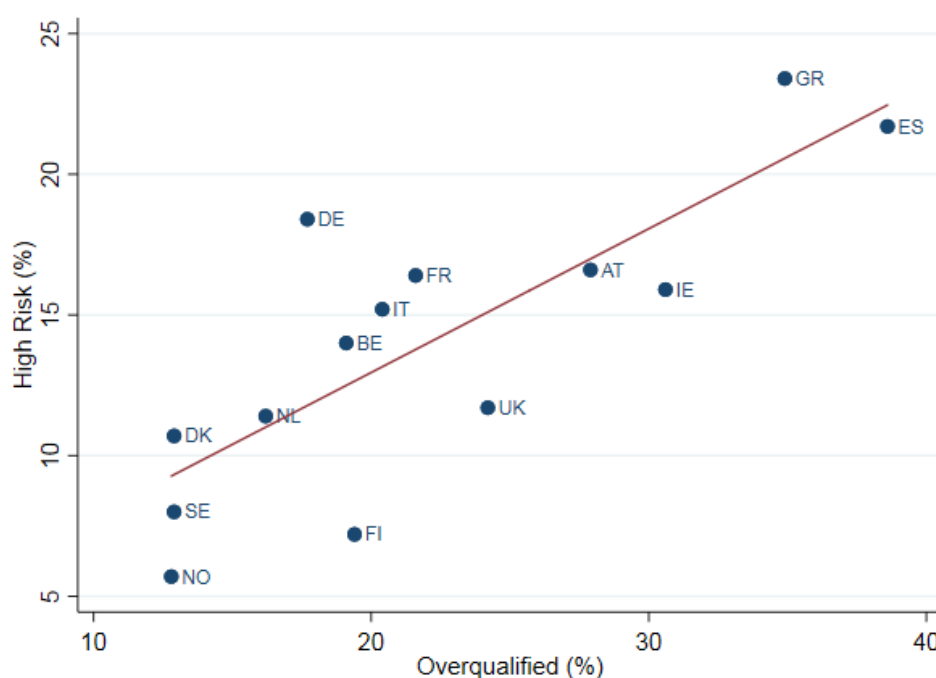
Recent work has attempted to quantify the threat of automation to existing jobs more precisely. Frey and Osborne (2017) asked ML experts to give subjective views on whether specific occupations can be easily automated in the near future.¹¹⁰ They mapped the answers to this question for 70 occupations to the full range of occupations available in O*NET, using the task content of each occupation, and calculated automation probabilities for each occupation, estimating that 47% of jobs in the United States have high (over 70%) automation risk. Subsequent studies were much more sanguine. Arntz et al. (2016) point out large differences in task content within occupations; only considering the average task content may yield misleading estimates. They show that the approach of Frey and Osborne assigns to most occupations extreme (low or high) automation probabilities. Instead, taking into account within-occupation variability, they obtained a balanced estimate, with few occupations at either extreme and with intermediate values for most occupations. They estimate that only 9% of jobs in the United States face a high automation risk.¹¹¹

¹¹⁰ The specific question was: “Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?”

¹¹¹ They use individual-level data from the Programme for the International Assessment of Adult Competencies (PIAAC), an internationally comparable survey of the OECD. Using the same data with a different approach, Nedelkoska and Quintini (2018) end up with similar estimates.

Chart 11

High automation risk and labour force overqualification, selected countries



Sources: OECD, Nedelkoska and Quintini (2018), ECB staff calculations. The "overqualified" are the highly educated who work at low or medium-skilled jobs.

Notes: Data for EU15 countries and Norway. Portugal and Luxembourg have missing data.

Precise numbers aside, there is undoubtedly a concern that task automation may threaten a substantial number of jobs. Even though, historically, technology has had a positive net effect of labour, there is a risk that the pace of automation may be too fast for some workers, who will not be able to reskill and be redeployed to new tasks. While education and retraining policies have an important role to play, they may be more challenging for more mature workers. At the same time, not only does education need to be sufficiently flexible to respond to market needs (International Monetary Fund, 2017c), it will not suffice if other public policies are not friendly to the creation of jobs that can withstand the threat of automation. Chart 11 shows the relationship between high automation risk and the overqualification rate for EU15 countries and Norway; while the relationship does not have causal attributes, it is clear that education on its own is not enough to abate automation risks. Policies that improve labour market matching or allow the formation of high-skilled jobs are just as important.

5.5 Beyond automation

The focus of this discussion has fallen squarely on automation, but other forces directly or indirectly related to technological change are certainly at play. First, further advances in ICT may further reduce the price of capital goods, which has already fallen substantially across advanced economies over the last few decades (Karabarounis and Neiman, 2013). Even abstracting from a task framework (which would involve directly replacing human tasks with machines), as long as some type of

labour is a substitute for capital, falling capital prices will bring a further increase in income inequality towards factors complementing capital (International Monetary Fund, 2017c).

Second, higher market power may also compress wages, at least for some types of worker. There is a substantial academic debate (see Box 9) on the extent and consequences of higher concentration in advanced economies, and there is some evidence that it is related to the rise of superstar technology (producing or using) firms (Autor et al., 2017b). Power in product markets may imply power in labour markets as firms become large enough employers that they become monopsonies or oligopsonies; there is substantial evidence that this is indeed happening in local labour markets in the United States (Benmelech et al., 2018; Azar et al., 2017). This phenomenon may be further entrenched by the enforcement of oligopsonistic practices, such as non-competing clauses or no-poaching agreements (Krueger and Ashenfelter, 2018). It seems likely that digitalisation, by allowing scale without mass and leading to lower labour share, is at least a contributor to this phenomenon. It is unclear whether this is occurring in the EU (although some indicators appear muted relative to the United States – see Cavalleri et al. (2019) – but institutional factors (e.g. higher unionisation, relative absence of oligopsonistic practices) would tend to reduce employer power.¹¹²

Finally, the boom in international trade with lower-wage countries has been another key force of labour market change in advanced economies. While digitalisation and the growth of emerging economies, especially China, are distinct events, digitalisation has been an enabling factor in the growth of trade, allowing for a substantial reduction in trade costs, in conjunction with other improvements in shipping technology. Advances in communication have substantially reduced search, transportation, tracking, and verification costs (Goldfarb and Tucker, 2019), enhancing international trade. ICT improvements have also enabled the offshoring of tasks, allowing firms to relocate parts of the production process to different parts of the world (Baldwin, 2016). Relatedly, and as a result of lower trade and communication costs, global value chains have made possible the production of composite goods (e.g. cars) in different locations, raising the contestability of national labour markets. Labour market effects of trade and technology appear to be distinct. Trade has been a smaller contributor to polarisation (Goos et al., 2014) but has had much more negative local employment effects, particularly for low-educated workers, even in non-manufacturing industries, while technology has not had negative aggregate net effects (Autor et al., 2015).¹¹³

¹¹² Another notable practice which has been shown to limit employee power is domestic outsourcing of non-core functions, such as cleaning and security services, common in the United States and Europe (Krueger, 2018; Goldschmidt and Schmieder, 2018). The role of technology for this phenomenon is unclear.

¹¹³ The local aspect is highlighted in Dauth et al. (2014), who find that while import-competing regions suffered, export-oriented regions boomed.

6 Supply side

Prepared by Malin Andersson, Vincent Labhard and Julian Morgan

The process of digitalisation involves intangible investment, such as software, algorithms, big data and related analytics as well as tangible investment in technological equipment and digital infrastructure. According to some estimates, between one-third (for the less digital economies) and two-thirds (for the more digital economies) of digital investments are in intangibles.¹¹⁴ There are also synergies between the two types of investment, as ICT technologies, for instance, require intangibles (e.g. technological, organisational or personal). This section reviews how digitalisation affects the supply side of the economy. It focuses in particular on the characteristics and limits of intangible capital in the national accounts, the role of intangibles in rising market power, features of big data, servicification and tangible investment. It also considers the implications of digitalisation for potential growth. A box examines the role of intangible investment and its measurement in terms of improving estimates of investment from the perspective of Tobin's Q. The measurement of several of the variables related to potential output may be affected by digitalisation.

6.1 Intangible capital

Intangible investment is very diverse compared with tangible capital investment and is increasingly important, as economies are shifting from physical-capital-intensive to knowledge-capital-intensive production. Intangible investment lacks a physical embodiment, unlike investment in equipment or buildings. Intangibles cover items such as software, databases, innovation (e.g. via R&D) and the value of firm-specific attributes (e.g. brands, firm-specific human capital, networks etc.).¹¹⁵ While overall investment has been making a decreasing contribution to potential output in many EU countries and other developed economies in recent decades, the recorded contribution from capital may not fully capture the faster growing investment in intangibles.¹¹⁶

An important element of intangibles is intellectual property. In the current definition in the European system of accounts, research and development has been added to the previous framework,¹¹⁷ alongside the already existing intangible items of mineral exploration, computer software and databases, entertainment, literary and artistic originals, and other intangible fixed assets (see Table A.1 in the Appendix for the corresponding definitions).¹¹⁸ As a result of introducing R&D, levels of fixed

¹¹⁴ See, for example, McKinsey (2013).

¹¹⁵ See Andersson and Saiz (2018).

¹¹⁶ See Andersson, Szörfi, Tóth and Zorell (2018).

¹¹⁷ The current and previous editions of the European system of accounts are known as ESA 2010 and ESA 1995 respectively.

¹¹⁸ For the United States, the Bureau of Economic Analysis released the corresponding data for the first time in 2013.

investment, GDP, gross national income, and gross national domestic income have increased.^{119,120}

Both the value of intangibles and their depreciation rates are difficult to measure. While in theory the value of intangibles is equal to the discounted future benefits of the investment, in practice the value tends to be computed on a cost basis. These costs represent for instance the amounts paid for exploration or the sum of price-adjusted production costs for computer software and entertainment and for literary or artistic originals. This approach may not fully capture the value, as documented by cases in which intangible assets are a major part of the value of a business or operation which is sold on, such as business models based on big data (see Section 6.2).¹²¹ As for depreciation rates, they are generally higher for intangible assets than those of construction and equipment.¹²² Theoretically, they can be derived from the lifespan of an intangible asset, where explicit, such as patents or brand rights, although such intangibles in practice may be of value beyond the official life span of the patent.

The importance of intangibles has risen over the past two decades¹²³ (Chart 12 a and b). This is true notably for intangible investment as a share of total investment, and especially for those countries in which the share was lowest at the beginning of this period. The rising trend in the share of intangible investment in GDP has been relatively smooth, with the exception of countries in which intangible investment has been affected by the activities of large multinational companies. The differences in investment ratios between countries may suggest that investment in intangibles is driven less by cyclical and more by structural factors, such as regulatory frameworks and the stocks of human capital and knowledge.¹²⁴ Business cycle fluctuations seem to have a relatively limited impact on intangible investment.

¹¹⁹ See, for example, Eurostat (2014).

¹²⁰ Expenditures for purchases and own-account research and development now enter the national accounts via fixed investment and their depreciation as consumption of fixed capital if they are associated with the business and government sector, i.e. the household sector is excluded.

¹²¹ In the national accounts, the present value of expected future receipts arising from using the asset is estimated only if it is not possible to establish the value by the cost method. The accounting is complicated further by the distinction made between market-produced (e.g. a corporation) and non-market-produced (e.g. government) intangibles. For details on this distinction and the implications for the European system of accounts, see Eurostat (2014).

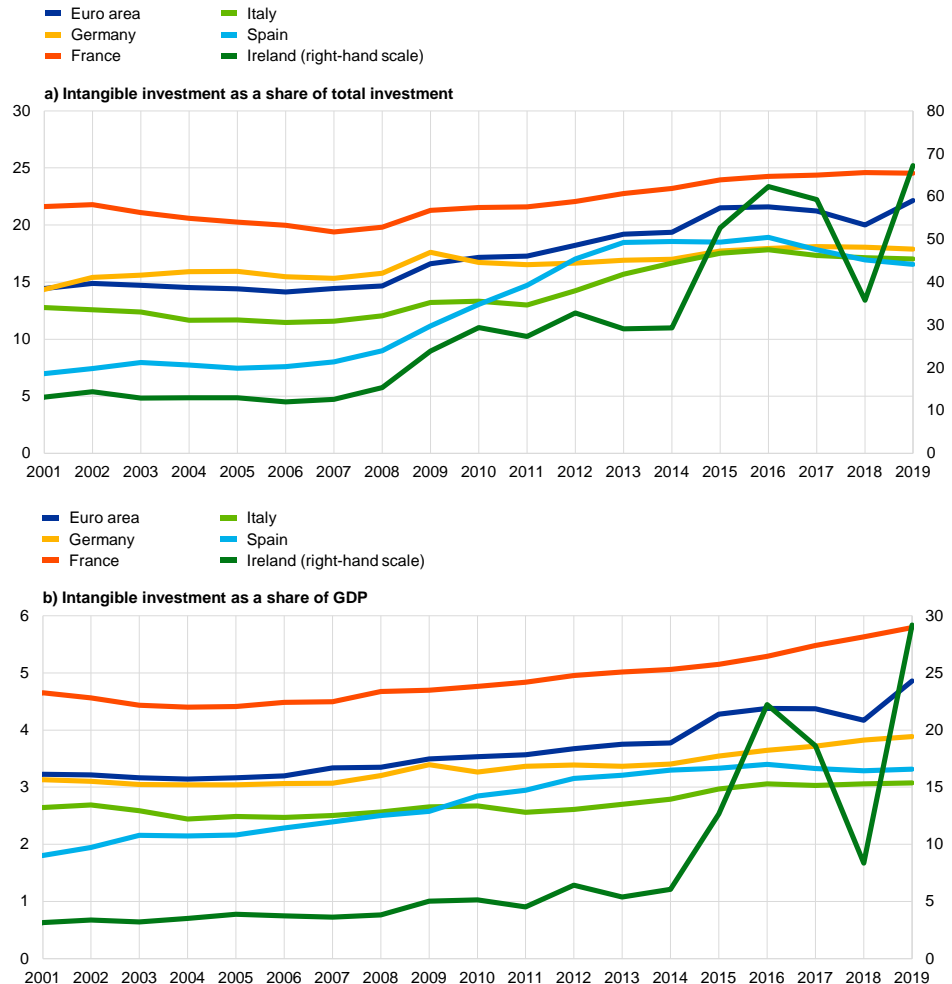
¹²² See, for example, www.intaninvest.net.

¹²³ See, for example, Box 1.3 in European Commission (2016).

¹²⁴ See, for example, Bilbao-Osorio, Maier, Ognyanova and Thum-Thysen (2017). See also European Commission (2017).

Chart 12
Investment in intangibles

(percentage)



Sources: Eurostat and ECB staff calculations. Latest observation: 2019.

Notes: Intangibles correspond to "intellectual property products" in the national accounts. Total investment corresponds to "gross fixed capital formation – fixed assets" in the national accounts.

In parallel, attempts have been made to better capture intangible investment, notably by broadening the definition and coverage of the corresponding statistics, which raises the level of intangible investment and therefore the levels of total investment and GDP.¹²⁵ Chart 13 shows a comparison of intangible investment as recorded by Eurostat in the national accounts and as recorded in the INTAN-Invest database. In particular, the current definition of intangibles in the national accounts¹²⁶ covers R&D, mineral exploration, computer software and databases, entertainment, and literary and artistic originals, while the INTAN-Invest database also includes expenditures which are considered intermediate costs in the national accounts, e.g. for design, branding, organisational capital and firm-provided training. Chart 13 highlights that the additional intangible investment captured in this way could be as large (or even twice as large) as the intangible investment as

¹²⁵ See, for example, Eurostat (2014).

¹²⁶ As defined in the System of National Accounts of the United Nations (SNA 2008) and in ESA 2010.

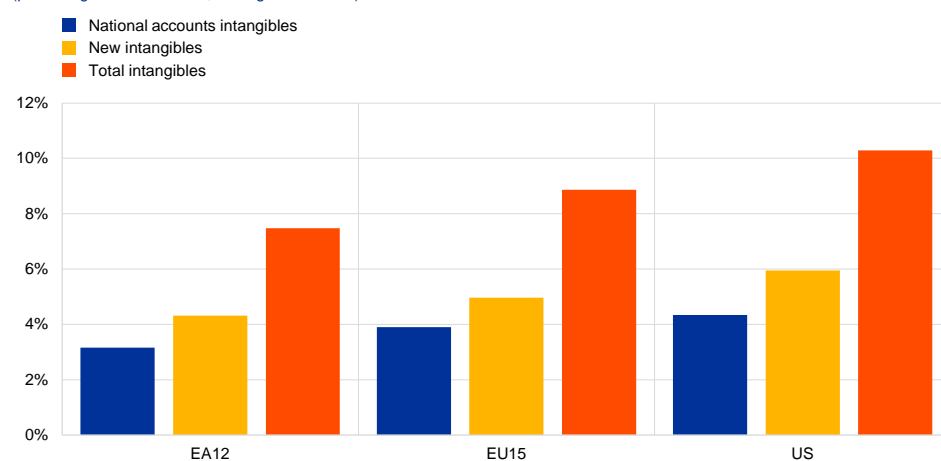
measured in the national accounts, depending on the country group that is being looked at (heterogeneity across countries appears to play a role in this regard).¹²⁷

Chart 13

Intangible investment according to different sources

Evidence from National Accounts and INTAN-Invest database

(percentage of value added; average 1997-2015)



Sources: Corrado, Haskel, Iommi, Jona-Lasinio, Mas and O'Mahony (2017) and ECB staff calculations.

Notes: The EA12 countries are Austria, Belgium, Finland, France, Germany, Greece, Italy, Ireland, Luxembourg, Netherlands, Portugal and Spain. The EU15 countries are the EA12 plus Denmark, Sweden and the United Kingdom. "New intangibles" are additional intangible investment items included in the INTAN-invest database, but not included in the National Accounts.

Digital investment is often investment in intangibles, as opposed to other digital investment such as hardware. According to some estimates, between one-third (for the less digital economies) and two-thirds (for the more digital economies) of digital investment are in intangibles (software, algorithms, big data and related analytics). It has been pointed out, for example, that in some cases, e.g. in the telecommunications industry (see Chen et al., 2016), investment in ICT technologies require complementary investment, for example in organisational structures, employee training and other intangible assets. This probably also holds for other businesses, industries and sectors. It suggests that intangible investment would increase because of digital investments and other investments made necessary by that digital investment, i.e. acting as a catalyst for further intangible investment.

Financing of intangible investment, which is hard to collateralise, may be better suited for alternative sources of finance than traditional bank financing. This arises from the higher uncertainty and risk associated with intangibles (due to their exploratory nature), combined with issues relating to their transferability in comparison with the more physical nature of tangible investment. Equity financing and venture capital (VC) may be more suitable for funding intangible investment. Box 8 below uses micro data to look at the role of intangible investment and its measurement in terms of improving estimates of investment from the perspective of Tobin's Q.¹²⁸

¹²⁷ The chart shows data from the INTAN-Invest database, available at www.intaninvest.org (used and described in Corrado, Haskel, Jona-Lasinio and Iommi (2016)). See also European Commission (2011).

¹²⁸ See Ahn, Duval and Sever (2020).

Box 8

Intangible investment and Tobin's Q in the euro area

Prepared by Malin Andersson and Lorena Saiz

This box looks at the relevance of intangible capital in terms of explaining the relationship between Tobin's Q and investment, focusing on explaining estimates of an investment gap.

Firms' investment in physical capital (i.e. tangible assets) has been rather sluggish in the euro area and clearly lower than suggested by Tobin's Q (a market-based proxy for firms' investment opportunities). Regression analysis using a panel of listed companies in the euro area suggests that investment in tangible assets was lower than the level suggested by Tobin's Q (while controlling for cash flow developments) even before the global financial crisis, but the crisis contributed towards widening the gap (Chart Aa). Interestingly, a similar gap has been observed in the United States since the beginning of the 2000s (Crouzet and Eberly, 2019).

The negative investment gap could either indicate an underinvestment problem or be a reflection of overvaluation in the markets. However, the poor empirical performance of the neoclassical model of investment in relation to competing models such as the accelerator model is well known. The literature has provided three possible explanations: (i) misspecification of the functional form of the capital adjustment costs, which are typically assumed to be convex (owing to financial frictions, for instance); (ii) measurement error in Tobin's Q, as market values for Tobin's Q (e.g. market to book value) are poor and noisy proxies for investment opportunities;¹²⁹ and (iii) missing variables in the investment equation. This box investigates the second and third explanations, and shows that intangible assets can indeed explain part of the gap between firms' investment in tangible assets and Tobin's Q.

The rising share of intangible assets helps to explain the investment gap in the euro area.¹³⁰

The investment gap in the euro area generally seems to be more pronounced the higher the intangible intensity (Chart Ab). By sector (not shown), the investment gap is negative in intangible-intensive sectors such as healthcare, high tech and retail trade but also in less intensive sectors such as manufacturing (including construction). This indicates that other factors besides intangible assets might be at play. Nonetheless, when intangible assets are taken into account in the regressions for the euro area as in Crouzet and Eberly (2019), the investment gap in the euro area gets smaller (red line in Chart Aa). Furthermore, if intangible assets that are not capitalised (i.e. not included in the balance sheet as assets) are included in both investment and Tobin's Q as in Peters and Taylor (2017), the size of the gap between the two is reduced further¹³¹. The sensitivity of investment to Tobin's Q also increases, although in all cases Tobin's Q explains only one-third of total variation in investment.

¹²⁹ The alternatives proposed in the literature are to use other sources of information such as bond prices (Philippon, 2009) or to correct the measurement error that biases the inference. Erickson and Whited (2002) propose using high order moments estimators as instruments in the errors-in variables model, while Erickson, Jiang and Whited (2014) propose the cumulant estimator (i.e. polynomials of moments).

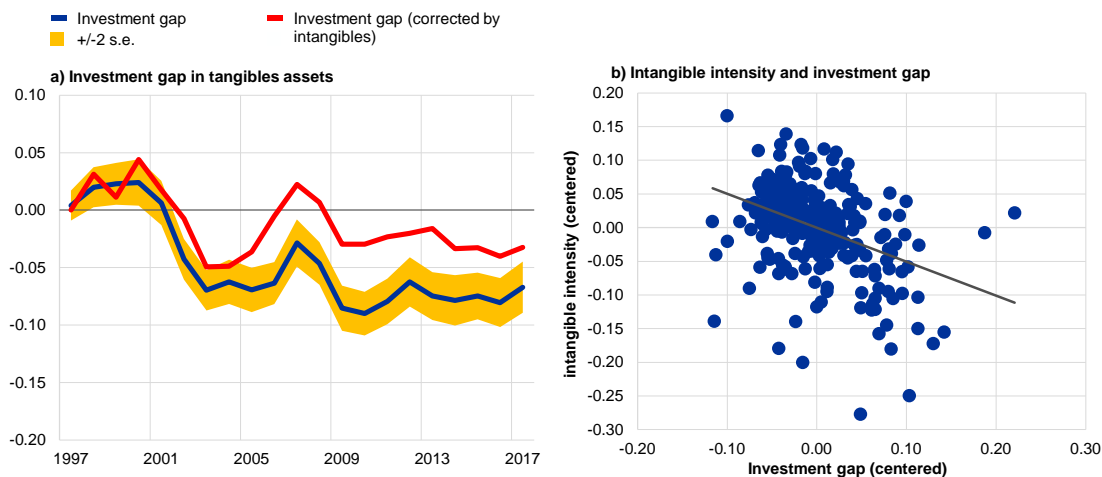
¹³⁰ For the United States, several recent papers have found that the rising share of intangible assets can help to explain the weakness in capital investment. In particular, Peters and Taylor (2017) argue that by ignoring intangible assets, both capital investment and Tobin's Q proxies are biased. They propose a simple, new Tobin's Q proxy that accounts for intangible capital and show that it is a superior proxy for explaining both physical and intangible investments for firms. Gutiérrez and Philippon (2017) find that intangible assets explain between a quarter and a third of the observed investment gap. More recently, Crouzet and Eberly (2019) have shown that the rise in intangible capital is an omitted factor biasing the estimates and that it can explain much of the weakness in investment and the investment gap.

¹³¹ See box in ECB (2018).

Chart A

Investment gap in tangible assets in the euro area

(left-panel: ratio of capital expenditure to tangible assets; right-panel: ratio of intangible assets to total assets and ratio of capital expenditure to tangible assets)



Sources: Worldscope and ECB staff calculations.

Notes: a) The investment gap (blue line) is proxied by the time-fixed effects in a standard regression of investment in tangible assets on average Tobin's Q and cash flow (all variables are scaled by tangible assets at book value) as in Crouzet and Eberly (2019). The investment gap correcting for intangibles (red line) is calculated as the residuals of the regression of the investment gap at sectoral level on the share of intangible assets (at book value) in total assets including sector fixed effects.

b) The investment gap is proxied by the time-fixed effects in a standard regression of investment in tangibles assets on average Tobin's Q and cash flow, and each point represents the average value for firms in one sector in a specific year. The analysis focuses on 12 Fama-French sectors during the period 1997-2017. The intangible intensity is the ratio of intangible assets over total assets (both at book value). Both the investment gap and intangible intensity are shown net of industry effects.

6.2 Big data

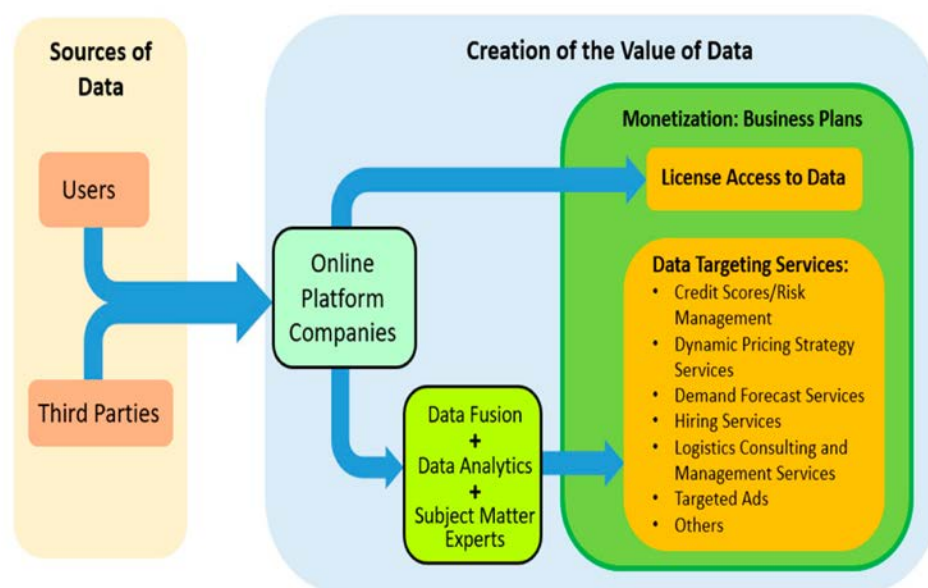
An important aspect of digital intangible investment is spending on big data and associated methodologies, most notably in the context of the online platform economy, but essentially across all sectors of modern economies. The term “big data” refers not only to the size and complexity of a dataset but also to its corresponding analytics. It appears to be one of the digital technologies with the largest take-up across firms.¹³² As with intangible assets in general, big data can take very different forms and are often highly firm-specific, i.e. not particularly valuable outside of the firm (an example of the “sunkness” of intangible assets according to Haskel and Westlake, 2017). Big data can be collected for example through online platforms (e.g. search engines or social media) and service providers (e.g. communications or financial). They can be processed and analysed and can generate revenues in many ways, e.g. through targeted advertising. The business models can be different, but they share a few key features. Chart 14 provides a stylised representation of the sources of some big data and how the value of data is created from those sources.¹³³

¹³² See Box 11 in this paper and ECB (2018).

¹³³ For how data might be used by businesses and how their value might be affected by their characteristics, see Nguyen and Paczos (2020).

Chart 14

The creation of the value of data from the different data sources



Source: Li, Nirei and Yamana (2019).

The value of such data capital is difficult to estimate, but is potentially very large. Recent estimates put the value of the data market in Europe at €300 billion in 2016 (see Chart 15). Likewise, a study of the value of big data has examined transactions of eight types of online platforms with data-driven business models, including concrete examples from the US economy, concluding that the value of data can be substantial and is growing by more than 20% per year.¹³⁴ Interestingly, the exact nature of the platform (e.g. e-commerce, resource sharing, financial, crowdsourcing, social network, auction/matching or searching) does not seem to matter for the growth rate of the value of data. A similar exercise was conducted by Statistics Canada, and the results are reported in Chart 16. In Canada, investment in data products, such as data, databases and data science, grew from CAD 6 billion in 1990 to around CAD 30-40 billion in 2018, depending on the methodology used. In particular, the paper which derived these estimates discusses the challenges in measuring “own-account” data:¹³⁵ while data that are sold on the market can be estimated using their market sales, the value of “own-account” data is computed using the costs of production and an estimated return on capital.

A particularly important use of big data, and in fact the driving force behind new automation technologies, lies in prediction algorithms. Prediction algorithms (typically machine learning or deep learning algorithms) read massive amounts of data and then make a prediction based on the patterns uncovered in the data. These predictions can range from how likely a consumer is to purchase a specific item given their past search history to whether a driverless car should slow down when it sees heavier traffic flow. As mentioned before, AI is expected to be the key GPT of the next

¹³⁴ See Li, Nirei and Yamana (2019).

¹³⁵ See Statistics Canada (2019).

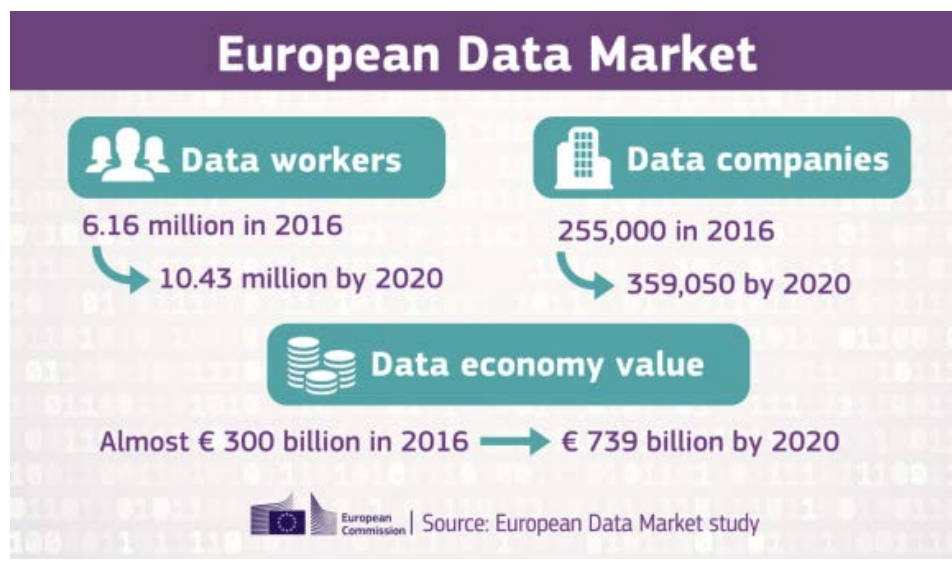
few decades, and it can only function with big data. While precise measurements of the impact of these technologies are scarce, an interesting recent application is by Bajari et al. (2019), who use e-commerce data to forecast demand and show that it is a misconception to think that more big data is always better; in fact data richness has diminishing returns, and how data is used to improve models can be important. Bajari (2019) emphasises that, through continuous incremental enhancements in data handling, data science has allowed firms to move from heuristics to scientific decision-making in many different areas (inventory, truck-load and itinerary, human resource management).

Chart 15

The importance and value of big data

Estimates by the European Commission for 2016

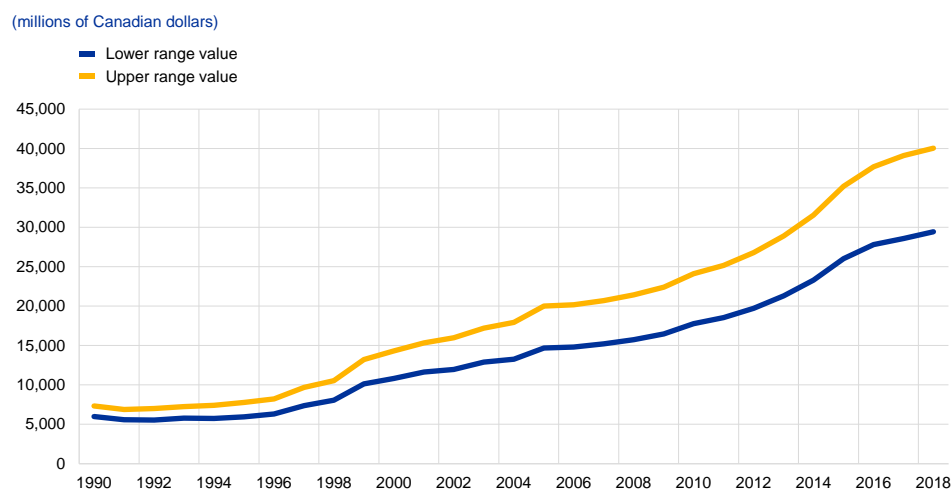
(millions of workers, number of companies, and EUR)



Source: European Commission.

Chart 16

Range of the value of investment in data products in Canada, 1990 to 2018



Source: Statistics Canada (2019).

6.3 Tangible capital and servicification

Tangible capital, defined as capital having a physical component, may also be affected by digitalisation. It has been argued, for example, that digital tools based on advanced analytics such as predictive maintenance, “intelligent” resource planning systems and the rise of big data might help to better utilise new and existing investment. This would tend to imply that investment in tangibles could be partially triggered by, and be complementary to, investment in intangibles. However, investment in some ICT technologies may also be a substitute for tangible non-digital capital goods, e.g. cloud storage and computing services, often considered a substitute for physical storage and archiving facilities. As a result, investment in tangible capital goods may be partly replaced as firms harness ever-greater ICT capabilities.

Some examples of where servicification may already be supported by ICT technologies are online platforms and the role that these may play in the more intensive use of capital assets. For instance, online platforms may enable more private cars to be used in place of taxis or car hire, and more residential accommodation in place of hotel rooms. The more intensive use of existing private assets may decrease the need for investment in new assets. More broadly, the development of the “sharing economy”, where citizens access online platforms to temporarily use equipment owned by others, may also reduce the demand for new consumer durables, particularly where they are not used intensively.

In addition to these platform-based “sharing economy” activities, technology increasingly allows the development of a more efficient use of capital assets. Increasingly, young people in European cities are opting to use temporary car rentals via “car clubs” which rely on digital technology to find conveniently located vehicles

and thus initiate a transition from a product-based sector to an integrated service-based industry.

6.4 Potential output

Digitalisation may affect all the usual contributions to potential output – namely labour, capital and TFP. While the impact of digitalisation on labour, capital and TFP has been discussed elsewhere in this paper,¹³⁶ this section highlights additional aspects specifically relevant to potential output. For instance, digital production and supply chains may raise TFP because of the greater efficiency in terms of time and quality of digitally enhanced or digitally supported (e.g. just-in-time) production technology.

Digital communication and connectivity may also support TFP by enabling faster collection and evaluation of data. At the same time, some digital and mobile communication applications could act as a distraction from productive activity. While it is unclear how the TFP contribution has been or is going to be affected by digital technology, it seems likely that the TFP contribution of digital technologies is supportive of potential growth, although it is noteworthy that this has not been sufficient to offset the decline in trend TFP growth (see Section 4 on productivity).¹³⁷

The effects on potential growth from labour and capital are more uncertain. Digital production and supply chains may lead to an increased need for labour for non-repetitive, non-routine tasks, digital skills and professions, or other skills and professions for the digital work environment (such as openness to change and/or adaptability to new technologies). At the same time, however, they may entail a reduced requirement for lower-skilled labour for more routine tasks and a corresponding shift to more (IT) capital (see Section 5 on the labour market).¹³⁸ While substantial investments in digital technology might be expected, the effect on the overall physical capital stock might be limited, particularly if the new technologies increase the intensity with which capital assets can be used. However, new ways of accessing capital, such as cloud computing, may substantially increase the extent and magnitude of the capital available to a large number of firms, which may significantly increase their potential. Another mechanism affected by digitalisation may be the relationship between potential output and marginal costs. For example, in contrast to the costs of supplying additional physical goods, the additional costs of supplying another user with an online computer game may be much smaller and even minimal.

The overall effect on potential growth depends on a number of factors. This includes the initial conditions: economies with an environment conducive to research and innovation are likely to see faster adoption and implementation of digital technologies and thus also a faster impact on potential output. Another factor is the

¹³⁶ See Sections 4, 5, and 6 of this paper on productivity, labour markets and the supply side, respectively.

¹³⁷ See Ahmad, Ribarsky and Reinsdorf (2017).

¹³⁸ See, for example, the World Economic Forum article entitled [Understanding the impact of digitalization on society](#). The article refers to global job losses of between 2 million and 2 billion by 2030 due to digitalisation but also refers to potential job creation of up to 6 million jobs worldwide between 2016 and 2025 in the logistics and electricity industries.

relative importance of catching up and leapfrogging versus pushing ahead, i.e. whether economies may be transforming faster from the technology backwater or the technology frontier.

In the broadest possible sense, the environment for research and innovation and the interaction of different dynamics of technology adoption depend on structural policies, including primarily labour market and product market policies, but also trade and investment policies, as well as fiscal policies (see Masuch et al., 2018). However, it is far from clear which policies are the most promising. Important elements of a policy strategy may be incentives to research and innovation, either raising the rewards to innovation and research activities or lowering the costs of those activities. This may include measures on intellectual property and the associated rights, or measures supporting funding and investment. Support for technology exchange, including across borders, may also be very relevant to creating a greater effect on potential growth.

The Digital Single Market and the capital markets union are important EU-level policies which can help to enhance the supply side. At the EU level, the aim of the Digital Single Market is to further the Single Market in the digital domain and to facilitate the process of digitalisation across the EU. This can deliver scale economies for digital firms, thereby facilitating start-ups and investment in intangible capital which could be further stimulated by greater provision of VC, including in conjunction with further advances in the capital markets union. Nevertheless, more can be done in terms of accelerating and broadening the ambition of the Digital Single Market.¹³⁹

¹³⁹ For suggestions on how to improve the Digital Single Market, see for example Scott Marcus et al. (2019).

7 Digitalisation and inflation

Prepared by Mario Porqueddu and Ieva Rubene¹⁴⁰

Most people associate digitalisation with a negative impact on both the price level and on inflation. As described in earlier sections, this corresponds to the general idea that digitalisation is a supply-side shock which can lead to lower inflation. This section reviews the main transmission channels through which digitalisation can affect consumer prices. Such effects can be observed directly via prices of digital products, or indirectly via a cost saving channel, higher price transparency and intensified competition, or productivity gains that may impact wage formation – all generally very difficult to disentangle empirically. In addition, there is also a view that “superstar” internet firms may actually reduce competition and lead to higher prices in the longer term. A box examines in further detail how digitalisation may affect competition and market power along with the possible implications.

The analysis presented in this section shows that: (i) the inflation rate of digital products has been persistently negative in the euro area; (ii) the degree of e-commerce varies across the euro area countries but is expanding in most of them; (iii) the estimated impact of e-commerce on euro area non-energy goods inflation is negative but fairly small; and (iv) the impact of digitalisation on wages is inconclusive, as various factors can have opposite effects. Overall, e-commerce impacts will emerge over time and can last for quite a long time but should be temporary by nature, ceasing when the diffusion of e-commerce technologies through markets has settled and generated a new cost/profit equilibrium.

7.1 Potential channels for the transmission of digitalisation to prices

The first, most direct channel that digitalisation has to consumer prices is via the prices of digital products purchased by consumers. Because such products are part of the HICP for the euro area and its member countries, this will have a direct impact on the price level and inflation as measured by the HICP.¹⁴¹ In an ever-more technology-intensive world it is difficult to clearly define what a digital product is. In the next subsection, however, by using a very basic approach it is shown that ICT-intensive products have directly dampened consumer price inflation over the last two decades.

¹⁴⁰ Parts of this section build on an earlier note by Valerie Jarvis and Patrick Schulte (2018), “Virtually everywhere? Digitalisation and the supply shock to the euro area”, circulated and presented to the G7 Digitalisation Working Group Meeting, Canada, December, 2018.

¹⁴¹ In the euro area, consumer price inflation is measured by the Harmonised Index of Consumer Prices (HICP). It measures the change over time in the prices of consumer goods and services acquired, used or paid for by euro area households. The main task of the ECB is to maintain price stability defined as an annual HICP inflation rate of below 2% over the medium term.

The indirect channels of digitalisation are via cost savings and higher competition owing to increased price transparency.¹⁴² The effects of digitalisation in this context are often associated with the somewhat narrower term “e-commerce”, which is typically used to describe buying or selling goods, services or information via the internet. E-commerce takes place between businesses (business to business, B2B), and between businesses and consumers (business to customer, B2C). This section will focus mainly on B2C. The price-lowering impact of a diffusion of e-commerce comes in two ways. First, compared with standard offline distribution channels, e-commerce creates scope for cost savings (e.g. online sales require lower expenditures than maintaining shops), which both traditional and online retailers may pass on to their customers. This effect alone would not change the profit margins in the retail sector. Second, however, e-commerce may be effective in lowering prices (or constraining their increase following cost rises) through higher transparency and intensified competition between suppliers as customers searching the internet for lower prices and bargains force both traditional and online suppliers to contain prices. This second effect may then erode profit margins, notably so in some traditionally face-to-face businesses. It should be noted that both effects can kick in when the share of e-commerce retail in the total business is still low. Box 9 explores in more detail the effects of digitalisation on competition.

Although e-commerce generally intensifies competition, the presence and wide use of e-commerce-based trade technologies also opens up new opportunities for tacit, non-overt collusion among suppliers, which may also impair competition. This is because e-commerce is used by consumers to better compare prices and qualities of goods, but it also facilitates opportunities for suppliers to check prices and possibly collude on pricing behaviour.¹⁴³ It cannot be ruled out that such effects may be relevant for specific markets, but the competition-enhancing impacts of e-based transaction technologies should dominate – notably as long as the technology is still relatively young and as long as online suppliers strive for market share in an effort to strengthen their position in the business.¹⁴⁴

Digitalisation is usually associated with productivity gains, which in turn can have an impact on wages. While higher productivity should give more scope for companies to pay higher wages, the composition effect of changes in the labour market may dominate.¹⁴⁵ As we show later, empirically, such effects are difficult to disentangle, as productivity developments are driven by a broad range of factors. Finally, price-lowering impacts from a more intensified use of e-commerce, if any, will last only until the diffusion of e-commerce technologies through markets has settled (see Meijers, 2006).

¹⁴² These channels found in theoretical literature are broadly corroborated by the evidence from large euro area corporations; see Box 11 in the Appendix.

¹⁴³ In 2015, the German competition authority (Bundeskartellamt) prohibited booking.com and HRS from continuing to apply their “best price” clauses (also called “most favoured nation” clauses). Best price clauses are only beneficial to the consumer at first glance; ultimately, they restrict competition between the hotel booking platforms, since booking portals which demand lower commissions from the hotels cannot offer lower hotel prices.

¹⁴⁴ See also Box 9 in this section, which addresses in more detail issues relating to digitalisation, competition and market power.

¹⁴⁵ See Section 5, “Labour markets”.

Box 9

Digitalisation, competition and market power

Prepared by Filippos Petroulakis

One important mechanism through which digital technologies, and in particular intangible capital, affect the economy is through their effect on market structure. The possible channels are too numerous to describe in detail, and this box simply outlines some of the key issues.

Digital technologies encompass some particular characteristics that make them conducive to higher concentration.¹⁴⁶ The increasing importance of intangible capital (data, software, R&D), which implies substantial fixed costs but very low marginal costs, together with the ability to use cloud computing as a way of rapidly increasing the size of a company at low cost, means companies are able to achieve “scale without mass” and to costlessly reproduce business processes (Brynjolfsson et al., 2008). In addition, some non-tech superstars with low markups, especially in retail, are very intensive users of ICT (Decker et al., 2016), increasingly employing some of the most advanced automation technologies for their warehousing and logistics needs. Many digital technologies are also associated with substantial network effects, which means that early movers can have a sizable advantage and dominate their markets.¹⁴⁷ The sunkness of intangible assets implies that the value attached to them may vary considerably from one user to the other, and so the value of intangibles often lies in how they are integrated into the production processes of specific firms, which can help solidify the market positions of such firms. Empirical analysis shows that the high rate of business dynamism associated with ICT firms in the 1990s (which pulled the entire US economy upwards) was followed by muted dynamism and a lower start-up rate in the 2000s (Decker et al., 2018), itself a potential sign of lower competition.¹⁴⁸

Digital technologies may also enhance competition in a variety of ways. They can increase the contestability of local markets, leading to higher local competition. As local retailers (but also local brick-and-mortar wholesalers) are under competition with potentially larger and more productive online firms, they may have to shave markups and/or lower their market shares. The lower search costs associated with e-commerce may further increase cross-price elasticities of various sellers, leading to lower geographic price dispersion (Cavallo, 2018). The evidence indeed points to substantial retail price reductions as a result of online competition (Lieber and Syverson, 2012).¹⁴⁹ Furthermore, some of the very same reasons that allow market power to expand rapidly may also reduce barriers to entry, by reducing costs of operations, and enabling access to diverse markets even for small firms (Lendle et al., 2013).

¹⁴⁶ See OECD (2018b), [Maintaining competitive conditions in the era of digitalisation](#).

¹⁴⁷ Often, in fact, it is not the first mover that ends up eventually dominating the market, but the second mover. This is because the second mover is in a position to offer an improved product and operate in a market that has become large enough that meaningful network effects already exist (Amazon and Facebook are cases in point).

¹⁴⁸ As remarked by Haltiwanger (2018): “In 1998, you wanted to be Google; in 2018, you want to be bought by Google.”

¹⁴⁹ It could, however, be argued that some of the competitiveness gains in retail markets could be short-term, since some of these firms are so large (even at a global scale) that they may eventually monopolise their market.

There are signs that market power and concentration is on the rise, particularly in the United States.¹⁵⁰ The topic was brought to the fore in recent years by De Loecker and Eeckhout (2020) who suggested that the average markup for US firms has risen sharply over the past three decades. They further link these developments to several secular macro trends, such as the decrease in the labour share, the decline in low skilled wages, and the decline in labour flows, labour force participation and migration rates, and the slowdown in aggregate output.¹⁵¹ In the same vein, Autor et al. (2017a) show that the fall in the labour share is explained by the rise of superstar firms that command large sectoral shares while having a low labour share. Although there is some debate on the extent of the rise of market power and the link between markups and concentration, as firms may keep markups very low to attract large market share, there is broad agreement that firm markups and concentration ratios have increased in the United States. The literature for the EU is much slimmer – primarily as a result of sparser data coverage – and, on balance, the conclusions are mixed. Cavalleri et al. (2019) do not find strong evidence of higher market power in the largest four euro area economies, whereas Bajgar et al. (2019) show an increase in market concentration in a number of European economies. Kalemli-Ozcan et al. (2019) provide a reconciliation based on accounts reported by different types of firms; overall though they find no clear patterns of an increase in concentration.

While a number of factors are certainly at play (see for example Gutierrez and Philippon, 2018), it seems likely that technology will matter. The high-markup, high-concentration, low-labour-share firms that Autor et al. (2017b) identify as superstars include some well-known tech giants. Bessen (2017) uses sectoral data for the United States to examine the role of proprietary ICT systems (proxied by the share of software developers in the workforce) and finds that it is strongly associated with both the level and growth of industry concentration and operating margins, accounting (together with intangibles) for most of the increase in concentration. It is also associated with the larger revenues and productivity of the top firms in each industry. Crouzet and Eberly (2019) also show that intangibles are associated with greater concentration in the United States, which could be either the result of changes in technology in a competitive environment or the result of market power. Calligaris et al. (2018a) use microdata from OECD economies and show that markups are higher in digitally intensive sectors, and that this difference has increased significantly over time, particularly for the top digitally intensive sectors (see Chart A). To the extent that digital technologies are an important driver of concentration, the lower share of ICT of value added in Europe on average could explain the less clear consensus as regards the increase in concentration in Europe compared with the United States (see Cavalleri et al. (2019) and Section 2 of this report).

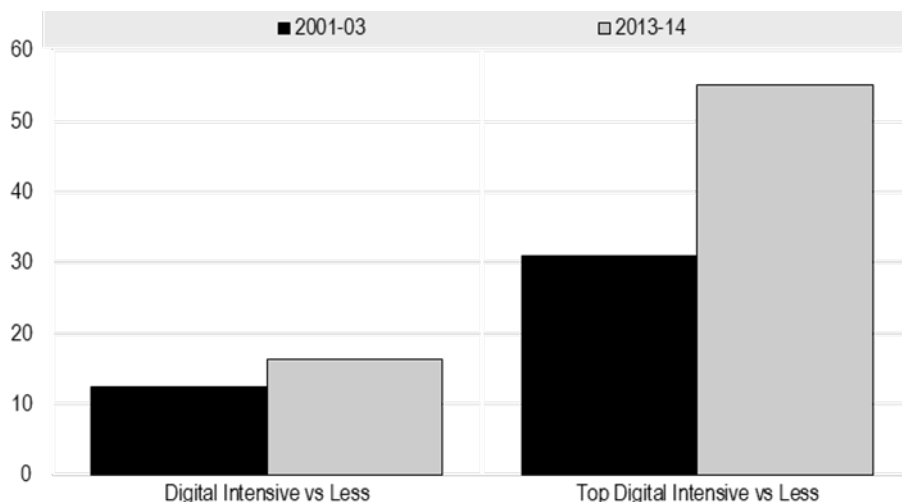
¹⁵⁰ An extensive review of issues and empirical evidence on market power is available in the Summer 2019 Issue of *The Journal of Economic Perspectives*, featuring contributions from Basu (2019), Syverson (2019) and Berry et al. (2019). For Europe, see Bajgar et al. (2019), Calligaris et al. (2018a), Cavalleri et al. (2019), Kalemli-Ozcan et al. (2019), Diez et al. (2018), Gutierrez and Philippon (2018), Weche and Wambach (2018), Canton and Thum-Thysen (2017) and Deutsche Bundesbank (2017).

¹⁵¹ Similar arguments are made also by Eggertsson et al. (2018) and Edmond et al. (2018).

Chart A

Differences in markups for firms by digital intensity across sectors

(percentage points)



Source: G7 Central Bank Digitalisation Working Group (2019), elaborations based on Calligaris et al. (2018a).

It is not clear to what extent we should have ex ante concerns about an increase in market power. To the extent that higher market power is the unavoidable market outcome of great innovations that enhance consumer welfare (even if they create rents and hence reduce the labour share), this may be a benign outcome. Innovation is a profit-seeking activity, and firms may not be as active in investing in R&D if the potential profits are reduced through some policy intervention. Aghion (2017) shows that innovation has an inverse U-shaped relationship with competition: very high competition may discourage innovation, as the post-innovation profits are low, while very low competition may imply high pre-innovation rents, discouraging innovation. This implies that the optimal level of market power is non-zero.¹⁵²

A related but distinct issue, which has remained largely unexplored, concerns the consequences of market power and of digitalisation in general for the conduct of monetary policy. Syverson (2018) shows that a monetary expansion would lead to a larger output expansion in conditions of perfect competition than under a monopoly.¹⁵³ Monetary policy affects firms by changing their cost of capital. As such, companies with high market power in general respond less to changes in costs, and hence to monetary policy, than perfectly competitive firms. This does not mean,

¹⁵² Schumpeterian models predict that competition fosters innovation in neck-and-neck sectors where firms operate at the same technological level. In such sectors, increased product market competition reduces pre-innovation rents, increasing the incremental profits from innovating and becoming a leader. This is the “escape-competition effect”. The models also predict a negative “Schumpeterian effect”: increased competition reduces the post-innovation rents of laggard firms and thus their incentive to catch up with the leader. At low levels of competition the “escape competition” outcome tends to dominate the “Schumpeterian” effect. When competition is high, the Schumpeterian effect is likely to dominate because a larger fraction of sectors in equilibrium have innovation being performed by laggards with low initial profits.

¹⁵³ In a simple demand-supply diagram, expansionary monetary policy would shift the supply curve to the right. As profit maximising firms produce until marginal revenue (MR) equals marginal cost (MC), the slope of the MR curve determines the new equilibrium. Under perfect competition (flat MR curve), a monetary expansion would lead to a larger output expansion than under a monopoly (steep MR curve).

however, that less market power will result in higher pass-through of cost shocks or transmission of monetary policy; this will depend on how the incentives of firms change as market power changes.¹⁵⁴

Taking a different perspective, Korinek and Ng (2018) analyse the role of digital innovation costs for superstar firms for the Phillips Curve. They find that, as innovation proceeds, factor costs will fluctuate less with demand, leading to a flatter Phillips Curve. They point out that as superstar firms gain market share, and as long as their innovation involved fixed costs, firms spend an increasing share of their factor demand on fixed costs, which by definition respond less to aggregate demand changes. Cavallo (2018) finds a decline in the degree of geographic price dispersion in the United States over the last ten years, attributed to the fact that online retailers have uniform pricing strategies and hence limit the opportunity for geographical price discrimination. As a result, the sensitivity of retail prices to global shocks, such as exchange rates and gas prices, has increased, suggesting a decline in price stickiness. This has important implications for conventional models, which ascribe an important role to nominal rigidities for monetary policy effectiveness.

7.2 Exploring the direct channel: the inflation rate of digital products

Declines in the prices of ICT products lowered the euro area annual HICP inflation rate by 0.15 percentage points on average each year in the period from 2002 to 2019.¹⁵⁵ The prices of ICT-intensive products have declined each year since 2000, as reflected in negative annual inflation rates. The impact was larger until around 2015 but subsequently decreased to some extent (see Chart 17a). The impact on HICP excluding food and energy was larger (around 0.2 percentage points per year) owing to the larger weight of the ICT items in this component. For individual euro area countries, ICT products lowered headline HICP by around 0.1 to 0.2 percentage points per year on average during the period 2002-2018 (see Chart 17b). Differences across the countries in the contributions of the ICT product inflation rate to headline HICP mainly reflect different inflation rates for telecommunication services. This sector has historically been more concentrated and had higher market power, but this market power has declined since 2003.¹⁵⁶ Inflation rates for audiovisual products and IT processing equipment and telephones were less diverse across euro area countries.

These estimates carry a number of caveats. First, digital products in the consumer basket do not only comprise the few categories used for the reported index. An analysis at a more disaggregated level would be limited to the time period from

¹⁵⁴ Specifically, higher market power implies a steeper demand curve, but whether it implies a steeper marginal revenue curve also depends on whether the demand curve flattens or steepens as output changes, as well as on the size of the change in the profit-maximising quantity as output changes.

¹⁵⁵ Following the HICP methodological manual published by Eurostat (see Eurostat, 2018b), the ICT product index consists of ECOICOP categories 08.2 Telephone and telefax equipment and 09.1 Audio-visual, photographic and information processing equipment as goods with predominantly electronic character. Additionally, it includes category 08.3 Telephone and telefax services, but excludes the category 12.3.1.2 Clocks and watches, because the data for the latter are available only as of 2016. The total weight of these items in the HICP is around 4% in 2019 in the euro area.

¹⁵⁶ According to the OECD sector regulation indicators, overall regulation in the telecom sector in most euro area countries has declined since 2003.

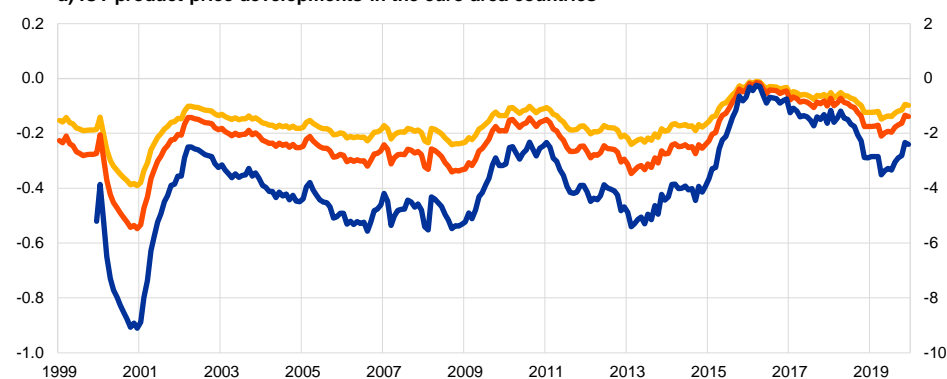
December 2016 onwards only, i.e. when indices based on the new more detailed European Classification of Individual Consumption according to Purpose (ECOICOP) classification became available.¹⁵⁷ Second, ICT products (or electronic goods) are subject to sudden and very fast technological upgrades and thus create challenges for inclusion in the HICP basket in terms of proper quality adjustment, replacement or expansion of the basket. Failure to appropriately incorporate such products in the HICP basket can lead to a bias (upward or downward) in the respective price indices.¹⁵⁸

Chart 17
ICT consumer products price developments and their impact on inflation

(left-hand side: percentage point contribution to annual inflation rate; right-hand side: annual inflation rate)

- ICT items inflation rate (right-hand-side)
- Contribution to headline HICP (left-hand-side)
- Contribution to HICP excluding food and energy (left-hand-side)

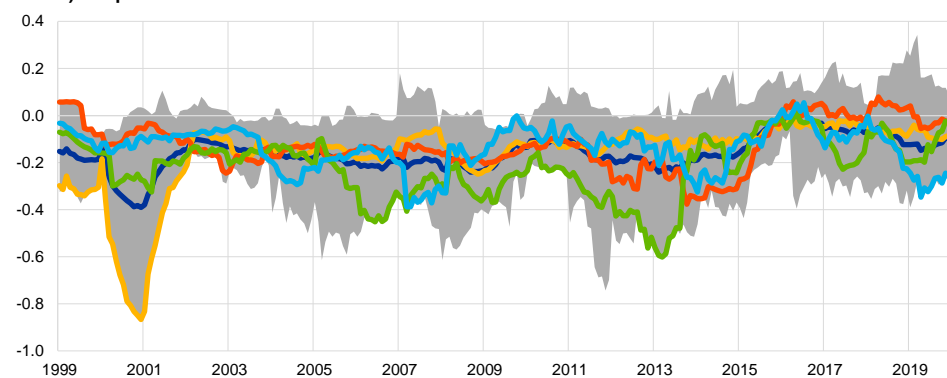
a) ICT product price developments in the euro area countries



(percentage points)

- Euro area
- DE
- ES
- FR
- IT
- Range

b) ICT product contribution to headline HICP annual inflation rate across euro area countries



Sources: Eurostat, ECB staff calculations.

Notes: Latest data refer to December 2019. The ICT products comprise audiovisual, photographic and information processing equipment along with telephone and telefax equipment and services. Inflation rates for 2000 and 2001 are distorted as they reflect the methodological impact of the inclusion of internet services in Germany's HICP. The range of euro area countries' is based on the changing composition of the euro area.

¹⁵⁷ The time period refers to the availability of the ECOICOP-5 classification for the euro area; see Eiglsperger (2019). It varies across euro area member countries.

¹⁵⁸ See Box 2, "Some measurement issues and the digital economy".

7.3 Exploring the indirect channel: the use of e-commerce in the euro area

The extent of indirect effects on inflation partly depends upon the prevalence of e-commerce in the euro area. The presence of e-commerce can be measured by a number of different indicators on the retailer side, such as the number of websites and the percentage of sales via online channels. It can be also characterised by indicators on the consumer side, such as the percentage of consumers buying online or looking for information on goods and services online. Overall, just having the opportunity to compare prices online may already be a competition-enhancing factor.

Electronic sales by enterprises (to other business and to consumers) in 2018 comprised 17% of total turnover of companies in the euro area (see Chart 18a). Companies in small and open economies (Belgium, Ireland, Slovakia and Finland) tend to have a higher share of electronic sales. Lower e-commerce sales in Southern countries (with the exception of Spain) may be partly explained by a large presence of small and medium firms which generally tend to sell less over the internet compared with large companies. However, in most countries, internet sales by companies have increased significantly over time. Data for Ireland and Luxembourg may also reflect the presence of multinationals serving the whole euro area or some of its countries.

Online sales to consumers comprised around 14% of total retail sales (excluding cars and motorcycles) in the euro area in 2017 (see Chart 18b). Over the last ten years, growth in online sales to consumers has substantially exceeded increases in sales in the regular brick-and-mortar shops. As a result, for most euro area countries, online sales as a share of total retail sales have more than doubled over the last ten years. According to the Eurostat data, the items most frequently purchased on the internet are clothing, accommodation and travel.

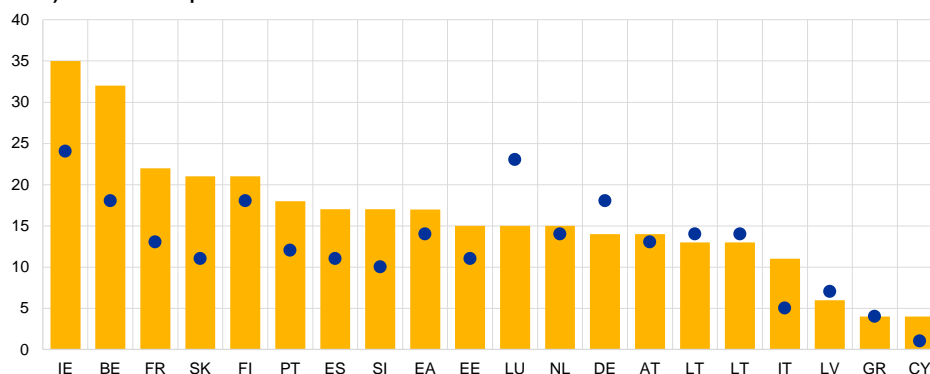
Chart 18

The size of e-commerce in the euro area

(percentage of total turnover; all enterprises, without financial sector; 10 persons employed or more)

● 2010
■ 2018

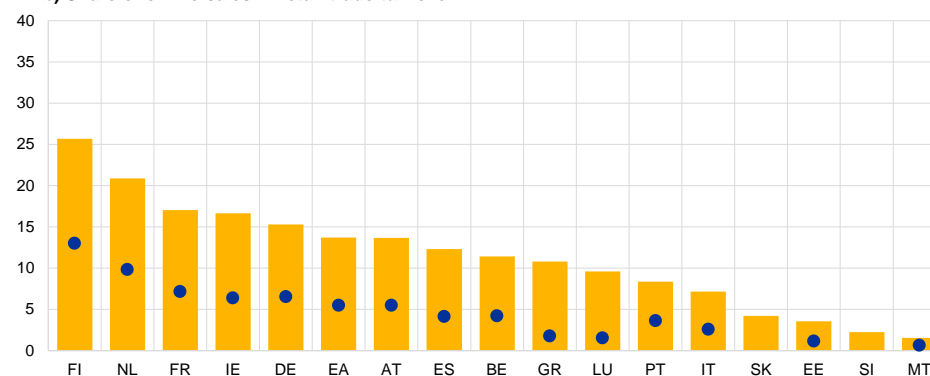
a) Share of enterprise turnover from e-commerce



(business to consumer online sales in percentage of retail trade turnover excluding motor vehicles and motorcycles)

● 2010
■ 2017

b) Share of online sales in retail trade turnover



Sources: Eurostat, Ecommerce Europe (The European eCommerce Association), ECB staff calculations.

Notes: Enterprise turnover data refer to 2011 for Greece and Malta, to 2012 for Luxembourg (instead of 2010) and to 2017 for Malta (instead of 2018). Data for online sales to consumers are not available for Latvia, Lithuania and Cyprus; for Slovenia and Slovakia, these data are not available for 2010. The value for euro area share of online sales in retail trade turnover is an aggregation of the available country data.

While sales over the internet still make up a relatively small share of total private consumption, the share of people using the internet either to obtain information about goods and services or to buy them is much higher and has more than doubled over the last 20 years. In 2018, around 70% of all individuals searched for information online, while around 60% actually made a purchase online – a significant increase compared with 2005 (see Chart 19a). While the majority of purchases are from national websites, the share of individuals making online cross-border purchases is rising. Among euro area countries, Germany and the Netherlands take the lead, followed by Luxembourg and France, with southern economies (Greece, Italy, Cyprus and Portugal) lagging substantially behind (see Chart 19b). Nevertheless, all euro area countries have shown the trend of a rising share of individuals searching for information and purchasing goods and services online over time.

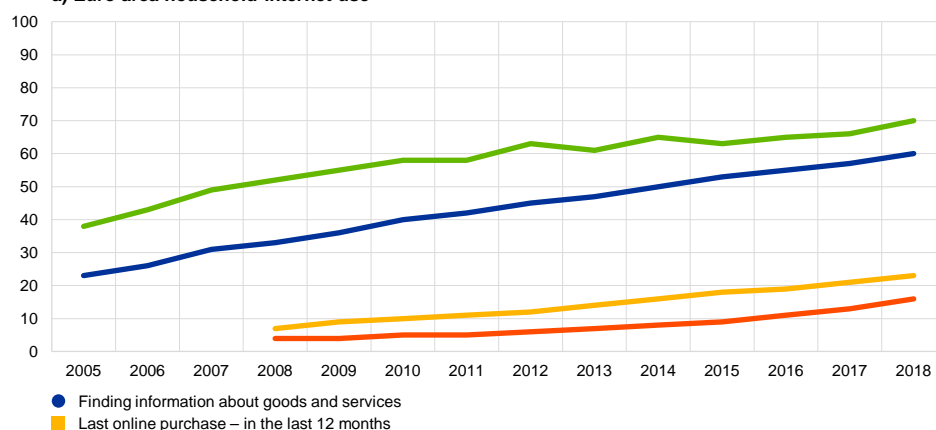
Chart 19

Household use of the internet for consumption and information gathering

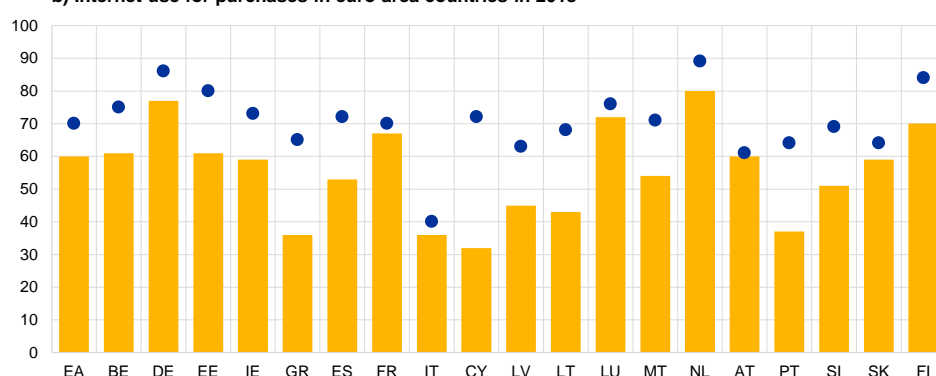
(percentage of age share of individuals)

- Last online purchase – in the last 12 months
- Online purchases from sellers from other EU countries
- Online purchases from sellers from non-EU
- Finding information about goods and services

a) Euro area household internet use



b) Internet use for purchases in euro area countries in 2018



Sources: Eurostat, ECB staff calculations.

7.4 Empirical evidence for the impact of e-commerce on inflation

It is important to distinguish the impact of digitalisation on the price level from that on inflation. The inclusion in the HICP of goods and services traded online will have an impact on HICP inflation only if the prices of such products and services change at different rates to the prices of goods and services traded offline. If prices change at similar rates in both trade channels, the incorporation of products traded online will not have a noticeable impact on HICP inflation. Increasing expenditure via the internet is reflected in adjustments to the weights of the respective HICP sub-items. However, price level differences between online and offline shop prices have no direct effect on the HICP.

Available evidence on possible measurement error in the consumer price indices resulting from incomplete incorporation of online sales is scarce and inconclusive. Statistical offices of the euro area countries continuously enhance their

data collection methods, and some online prices are already reflected in the HICP. For example, some statistical offices collect data on prices for accommodation and travel from online sources.¹⁵⁹ To the extent that online prices are not yet fully captured in the HICP, the evidence that there might be a bias in the HICP is not conclusive. Lünemann and Wintr (2006) find that changes in the prices of products traded online are on average smaller than the corresponding price changes reported in the consumer price index data. This would indicate a possible measurement error in HICP inflation. In contrast, Gorodnichenko et al. (2018), analysing US and UK data, find that prices are adjusted in online shops by about the same amount on average as those in brick-and-mortar shops, which is also confirmed by Cavallo (2017), who analyses prices of retailers selling online and offline for a number of advanced economies, including Germany.¹⁶⁰ Overall, there is evidence that the frequency of price adjustment has declined in recent years. However, this evidence is not conclusive as to whether the frequency differs between online and brick-and-mortar shops. Cavallo (2017) and (2018) documents that prices for online and brick-and-mortar shops change with a similar frequency (although they have significantly declined for both retail channels over the last years), whereas Gorodnichenko et al. (2018) find higher frequency of price changes for online stores.¹⁶¹ Overall, these findings suggest that the price index measurement error in terms of the upward or downward bias due to partial or full exclusion of online sales is likely to be small.¹⁶²

Empirical evidence on the effects of e-commerce on inflation is scarce but points to a small negative effect. Taking a panel of 207 countries, Yi and Choi (2005) find that a 1 percentage point increase in the share of people using the internet per annum decreases the annual inflation rate by an amount in the range of 0.04-0.1 percentage points. This outcome is broadly in line with Lorenzani and Varga (2014), who estimate the impact of online purchases of goods and services in the EU on the basis of the degree of price competition. They project that changes in the share of online purchases of goods and services in the retail sector from 2010 to 2015 could, overall, lower price increases in the retail sector in the EU27 as a whole by 0.1 percentage point each year between 2011 and 2015. A considerable level of uncertainty surrounds such estimates, owing, inter alia, to the limited data sample

¹⁵⁹ For example, Belgium's statistical office collects data on internet prices for student housing and accommodation services, the statistical office in the Netherlands collects data on prices for clothing, and the German statistical office collects data on prices for long-distance buses and railway tickets.

¹⁶⁰ Cavallo uses data collected in the context of the Massachusetts Institute of Technology's Billion Prices Project for offline and online prices; see the website for [The Billion Prices Project](#). The retailers included in the study for Germany are Galeria Kaufhof, Obi, Real, Rewe and Saturn.

¹⁶¹ In a case study with 14 German online shops, Blaudow and Burg (2018) find that the price for around 65% of products in these shops changes one to three times over a period of three months. This frequency would be captured by the traditional price collection methods in brick-and-mortar shops and reflected in HICP. The rest of the products have more frequent price changes. They also show that the frequency of price changes differs significantly across various online shops.

¹⁶² Goolsbee and Klenow (2018) construct a digital price index (DPI) using Adobe transaction prices of online sales and find online inflation to be about 1 percentage point lower than for the CPI. However, the DPI has a downward bias compared with the CPI for two methodological reasons. First, when constructing the index they do not match the new products with the old ones (the price difference between an outgoing product and its replacement is not reflected in the DPI), but many companies increase prices only by introducing new products, and the actual price for a given product over its lifetime usually decreases. Both euro area HICP and US CPI link the new products to the old, avoiding this downward bias. Second, the DPI is constructed with different weights than the CPI: the DPI uses a Fisher index which, when used for transaction data, can be prone to a downward index drift (see de Haan and van der Grient, 2011).

available and the previously mentioned caveats when it comes to measuring the consumer price index.

For the euro area, the estimated e-commerce effect on inflation is also found to be disinflationary. Using macroeconomic data, the e-commerce effect is estimated following Yi and Choi (2005), using annual panel data covering EU Member States (plus Norway and excluding Croatia). The data available for the internet indicator are for the period 2003-2018.¹⁶³ In the following regression equation:

$$\text{Inflation}_{i,t} = \beta_0 + \beta_1 \Delta \text{Internet}_{i,t} + \beta_2 \Delta \text{Money}_{i,t-1} + \beta_3 \text{Unemployment}_{i,t-1} + \beta_4 \Delta \text{Import Prices}_{i,t-1} + D1012_t + \varepsilon_{i,t} + \epsilon_i,$$

$\text{Inflation}_{i,t}$ refers to the annual inflation rate for industrial goods excluding energy in country i at time t , while the variable $\Delta \text{Internet}_{i,t}$ denotes the change in percentage points in individuals looking for offers of goods or services online. The other variables $\Delta \text{Money}_{i,t-1}$, $\text{Unemployment}_{i,t-1}$ and $\Delta \text{Import Prices}_{i,t-1}$ denote country-specific annual M3 growth, the unemployment rate and annual growth in the import price deflator for goods and services. All of the variables are lagged by one year. Finally, $D1012_t$ denotes a time dummy for the years 2010 to 2012; the expressions $\varepsilon_{i,t}$ and ϵ_i indicate independently and identically distributed error terms over countries and time and a fixed country effect respectively.¹⁶⁴ The negative value of the internet coefficient β_1 would suggest a disinflationary effect of e-commerce reflecting increasing price transparency, improving productivity and falling markups. A caveat regarding interpretation of the results below: this reduced-form analysis can only be used to estimate the correlation between the variables of interest and cannot be interpreted in a causal way.

The internet coefficient has a statistically significant value of -0.025. The parameters estimated for the other variables also have the expected signs and are statistically significant.¹⁶⁵ This means that a 1 percentage point increase in the share of people reported as looking online for goods or services reduces annual non-energy industrial goods inflation by 0.025 percentage points. While this estimated value of the internet parameter appears to be small, large annual changes in the percentages of internet use would still yield notable effects on inflation. The result suggests that past changes in the percentage of people looking online have contributed to a decrease in annual non-energy industrial goods inflation in the euro area by 0.06 percentage points on average per year (the average annual inflation rate for non-energy industrial goods prices was 0.6 percentage points over the same period). For the euro area, this implies a negative cumulative impact on inflation of 0.8 percentage points from 2006 to 2018. This effect is larger for countries that have experienced larger increases in the share of households looking for information online (see Chart 20)

¹⁶³ This is an update of the analysis included in Box 3 in Ciccarelli and Osbat (2017).

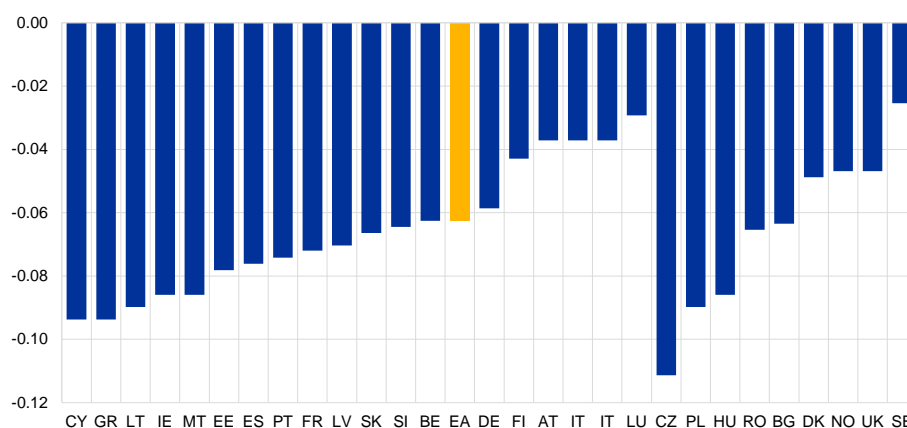
¹⁶⁴ The panel equation is estimated with random effects (not rejected by the Hausman test) and with heteroscedasticity and autocorrelation-consistent standard errors. All variables on the right-hand side are lagged to avoid endogeneity; the exception is the internet indicator, which is unlikely to be correlated with the inflation rate of a given year.

¹⁶⁵ The coefficients for money growth and import prices are positive, while that for the unemployment rate is negative; all coefficients are statistically significant at the 95% confidence level.

Chart 20

The average annual effect of e-commerce on the inflation rate of non-energy industrial goods

(percentage points; 2006-18)



Source: ECB staff calculations based on own estimates and Eurostat data.

7.5 Other channels

Digitalisation can also affect inflation via additional channels by lowering firms' operational costs, owing to efficiency gains, automation and new business models. When digital innovation acts as a complement to labour, higher productivity translates directly into a lower cost of production. When digitalisation creates productivity improvements through the substitution of labour, for instance with automation, apart from the direct impact on the cost of production (as in the first case), disinflationary effects may be associated with aggregate demand being suppressed owing to the displacement of workers (because of a skills mismatch). The impact of digitalisation on aggregate demand depends also on its overall impact on wages.

Digitalisation can affect wage growth in many ways and via numerous channels, which often work in different directions. Effects on wages can result from changes in skill demand due to automation but also as a result of digitalisation fostering offshoring and outsourcing. Furthermore, effects of digitalisation on wage growth can result from lower search frictions, improved matching on the labour market and changes in the bargaining powers of employees and employers. Based on the existing literature¹⁶⁶, the overall impact of digitalisation on wage developments in the euro area remains unclear, partly because of offsetting positive and negative effects and partly owing to measurement issues, which could at least to some degree be overcome with microdata. Looking ahead, the importance of digitalisation on wage growth might increase especially if – as anticipated in the literature¹⁶⁷ – the share of jobs that can be automated increases further.

¹⁶⁶ For a review of the literature, see Venus, Nickel and Koester (2019).

¹⁶⁷ See Section 5, "Labour market".

Although productivity gains can generally be expected to lead to higher real wages, the apparent disconnect between productivity and real wage growth in the euro area over the last few decades means that the impact of digitalisation on wages and consumer price inflation cannot be assessed with certainty. In a survey of large European companies, almost all respondents from the manufacturing and services sectors reported that they expected productivity gains, driven by the ease of sharing knowledge and more efficient production processes as a result of digitalisation.¹⁶⁸ However, there is evidence that from the early 1990s, the link between productivity and real wage growth weakened considerably in the euro area, also leading to a fall in the labour share (see International Monetary Fund (2017a), (2017c) and OECD, 2018a). Differences in the existence, extent and timing of any disconnect across euro area countries could partly reflect differences in technological advancements, global integration and institutional characteristics, including regulations (see International Monetary Fund, 2017c).

Last but not least, as described in Box 9, another factor to consider is that the adoption of digital technologies may be associated with market concentration among a handful of superstar firms, which may result in some inflationary effects in the longer run.¹⁶⁹

¹⁶⁸ See Box 11 and Elding and Morris (2018).

¹⁶⁹ See, for example, the speech by Andrew Haldane, Executive Director and Chief Economist of the Bank of England in Haldane (2018) and Shapiro (2019).

Appendix

Box 10

Trust and digital technologies

Prepared by Lara Vivian

Low levels of trust in new technologies could potentially hinder adoption and therefore limit the benefits of digitalisation on the economy. While a large body of literature investigates the relevance of trust for growth (Beugelsdijk et al., 2004), little has been written on the relevance of trust for technology adoption. However, in order to deploy the potential of technologies for growth and productivity, individuals, firms and governments need to rely on the security of the new digital environment. Chart A summarises some selected indicators of trust.¹⁷⁰ We focus on three indicators of trust that cover both enterprises' and individuals' behaviour: (a) enterprises which had a formally defined ICT security policy in 2015, suggesting that ICT security and data protection tasks are integrated into their business practices; (b) the percentage of internet users who experienced online privacy violations within 12 months prior to being surveyed; and (c) the percentage of internet users who did not buy goods or services over the internet owing to payment and privacy concerns during the previous year.

A fairly small fraction of enterprises formally integrate security risks related to internet usage into their business processes. Chart A plots the distribution across countries of the above-mentioned indicators. The first indicator, "enterprises had a formally defined ICT security policy (as of 2015)", is on average around 35, suggesting that almost two-thirds of enterprises are not managing ICT security in order to ensure integrity and confidentiality of their data and ICT systems. Various explanations may drive this behaviour; the low levels of internet and data usage of most enterprises, for instance, could potentially make setting up an infrastructure that protects against the risks of the internet largely irrelevant. Likewise, the enterprise may not be aware of the possible risks of using the internet and may therefore decide against the need to invest in the protection of their systems. In terms of country heterogeneity, half of the enterprises in Belgium and Portugal had a formally defined ICT security policy in 2015, while only 20% or fewer of businesses are concerned with security risks related to the internet in countries such as Bulgaria, Estonia, Hungary and Poland.

Privacy violation episodes are still rare, but security concerns held back purchases online in countries such as Sweden and Romania. The share of individuals who experienced privacy violation is relatively low, reaching at most 7% in Italy. By contrast, for a notable number of countries, a large majority of internet users refrained from purchasing goods or services online owing to security concerns during 2015. In Romania, for instance, this indicator of security concerns was above 35%, while it ranged between 35% and 40% for Sweden, France and Portugal. However, any comparison of these statistics across countries should be carried out with caution, as they might be affected by the different frequency of internet usage across countries, meaning that frequent internet users may be exposed to higher risks than individuals who seldom surf the internet. Nevertheless, although the selected indicators need to be interpreted with caution, they may highlight possible channels through which lack of trust may hinder full adoption and deployment of new technologies.

¹⁷⁰ These indicators of trust are based on the Eurostat datasets relating to ICT use by households, individuals and enterprises.

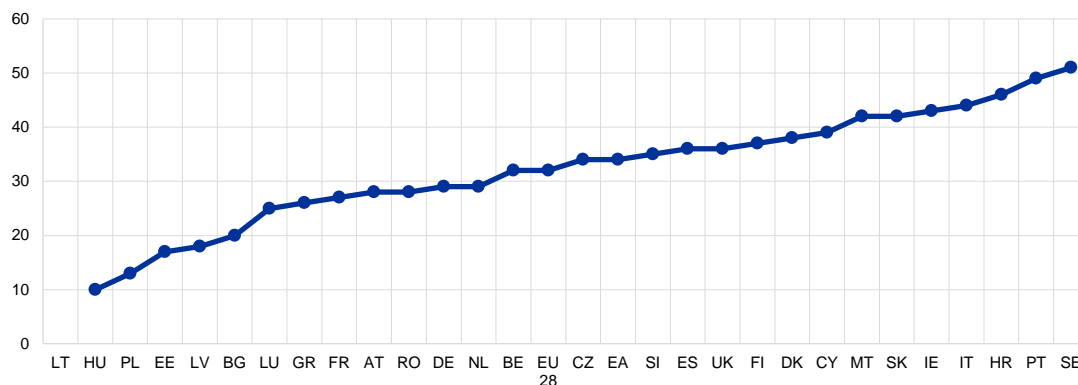
Chart A

Selected countries: indicators of trust related to digitalisation

(percentages; 2015)

● Enterprises had a formally defined ICT security policy (as of 2015)

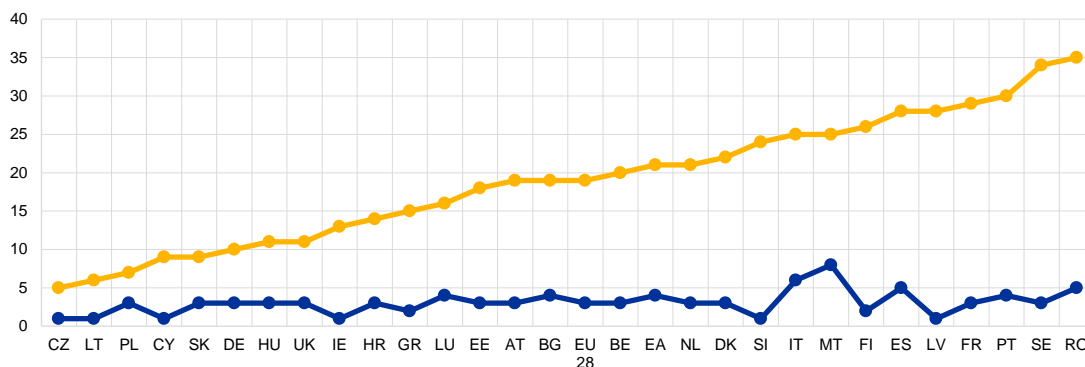
a) Percentage of enterprises which use the internet



● Abuse of personal information sent on the internet and/or other privacy violations

● Security concerns limited or prevented individuals from ordering or buying goods or services

b) Percentage of individuals who use the internet



Sources: Eurostat databases on ICT usage in households and by individuals and ICT usage in enterprises.

Box 11

Digitalisation and its impact on the economy: insights from a survey of large companies

Prepared by Catherine Elding and Richard Morris

This box summarises some of the findings of an ad hoc ECB survey of leading euro area companies carried out in 2018 looking at the impact that digitalisation has on the economy.¹⁷¹

The survey asked companies about their take-up of digital technologies and the main obstacles to the adoption of such technologies. It then asked about the various channels through which they saw digital transformation affecting key variables such as their prices, productivity and employment, as well as the expected overall direction and magnitude of the impact over the next three years.¹⁷²

The take-up of digital technologies among the companies is very high, with big data and cloud computing being the most widely adopted (Chart A). The take-up of big data and cloud

¹⁷¹ This is a shorter summary of the ECB Digitalisation Survey which was conducted in spring 2018, with the full survey results reported in Box 4 in Elding and Morris (2018).

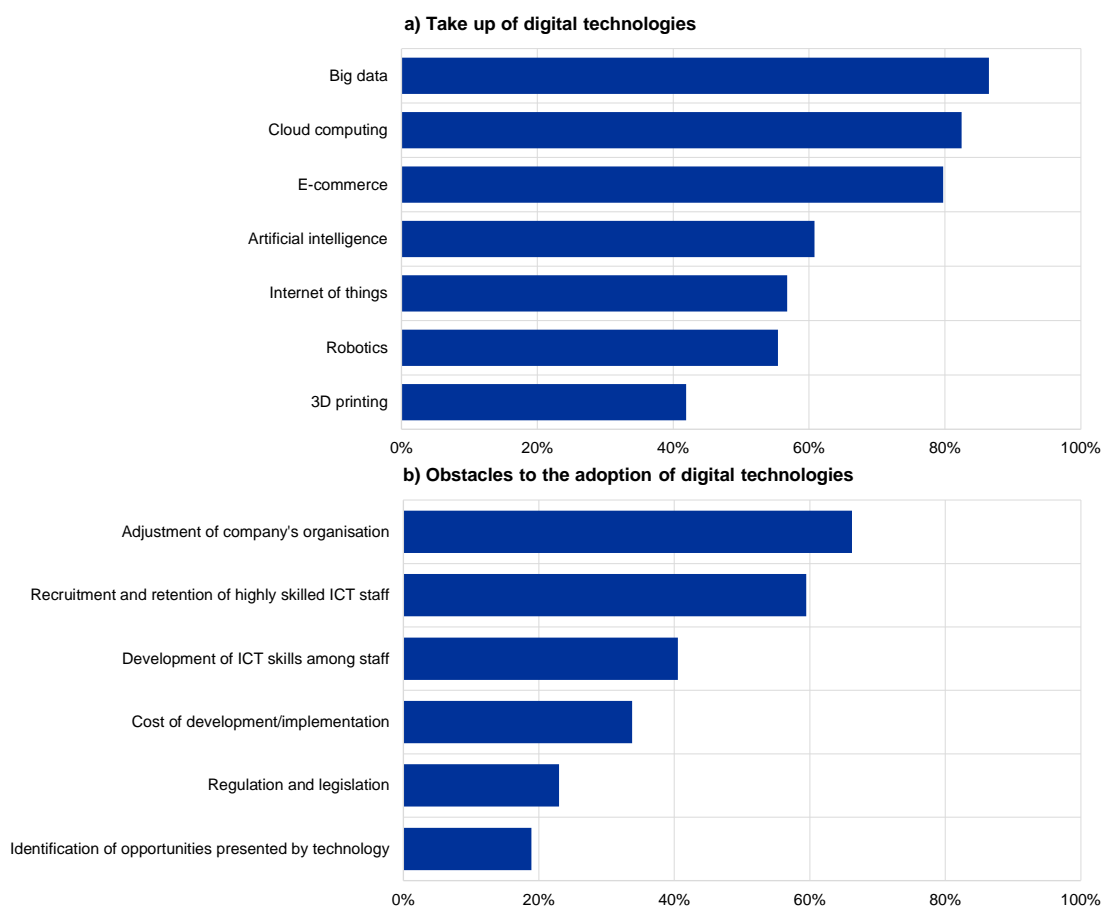
¹⁷² Responses were received from 74 leading non-financial companies, split equally between producers of goods and providers of services. Those companies were generally very large, accounting for a combined total of around 3.7% of output and 1.7% of employment in the euro area.

computing is pervasive across all sectors, as is the use of e-commerce, which is crucial in business-to-consumer segments. In the manufacturing and energy sectors, AI, IoT, robotics and 3D printing are almost equally widespread, with respondents tending to report that the real impact comes when these technologies are combined. The main obstacles to the adoption of digital technologies are the difficulty of adjusting the organisation of the company and the need to recruit and retain highly skilled ICT staff. Regulation and legislation were not typically seen as a major obstacle, although some firms noted that, while not a hindrance, regulatory frameworks need to evolve.

Chart A

Take-up of digital technologies and obstacles to their adoption

(percentages of respondents; responses ranked by overall rating)



Sources: ECB Digitalisation Survey and ECB staff calculations.

Note: Based on responses to the following two questions: "Which digital technologies has your company adopted, including those you are in the process of adopting?" and "What are the main obstacles your company faced in relation to the adoption of digital technologies?"

Respondents see digitalisation increasing their flexibility when it comes to price setting

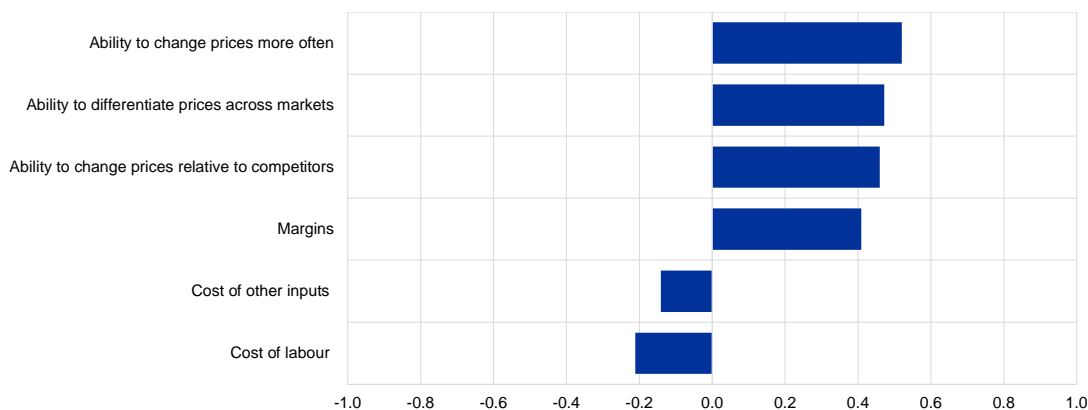
(Chart B). Around half of respondents said that the adoption of digital technologies had increased their company's ability to adjust prices in relation to their competitors. In particular, respondents stressed the ability to "leverage more accurately peaks in demand" and thereby "capture the value" of the goods and services provided to customers. At the same time, digitalisation also makes it possible to "manage and optimise sourcing much better" and "get rid of waste and friction across the value chain". While most companies, particularly manufacturers, tended to see digitalisation reducing costs and increasing margins, retailers were more likely to see input costs increasing and margins being squeezed.

Chart B

Impact of digitalisation on prices

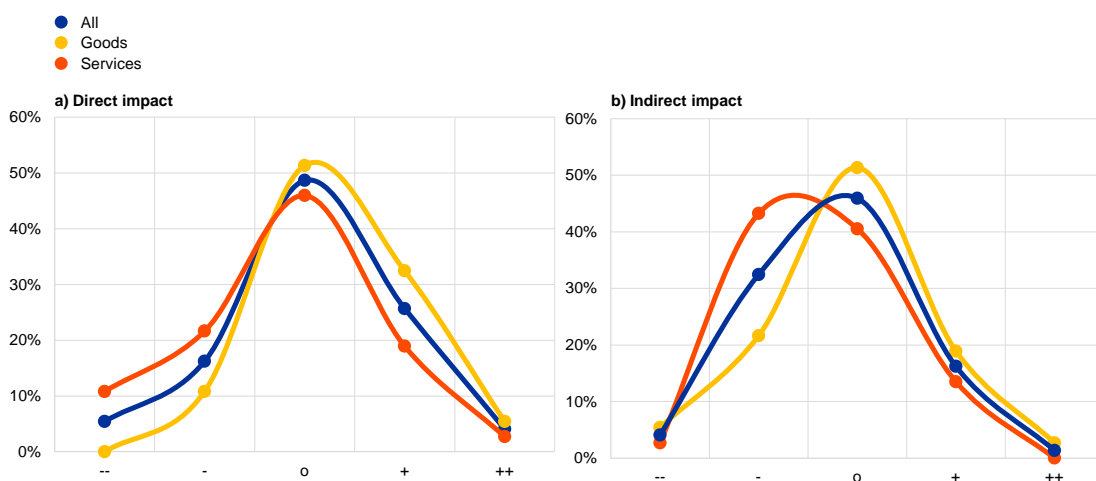
a) Channels through which digitalisation impacts prices

(average scores across all replies: -1 = decrease; 1 = increase; 0 = no change)



b) Overall impact on prices

(percentages of respondents)



Sources: ECB Digitalisation Survey and ECB staff calculations.

Note: Based on responses to questions about (i) how the adoption of digital technologies affects the respondent company's prices and costs and (ii) the overall impact that the adoption of digital technologies by (a) the respondent company and (b) other parties (i.e. suppliers, customers and competitors) is expected to have on sales prices over the next three years, with answers ranging from "significant decrease" (--) to "significant increase" (++)

The impact that digitalisation is having on prices is unclear, with downward pressure being observed mainly in the consumer services segment. Respondents were asked about the impact that the adoption of digital technologies by (i) their own company ("direct impact"); and (ii) other parties, i.e. suppliers, competitors and customers ("indirect impact"), was expected to have on prices. In both cases, the number of respondents who expected little or no impact, or were unsure, was relatively high (around 50%). On balance, producers of goods tended to see their own adoption of digital technologies as enabling them to increase prices.¹⁷³ In contrast, service providers (especially retailers) were more inclined to see the adoption of digital technologies by others as putting downward pressure on their sales prices.

¹⁷³ However, to the extent that higher sales prices reflect greater added value, this could still be consistent with digitalisation putting downward pressure on producer prices for goods and services on a like-for-like basis.

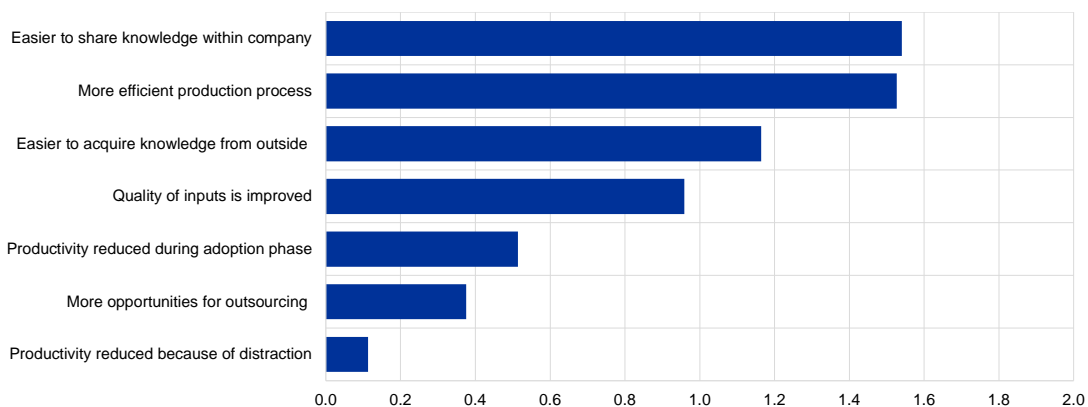
Respondents see digitalisation increasing productivity, with the increase driven by the ease of sharing knowledge and more efficient production processes (Chart C). Virtually all respondents regarded the easier sharing of knowledge (especially within the company) as being an important channel through which digitalisation raises productivity, with around half considering that aspect to be very important. The role that digitalisation plays in making the production process more efficient via automation, is equally important. Many respondents emphasised that the increase in the amount of data and information that they collected, both inside and outside of the organisation, was helping them to satisfy their customers. The overall effect on productivity was perceived to be overwhelmingly positive, with a stronger effect typically being reported in service sectors, particularly in the business-to-business segment.

Chart C

Impact of digitalisation on productivity

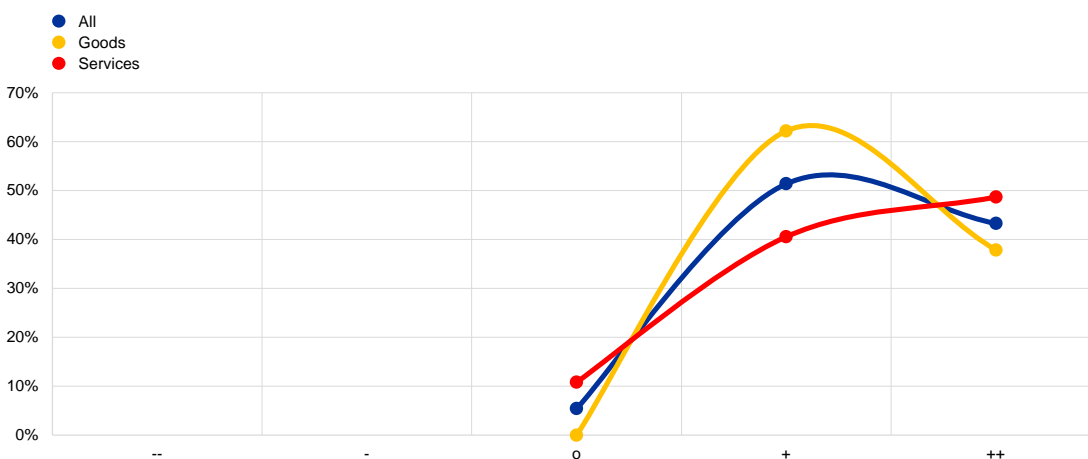
a) Channels through which digitalisation affects productivity

(average scores across all replies: 0 = not important; 1 = important; 2 = very important)



b) Overall impact on productivity

(percentages of respondents)



Sources: ECB Digitalisation Survey and ECB staff calculations.

Note: Based on responses to questions about (i) how digital technologies affect the respondent company's productivity and (ii) the overall impact that the adoption of digital technologies is expected to have on productivity over the next three years, with answers ranging from "significant decrease" (--) to "significant increase" (++)

On balance, respondents see digitalisation having a small negative impact on employment, while emphasising the importance of retraining and upskilling (see Chart D). Around one-third of respondents expected digitalisation to reduce employment in their company over the next three

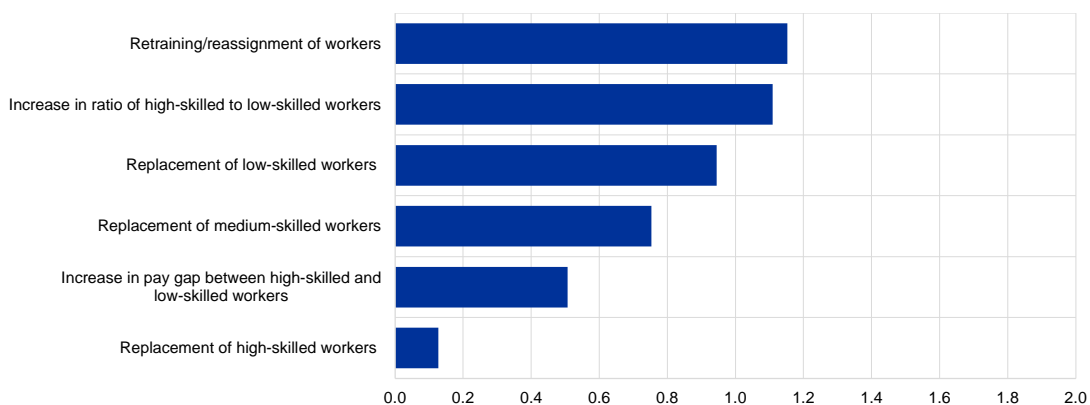
years, while around one-fifth foresaw increases in employment. Digitalisation was seen as replacing low and medium-skilled jobs, but not high-skilled jobs. Above all, digitalisation was regarded as increasing the ratio of high-skilled to low-skilled workers, with emphasis on retraining and the reassignment of workers to new tasks supported by digital technologies.

Chart D

Impact of digitalisation on employment

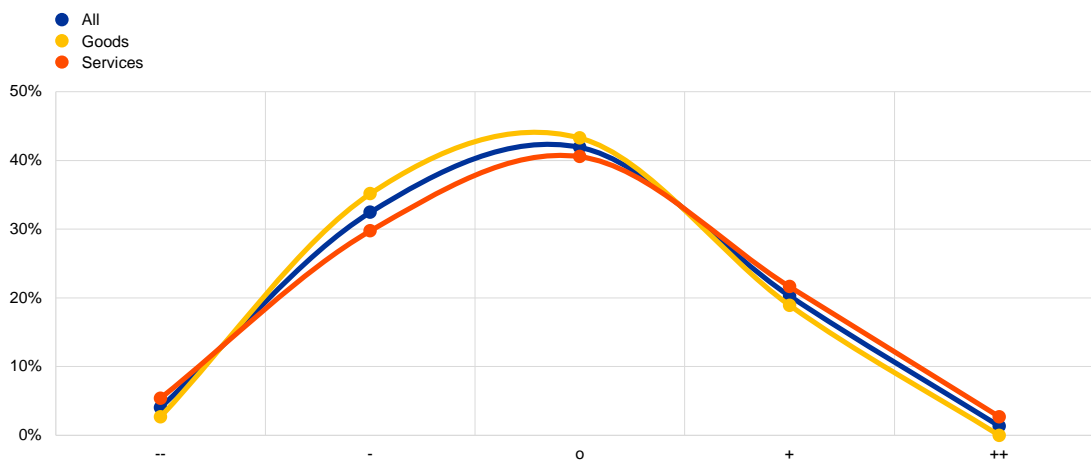
a) Channels through which digitalisation affects employment

(average scores across all replies: 0 = not important; 1 = important; 2 = very important)



b) Overall impact on employment

(percentages of respondents)



Sources: ECB Digitalisation Survey and ECB staff calculations.

Note: Based on responses to questions about (i) how digital technologies affect the respondent company's employment and (ii) the overall impact that the adoption of digital technologies is expected to have on employment over the next three years, with answers ranging from "significant decrease" (--) to "significant increase" (++)

Table A.1

The definition and classification of investment in intangibles

Intangibles (IPPs, intellectual property products) covered in the ESA2010

(definitions)

A1.10 Intellectual Property Products (AN.117)

Fixed assets that consist of the results of research and development, mineral exploration and evaluation, computer software and databases, entertainment, literary or artistic originals and other intellectual property products, as defined below, intended to be used for more than one year.

A1.11 Research and Development (AN.1171)

Consists of the value of expenditure on creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and use of this stock of knowledge to devise new applications

The value is determined in terms of the economic benefits expected in the future. Unless the value can be reasonably estimated it is, by convention, valued as the sum of costs, including those of unsuccessful research and development. Research and development that will not provide a benefit to the owner is not classified as an asset and is instead recorded as intermediate consumption.

A1.12 Mineral exploration and evaluation (AN.1172)

The value of expenditure on exploration for petroleum and natural gas and for non-petroleum deposits and subsequent evaluation of the discoveries made. This expenditure includes pre-licence costs, licence and acquisition costs, appraisal costs and the costs of actual test drilling and boring, as well as the costs of aerial and other surveys, transportation costs, etc. incurred to make it possible to carry out the tests.

A1.13 Computer software (AN.11731)

Computer programs, program descriptions and supporting materials for both systems and applications software. Included are the initial development and subsequent extensions of software as well as acquisition of copies that are classified as AN.11731 assets.

A1.14 Databases (AN.11732)

Files of data organised to permit resource-effective access and use of the data. For databases created exclusively for own use the valuation is estimated by costs, which should exclude those for the database management system and the acquisition of the data.

A1.15 Entertainment, literary or artistic originals (AN.1174)

Original films, sound recordings, manuscripts, tapes, models, etc., on which drama performances, radio and television programmes, musical performances, sporting events, literary and artistic output, etc. are recorded or embodied. Included are works produced on own-account. In some cases, such as films, there may be multiple originals.

A1.19 Other intellectual property products (AN.1179)

New information, specialised knowledge, etc., not elsewhere classified, whose use in production is restricted to the units that have established ownership rights over them or to other units licensed by such units.

Source: Eurostat (2014).

Note: Intangibles proxied by "intellectual property products".

Table A.2

Qualitative review of the effects of digitalisation on the economy

Labour market

Topic	Authors	Dependent Variable	Estimate	Independent variable	Data sources	Countries	Years
Employment	Acemoglu et al., (2017)	Employment to population ratio	-1.330 to -0.751	Exposure to robots	Census, American Community Survey and International Federation of Robotics	US	1993-2007
	Akerman et al., (2015)	log hourly wage	0.0178 to 0.0202	Broadband interacted with high-skilled skill	Statistics Norway	NO	2001-2007
	Berman et al., (1994)	Annual change in nonproduction workers' share (High-skilled)	0.025 to 0.032	Computer over total Investment	Annual Survey of Manufactures	US[1]	1979-1987
	Dauth et al., (2018)	log of total employment	0.2310 to 0.3845	local robot exposure	IEB IFR	DE177	1994-2014
	Gallipoli et al., (2018)	manufacturing employment share	-0.23 to -0.67	ICT/IT/Technology	KLEMS	US177	1970-2014
	Gregory et al., (2016)	changes in the log of employment	-1.7	Technological change is modelled by the occupational RTI measure interacted with a linear time trend $R_j \times t$ to reflect the change of relative cost of capital in routine tasks	EU-LFS Dictionary of Occupational Titles	OECD subset	1999-2010
Hours	Gallipoli et al., (2018)	log of annual hours	0.08 to 0.10	ICT/IT/Technology	KLEMS	US	1970-2014
	Goos et al., (2009)	log of hours worked	-0.67 to -0.85	Routine Task Intensity: routine tasks, intense in both cognitive and non-cognitive routine skills	EU-LFS ONET	OECD subset	1993-2006
	Graetz et al., (2018)	changes in the log of hours worked	-0.266 to -0.289	Percentile of the distribution of robots per hours worked	KLEMS IFR	OECD subset	1993-2007
Labour Share	Goldin et al., (1998)	log change in the nonproduction-worker share of the wage bill between 1909 and 1919	0.046	Change in the fraction of total horsepower run by purchased electricity	NA US. Department of Commerce, Bureau of the Census	US	1909-1929
	Graetz et al., (2018)	changes in the log of the labour share	-0.061 to -0.153	Percentile of the distribution of robots per hours worked	KLEMS IFR	OECD subset	1993-2007
	Michaels et al., (2014)	High-Skilled Wage Bill Share	46.92 to 163.94	ICT over Value Added	KLEMS	OECD subset	1980-2004
		Medium-Skilled Wage Bill Share	-288.02 to -41.59	ICT over Value Added	KLEMS	OECD subset	1980-2004
Task	Almeida et al., (2018)	log of the ratio of cognitive to manual tasks	0.035 to 0.043	Broadband interacted with industry's technological-intensity	RAIS	BR	1999-2006
		log of the ratio of non-routine to routine tasks	0.068 to 0.077	Broadband interacted with industry's technological-intensity	RAIS	BR	1999-2006

	Autor et al., (2003)	Within-occupation change in quantile of task measure (Non-routine Analytics)	7.49 to 14.02	Computer use	CPS	US	1960-1998
		Within-occupation change in quantile of task measure (Routine cognitive)	-3.90 to -17.57	Computer use	CPS	US	1960-1998
		Within-occupation change in quantile of task measure (Routine manual)	-24.72 to 4.15	Computer use	CPS	US	1960-1998
		Within-occupation change in quantile of task measure (Non-routine interactive)	7.55 to 17.21	Computer use	CPS	US	1960-1998
	Lordan et al., (2018)	Share of automatable employment	-0.031	Minimum wage	CPS	US	1980-2005
			-0.073	Minimum wage	CPS	US177	1980-2005
	Spitz-Oener, (2006)	Annualized changes in task inputs (Non-routine Analytics)	0.086	Computer use	IAB	DE	1979-1999
		Annualized changes in task inputs (Non-routine Interactive)	0.188	Computer use	IAB	DE	1979-1999
		Annualized changes in task inputs (Routine Cognitive)	-0.312	Computer use	IAB	DE	1979-1999
		Annualized changes in task inputs (Routine Manual)	-0.561	Computer use	IAB	DE	1979-1999
Unemployment	Kuhn et al., (2014)	log unemployment spell	-0.12 to -0.27	Internet Job Search	CPS + NLSY97	US	2008-2009
Wage	Abdih et al., (2018)	log hourly wages	-0.0021 to -0.0078	Routine Task Intensity	CPS	US	1997-2017
			0.0143	Routine Task Intensity interacted with high school	CPS	US	1997-2017
			0.0224	Routine Task Intensity interacted with some college	CPS	US	1997-2017
			-0.0589	Routine Task Intensity interacted with college plus	CPS	US	1997-2017
	Acemoglu et al., (2017)	log hourly wage	-2.273 to -1.409	Exposure to robots	Census and American Community Survey IFR	US	1993-2007
		log weekly wages	-2.982 to -2.068	Exposure to robots	Census and American Community Survey IFR	US	1993-2007
	Aghion et al., (2017)	log hourly wage	0.001 to 0.030	log of R&D intensity	ONS: ASHE & BERD	UK	1994-2014
	Akerman et al., (2015)	employment rate	0.0208 to 0.0225	Broadband interacted with high-skilled skill	Statistics Norway	NO	2001-2007

Brynjolfsson et al., (2008)	earnings before interest, taxes, depreciation and amortization (EBITDA)	0.51 to 0.75	ICT/IT/Technology	Compustat	US	1987-2006
Gallipoli et al., (2018)	log of annual earnings	0.43 to 0.63	ICT/IT/Technology	KLEMS	US	1970-2014
Graetz et al., (2018)	changes in the log of average wages	0.004 to 0.070	Percentile of the distribution of robots per hours worked	KLEMS IFR	OECD subset	1993-2007

Prices

Topic	Authors	Dependent Variable	Estimate	Independent variable	Data sources	Countries	Years
Prices	Brown et al., (2002)	log of real price of insurances	-0.182 to -0.5109	Internet Job Search: Percentage from the internet	LIMRA	US[1]	1992-1997
	Gorodnichenko et al., (2018)	frequency of price changes	-0.6 to -5	Internet Job Search: log of total clicks	Online Shopping Platform	US[2]	2010-2012
			-2.5 to 0.5	Internet Job Search: log of total clicks	Online Shopping Platform	UK179	2010-2012
		price dispersion	4.34 to 4.98	Internet Job Search: log of total clicks	Online Shopping Platform	US179	2010-2012
			1.61 to 2.92	Internet Job Search: log of total clicks	Online Shopping Platform	UK179	2010-2012
	Morton et al., (2001)	prices of cars	-0.015	Internet Job Search: use of a website	Autobytel.com + JDPA	US179	1999-2000
	Orlov, (2011)	dispersion prices of flights	0.48 to 0.61	Internet Job Search: log(internet)	Origin and Destination (O&D) + various	US179	1997-2003
prices of flights		-0.28 to -0.54	Internet Job Search: log(internet)	Origin and Destination (O&D) + various	US179	1997-2003	
Yi et al., (2005)	Inflation	-4.264	Broadband	WB	OECD subset	1991-2000	

Sales and production

Topic	Authors	Dependent Variable	Estimate	Independent variable	Data sources	Countries	Years
Sales	Brynjolfsson et al., (2008)	Sales	0.26 to 0.62	ICT/IT/Technology	Compustat	US	1987-2006

Technology adoption

Topic	Authors	Dependent Variable	Estimate	Independent variable	Data sources	Countries	Years
Technology adoption	Acemoglu et al., (2018c)	change in the stock of industrial robots per thousand workers	0.559 to 1.622	Aging	IFR, KLEMS, Census	OECD subset	1993-2014
	Akcigit U. et al., (2018)	Citations	-0.059	Marginal Tax Rate	Various	US	1921-1970
		Inventors	-0.051 to -0.056	Marginal Tax Rate	Various	US	1921-1970
		Patents	-0.063 to -0.068	Marginal Tax Rate	Various	US	1921-1970
	Andrews et al., (2018)	adoption of CC, ERP, CRM etc..	0.146 to 0.316	Broadband	OECD	OECD subset	2013-2016
Criscuolo et al., (2010)	Innovation	0.016 to 0.007	R&D Personnel	ONS: ASHE & BERD	UK	1994-2000	

De Backer et al., (2017)	percentage of enterprises	97	Broadband	OECD	OECD subset	2015-2015
		78	Website	OECD	OECD subset	2015-2015
		42	E-purchases	OECD	OECD subset	2015-2015
		39	Social Media	OECD	OECD subset	2015-2015
		34	ERP	OECD	OECD subset	2015-2015
		25	CC	OECD	OECD subset	2015-2015
		22	E-sales	OECD	OECD subset	2015-2015
		18	Supply chain mngt. (ADE)	OECD	OECD subset	2015-2015
		10	RFID	OECD	OECD subset	2015-2015
Manaresi et al., (2018)	Number of patents applications	0.042	Credit supply: idiosyncratic shock to firm credit supply	CADS, ICR, INVID	IT	1997-2013
	Pcs per unit of capital	0.672	Credit supply: idiosyncratic shock to firm credit supply	CADS, ICR, INVID	IT	1997-2013

Value added/TFP/labour productivity

Topic	Authors	Dependent Variable	Estimate	Independent variable	Data sources	Countries	Years
Labour productivity	Bertschek et al., (2017)	Labour productivity	0.212	ICT	Micro Moments Database	OECD subset	2001-2010
	Black et al., (2001)	Labour Productivity	0.06	R&D Center	EQW-NES + LRD	US	1987-1993
			0.015	Share of non-managers using computers	EQW-NES + LRD	US	1987-1993
	Crespi et al., (2007)	Changes in the log of labour productivity	0.1212 to 0.299	ICT/IT/Technology	WB Various	UK	1998-2000
	Engelstätter, (2009)	Labour Productivity	0.120 to 0.138	ERP	ZEW ICT survey	DE	2004-2007
			0.135 to 0.152	Supply chain mngt. (ADE)	ZEW ICT survey	DE	2004-2007
			0.57	Share of computer workers	ZEW ICT survey	DE	2004-2007
	Graetz et al., (2018)	changes in the log of labour productivity	0.359 to 0.873	Percentile of the distribution of robots per hours worked	KLEMS IFR	OECD subset	1993-2007
	Guellec et al., (2017)	Industry labour compensation over value added	-0.054 to -0.068	Patent intensity	OECD	OECD subset	1992-2013
	Gust et al., (2004)	Labour productivity growth	0.934 to 1.411	IT production/GDP	OECD	OECD subset	1992-1999
0.896 to 1.226			IT Expenditures/ GDP	OECD	OECD subset	1992-1999	
-1.179			R&D Spending/GDP	OECD	OECD subset	1992-1999	
Roth et al., (2013)	0.29	Intangible services growth	INNODRIVE	OECD subset	1998-2005		

TFP	Autor et al., (2018)	Changes in the log of TFP	0.175	Robots per 1,000 workers	KLEMS IFR	OECD subset	1996-2015
			0.254	log of patent citations	KLEMS	OECD subset	1996-2015
	Basu et al., (2007)	TFP	7.15 to 9.51	Technology capital	NAICS and BLS	US[1]	1987-2004
	Bergeaud et al., (2018)	0.938 to 1.585	ICT/IT/Technology	Long run prod dataset	OECD subset		1890-2013
	Graetz et al., (2018)	changes in the log of TFP	0.366 to 0.663	Percentile of the distribution of robots per hours worked	KLEMS IFR	OECD subset	1993-2007
	Pellegrino et al., (2017)	-1.606	ICT Contribution	Amadeus (EFIGE) and KLEMS	OECD subset		1995-2006
	Rincon et al., (2005)	firm's productivity performance	0.324	E-purchases	IDBR E-commerce survey	UK	2001-2001
			0.247	E-sales	IDBR E-commerce survey	UK[2]	2001-2001
			0.389	E-trade	IDBR E-commerce survey	UK181	2001-2001
Value added	Akerman et al., (2015)	production function	0.0755 to 0.0645	Broadband interacted with high-skilled skill	Statistics Norway	NO	2001-2007
	Bloom et al., (2012)	0.0287 to 0.0935	IT capital per employee	ABI matched with IT data from QICE, BSCI, and FAR	UK177		1993-1993
			0.0202 to 0.038	USA ownership per IT capital per employee	ABI matched with IT data from QICE, BSCI, and FAR	UK177	1993-1993
	Chen et al., (2016)	0.066 to 0.087	ICT/IT/Technology	INTAN-invest	OECD subset		1995-2008
0.126 to 0.161			Intangibles	INTAN-invest	OECD subset	1995-2008	
Graetz et al., (2018)	changes in the log of value added	0.366 to 0.607	Percentile of the distribution of robots per hours worked	KLEMS IFR	OECD subset	1993-2007	

Note: The "Estimates" column shows the value, or range of values, of the coefficient of interest of the regression model which is estimated in the respective paper.

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