CHAPTER 4

BUSINESSES AND SKILLS IN THE DIGITAL AGE

CHAPTER
4.1

PRODUCTIVITY

KEY FIGURES

11 %
overall labour productivity growth from 2010 to 2019 in the European Union

50 %
of productivity levels in the European Union is explained by human capital

8 %
of productivity growth in the European Union is explained by R&D

19 %
of productivity growth in the European Union is explained by software and computerised information

KEY QUESTIONS WE ARE ADDRESSING

- Why is productivity relevant for society?
- What are the main drivers of productivity in the EU?
- How can we explain the productivity slowdown?

KEY MESSAGES

What did we learn?

- Productivity and economic growth are important for boosting competitiveness, socio-economic development and tackling poverty.
- Economic growth can be enabled within a sustainable and inclusive economic model, supported by a broader diffusion and uptake of digital and clean technologies, as well as significant investments in breakthrough technologies.
- It is possible to decouple economic growth from environmental damage.
- The EU outperforms its international competitors in directing its accumulated wealth toward the achievement of the UN's Sustainable Development Goals.
- Human capital is the most crucial contributor toward labour productivity, followed by physical capital and R&D investments.
- Control of corruption is the main framework condition driving higher productivity levels.
- Despite the huge potential of the ICT revolution, there is a secular stagnation in productivity growth. This productivity puzzle is partly explained by increasing productivity polarisation, declining business dynamism and the high cost of human capital for firms adopting new digital technologies.
- The COVID-19 pandemic has impacted the economy, industries, firms and individuals in very diverse and uneven ways. The most negatively affected have been low productivity sectors, low-income households and young people.

What does it mean for policy?

- Enhanced productivity in combination with political and electoral will can be the means to achieve inclusive growth and desirable outcomes.
- Human capital policies will be important to improve future productivity and wellbeing.

- Organisation management, physical capital, international trade and competition can positively affect economic growth and productivity.
- Tackling corruption and easing access to finance are low-cost policy tools to improve productivity levels.
- The disproportionally large impact of COVID-19 on youth and other specific groups calls for specific attention and includes compensatory policies to mitigate the risks to inclusive growth.

1. Productivity, economic growth and well-being

Productivity is an important economic indicator that is closely linked to economic growth, competitiveness and living standards within an economy. All measures of productivity refer to the efficiency with which we are able to transform input such as resources into output such as products. In other word, productivity is efficiency in production: how much output is obtained from a given set of inputs.

Productivity is typically measured as Labour Productivity or Total Factor Productivity (TFP):

- TFP is a proxy for technological progress. It represents the efficiency with which factors of inputs (labour and capital) are combined. It depicts the effect in total output not accounted for by labour and capital inputs through other factors such as technology, efficient organisational management and the quality of institutions. TFP is computed through an accounting exercise, following the methodology introduced by Solow (1957).
- Labour Productivity is a proxy of the efficiency and quality of human capital in the production process for a given economy. It is measured as the total volume of output (measured in terms of Gross Domestic Product, GDP) produced per unit of labour (measured as the number of employed persons or as hours worked) during a given time reference period.

Economic growth and productivity are relevant to the goals of tackling poverty and freeing individuals from misery. Economic growth is often the main contributor to poverty reduction (White and Anderson 2001, Dollar and Kraay 2002). Kraay (2004) finds that economic growth (measured by growth in average incomes) explains around 70 % of the changes in poverty (measured by the headcount ratio) in the short term, and around 97 % in the long term. Within the European Union, Beugelsdijk et al. (2018) find that a large part of the persistent differences in economic development across subnational European regions can be attributed to differences in TFP. Productivity positively affects firms' financial performances (Grifell-Tatjé et al., 2018). It enhances corporate financial performance through lower costs, to the benefit of consumers through lower prices (Syverson 2011). At the same time, productivity can be employed to achieve desirable societal objectives (see Box 4.1).

Isaksson et al. (2005) describe productivity as a key element for raising living standards and reducing poverty. Amartya Sen (1999) and Acemoglu (2008) reach similar conclusions by arguing that economic development is deeply linked to economic growth, with however the institutional and political dimension playing a crucial role in the redistribution effort of such generated resources.

'Without productivity growth there would be no social advancement. Without productivity gains there cannot be welfare gains. Yet, it must be admitted that productivity gains are only the wherewithal to welfare improvement. Economic mechanisms may offer a productivity outcome and propose a distribution between consumers (by way of price reductions) and factors connected to production (by way of remuneration of their services). But how this distribution will actually occur, and how effectively it will be directed to welfare improvement, is another story. Here, it is the interplay of socio-political processes that will have the last word.' (Isaksson)

'Productivity is not everything, but in the long run it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker.' (Krugman)

Box 4-1 Productivity and societal objectives

Productivity can also be a useful tool to achieve desired societal objectives. Figure 4.1-1 depicts the relationship between different productivity measures and various measures of meritorious societal objectives: Sustainable Development Goals Index[1] (SDG Index), Human Development Index[2] (HDI) and Environmental Performance Index[3] (EPI). The scatterplots contain cross-country level data for 193 nations, related to the last available year.

Economic growth makes it possible for nations to choose to invest in policies and ambitious programmes that lead to environmentally and socially desirable outcomes. Figure 4.1-1 shows that the Sustainable Development Goals Index (SDG Index) is positively correlated with per capita gross domestic product and total factor productivity. Figure 4.1-1 also shows that the Human Development Index (HDI) is positively correlated with per capita gross domestic product and total factor productivity. Third, and finally, Figure 4.1-1 shows that the Environmental Performance Index (EPI) is positively correlated with per capita gross domestic product and total factor productivity.

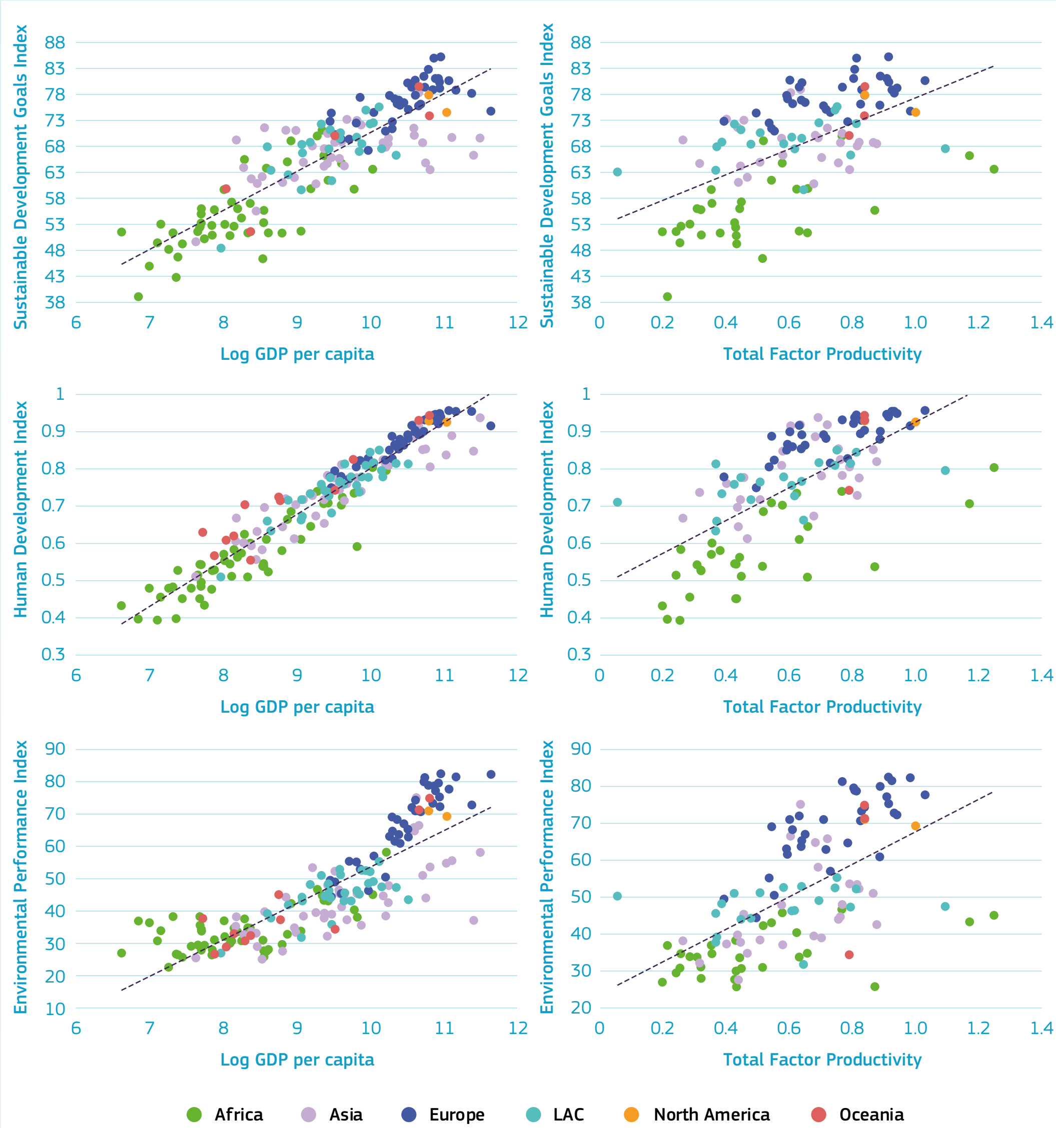
Even though the presented plots do not represent causal evidence, they are an instructive descriptive depiction of the relationships at play. Interestingly, we can observe that European countries are, in most of the cases, above the fitted line, meaning that they are overperforming their peers in term of sustainable/ meritorious use of their generated wealth.

1 In 2015, the United Nations introduced the 17 Sustainable Development Goals (SDGs). The SDGs provided a shared blueprint for peace, prosperity, people and the planet. They measure how well countries are performing in terms of improving health and education, reducing inequality and poverty, tackling climate change and preserving oceans and forests. The SDG Index is a composite index introduced by Schmidt-Traub et al. (2017) to provide a standardised and quantitative measure of SDG baselines for 149 countries. It synthesises 63 global indicators plus 14 additional indicators for OECD countries into an overall assessment of countries' SDG performances.

2 The Human Development Index (HDI) is a composite index developed by the United Nations Development Programme. It measures the average achievement of 195 countries on three dimension of human development: long and healthy life, education and decent standard of living.

3 The Environmental Performance Index (EPI) is a composite index for country performance on sustainability issues developed by the Center for Environmental Law & Policy of Yale University. EPI ranks 180 countries on environmental health and ecosystem vitality, employing 32 indicators of environmental performance related to Air Quality, Sanitation & Drinking Water, Heavy Metals, Waste Management, Biodiversity, Fisheries, CO_2, etc.

Figure 4.1-1: Productivity vs societal and environmental outcomes, 2019



Source: DG Research and Innovation – Common R&I Strategy and Foresight Service - Chief Economist Unit's own elaboration.
Note: GDP per capita, PPP (constant 2017 international $) is collected from the World Bank's database. TFP level at current PPPs is collected from the Penn World Table version 10.0. Overall, up to 193 countries are plotted.
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Yet productivity should not be interpreted as panacea for all issues in society, rather as a tool to generate the necessary resources to invest in the public and private goods. In other words, higher levels of productivity and economic performance on their own do not ensure the achievement of societal goals. A higher productivity level increases countries' resources and tools to reach a goal, given that nations want to do so. The political will to employ economic means toward desirable goals remains a political choice, one that depends on electoral outcomes. Having the resources is a necessary but non-sufficient condition.

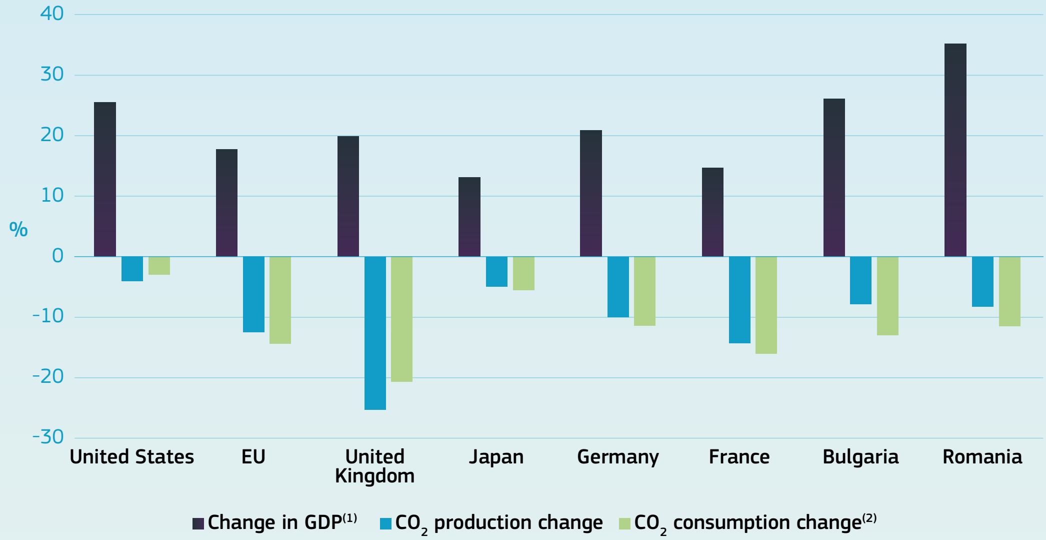
With the adoption of the European Green Deal, the European Commission has showed a strong will to employ economic means toward the achievement of the Paris Agreement objectives in line with UN's Sustainable Development Goals. The Intergovernmental Panel on Climate Change (IPCC) report[4] has been taken into consideration for the construction of the EU's strategy for long-term greenhouse gas emission reduction[5]. The European Commission's communication *A clean planet for all* highlights how the EU's climate policy strategy should engage all sectors of the economy and society, ensuring that the transition toward emission neutrality is socially fair, enhances the competitiveness of the EU's economy and industry on global markets, and secures quality jobs, sustainable growth, eradicate poverty, while providing synergies with other environmental challenges, such as air quality and biodiversity loss[6].

The new EU annual sustainable growth strategy (ASGS) is structured around four dimensions: environmental sustainability, productivity, fairness and macroeconomic stability. It represents the EU's ambition to transform to a fair and prosperous society with a resource-efficient and competitive economy[7]. Climate change related damage is likely to negatively affect future labour productivity, with high related economic and social costs. Hence, employing economic means, as well as research and innovation, to succeed in the twin transition is increasingly seen as a crucial policy priority for the EU.

Addressing the climate and environmental crisis is the defining challenge of our time and it is an opportunity to relaunch our economies in a sustainable manner. To do so, it is fundamental to put the economy on the right track to long-term sustainable growth and employment aiming at reaching climate neutrality by 2050 and decoupling economic growth from resource use (European Commission, 2021). Recent data shows that increasing economic prosperity while reducing CO_2 emissions is possible. In the last 10 years, different countries managed to improve their GDP while reducing their CO_2 emissions (both adjusted and non-adjusted for trades). Such a result was possible for both rich economies, such as the US, Germany, France, UK and Japan, and emerging economies, such as Bulgaria and Romania (see Figure 4.1-2). As an example, from 2009 to 2019 Germany's GDP grew by 21%, while CO_2 emissions fell by around 10%. During the same time period, Bulgaria saw its GDP growing by 26%, while its CO_2 emissions falling by 8%.

4 See here for more.
5 Cutting emissions by at least 55% by 2030 and achieving climate neutrality by 2050.
6 See here for more.
7 See here for more.

Figure 4.1-2: Percentage change in GDP and CO_2 emissions between 2009 and 2019



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Source: Global Carbon Budget – Global Carbon Project (2021) and World Development Indicators – World Bank.

Note: [1] Gross Domestic Products is expressed as PPP (constant 2017 international dollars).

[2] Consumption-based emissions are national emissions which have been adjusted for trade (i.e. territorial/production emissions minus emissions embedded in exports,- plus emissions embedded in imports).

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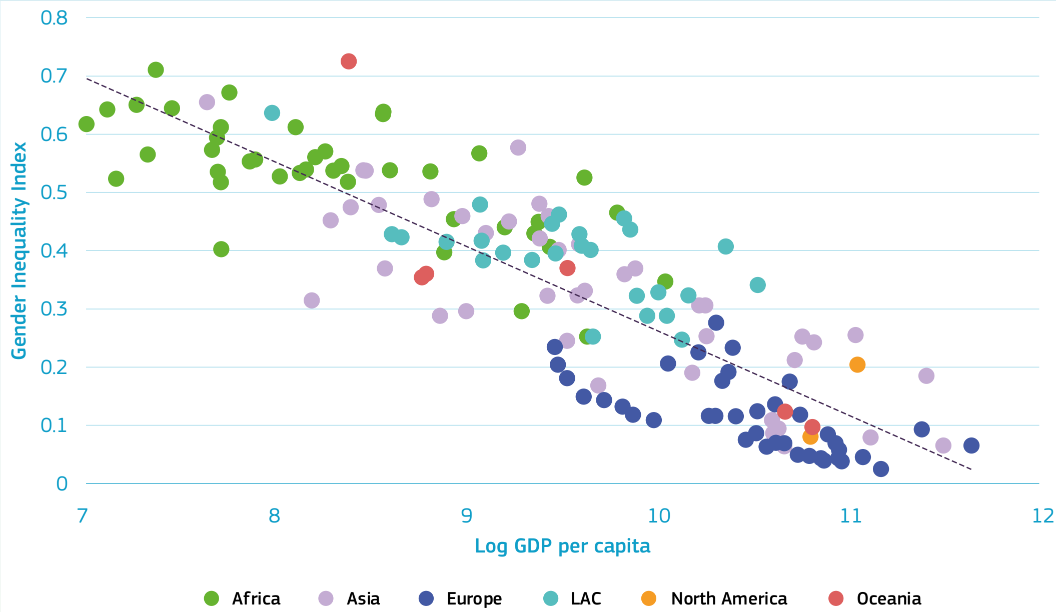
Higher levels of productivity worldwide are also associated with less gender inequality. Indeed, the countries were women are treated fairer are also those that perform better economically, and societies become more productive as they treat women better. Hudson et al. (2012) uses micro and macro data from around the world to highlight how nations fail when women are treated unequally, as they end up being less meritocratic, less stable and more violent. Figure 4.1-3 depicts the relationship between productivity and gender inequality, confirming that superior levels of productivity are associated with lower levels of gender inequality. European countries are, in most of the cases, below the fitted line, meaning that they are over performing their peers in term of gender equality given a similar obtained wealth.

Figure 4.1-3: **Productivity vs gender inequality, 2019**



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Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit based on the Gender Inequality Index (higher levels of the GII imply more gender inequality) produced by the United Nations and GDP per capita, PPP (constant 2017 international $) collected from the World Bank database.
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Less clear is evidence of the effect of productivity growth on income inequality. Indeed, the empirical evidence is so far rather mixed and inconclusive. Easterly (1999) finds that economic growth has a positive impact on different indicators of quality of life. Lopez (2004) finds that regardless of their impact on inequality, pro-growth policies lead to lower poverty levels in the long term, even though mixed distributional effects in the short term are possible. Dollar and Kraay (2002) find that the average incomes of the poorest quintile rise proportionately with average incomes. Ravallion and Chen (1997) find that changes in inequality and polarisation are uncorrelated with changes in average living standard.

The effect of inequality on productivity growth is mixed too. Alesina and Rodrik (1994), Persson and Tabellini (1994), and Perotti (1996) find a negative relationship between inequality and growth. Li and Zhou (1998), Forbes (2000), and Banerjee and Duflo (2003) find a positive relationship. Barro (2000) finds no relationship. More recently, Ostry, Berg and Tsangarides (2018) find that low inequality (as long as this is not obtained through extensive redistribution policies) is positively correlated with faster and more durable growth. Banerjee and Duflo (2003) find an inverted U-relationship between growth rates and inequality. Van der Weide and Milanovic (2014) find that high levels of inequality reduce the income growth of the poor, while increasing the income growth of the rich.

To sum up, the existing evidence presents productivity and economic growth as important for boosting competitiveness, socio-economic development and tackling poverty, while their link with inequality is yet to be clarified. The unclear link between productivity and inequality is likely driven by the major role played by institutions and citizens' political preferences regarding the reallocation decisions of the resources generated by the economic system. This makes productivity a useful metric for policymakers to measure economic competitiveness and resource capacity to address politically defined objectives.

2. The main drivers of productivity

Given the importance of productivity, a central issue for policymakers is to uncover its main drivers. In other words, **how can we boost productivity?**

There are both firm level and institutional drivers of productivity. At the firm level, it has been found that innovation, management practices and human capital are key determinants of higher productivity. In the aggregate, a stable macroeconomic environment, property right enforcement, openness to trade, effective government, and properly regulated markets are other key factors (Grifell-Tatjé et al. 2018, Syverson 2011, Bartelsman and Doms 2000).

Innovation is a crucial driver of productivity. Innovation boosts productivity through the development and deployments of new products and processes. This enables firms to generate greater output with the same input, which increases the production of goods and services, culminating in higher incomes for employees and entrepreneurs. Innovation usually starts on a small scale, for example when a new technology is first applied by the company where it has been developed. However, to realise the full benefits, innovations needs to spread across the economy and benefit companies in different sectors and of different sizes. This process of innovation diffusion will boost productivity and income levels. Innovation at the firm level can be divided into different categories: product, process, organisational and marketing innovation. Empirically, regardless of the innovation measurement employed, innovation has been found to explain differences in productivity not only across firms, but also across industries and nations (Mohnen and Hall 2013, van Leeuwen and Klomp 2006, Raymond et al. 2015). In addition, the number of patents a company introduces has been positively associated with productivity (Balasubramanian and Sivadasan 2011). Belderbos, Carree, and Lokshin (2004) find that R&D cooperation with competitors, suppliers, customers, and universities and research institutes raises productivity levels.

As already mentioned, other important drivers of productivity are:

- **Human capital.** The importance of human capital for individual wage and productivity has been extensively studied in economics micro-level analysis reveals a strong positive link between measures of human capital (such as education attainment, professional training and experience) and productivity (Abowd et al. 2009, Beaulieu et al. 2014, Chang et al. 2016). See Chapter 5.4 for more.

- **Organisation management.** Different studies have explored the role of management practices and firms' organisation on productivity. Bloom and Van Reenen (2007) interviewed 732 medium-sized firms in the United States, France, Germany, and the United Kingdom and ranked them based on their use of 'best managerial practice' (using management consultancy evaluation tools). The finding shows that the presence of best practices is strongly associated with firm-level productivity, profitability, and survival rates. Bloom et al. (2013) run a management field experiment on large Indian textile firms. The authors provided free consulting on management practices to randomly chosen treatment plants, and compared their performance to a set of control plants. The adoption of such management practices was found to raise firms' productivity. Among the reasons for the lack of adoption of 'managerial best practices' are information barriers, transition costs and the sorting of less competent managers into dysfunctional companies.

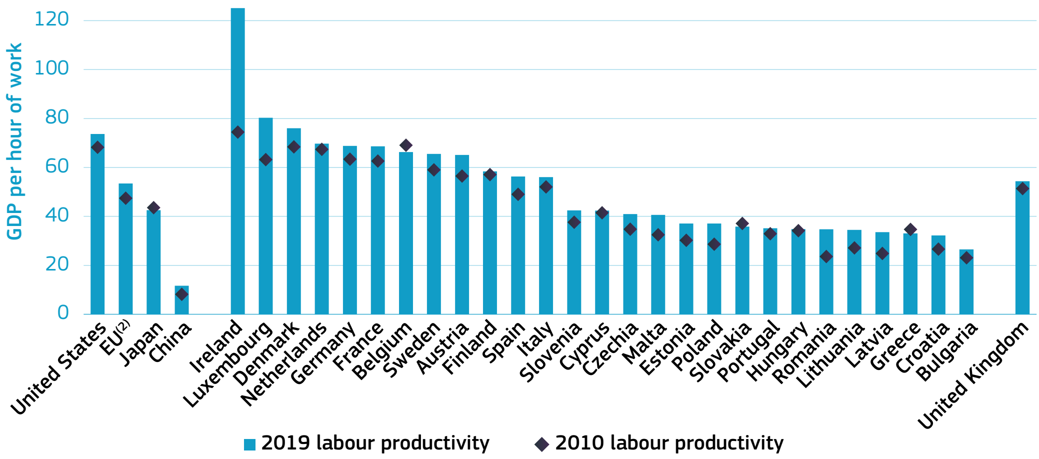
- **Physical capital.** Investment in tangible goods, such as land, buildings, machinery and equipment, improves firms' productivity.

- **Trade.** International trade, both import and export activities, represents a relevant driver of productivity growth. Theoretically, the positive impact of international trade on innovation and productivity comes from both knowledge spillovers and increased competition (Silva, Afonso, and Africano 2012, Bas and Strauss-Kahn 2014). Empirically, both exporting firms and importing firms have been found to be more productive than non-exporting and non-importing ones (Bartelsman and Doms 2000, De Loecker and Goldberg 2014, Kasahara and Lapham 2013). This is not only because of self-selection of more productive firms into importing or exporting activities (Bernard and Jensen 1999), but there is also an additional positive impact of export on productivity thanks to 'learning by exporting effects' (Atkin, Khandelwal and Osman 2017, De Loecker 2007). Similar 'learning by importing effects' are detected by Augier, Cadot, and Dovis (2013) and Kasahara and Rodrigue (2008).

- **Competition.** Competition can affect productivity through Darwinian selection and the escape-competition mechanism. Darwinian selection raises average productivity by pushing less productive firms out of the market, while fiercer competition increases the incentives for firms to innovate in order to escape competition (Aghion 2001, Syverson, C. 2011). Empirically, Aghion, P. (2018) shows an example of escape competition. Aghion (2005) also finds strong evidence of an inverted-U relationship between product market competition and innovation. Schmitz (2005) offers an example of heightened competition. Syverson (2004) shows the importance of pro-competitive environment in the US and Giuseppe Nicoletti and Scarpetta (2006) shows the same in OECD countries. At the same time, poorly regulated markets can generate perverse incentives that diminish productivity. See Chapter 7.2 for more information.

Figure 4.1-4 depicts the labour productivity across European countries, the US, Japan and China. Figure 4.1-5 depicts the Total Factor Productivity levels across European countries, the US, Japan and China. Overall, in the EU labour productivity grew by 11 % from 2010 to 2019. Ireland and Luxemburg present the highest level of labour productivity, yet such results should be taken with caution due to measurement issues of the GDP. Indeed, Ireland's high concentration of foreign multinationals drives its largest productivity gains: many tech giants like Google, Facebook, and Apple book profits in Ireland from other jurisdictions. This inflates the country's GDP, making labour productivity measurement likely overstated. On the other hand, Luxembourg's high productivity levels is driven by financial sector and high share of border workers. The US has a higher level of productivity than EU, the UK and China. Despite China's remarkable economic growth over the last decade, the country still remains behind in terms of productivity per worker, with performances lower than all EU Member States. Total factor productivity figures show a similar trend and ranking to labour productivity ones.

Figure 4.1-4: **Labour productivity⁽¹⁾, 2010 and 2019**



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Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit own elaboration

Note: [1] Labor productivity is calculated using data from the Penn World Table version 10.0 as gross domestic product (GDP PPP constant 2017) per hour of work by employing the formula: (rgdpo) / (avh * emp). [2] EU is computed by DG Research and Innovation - Common R&I Strategy and Foresight Service - Chief Economist Unit.

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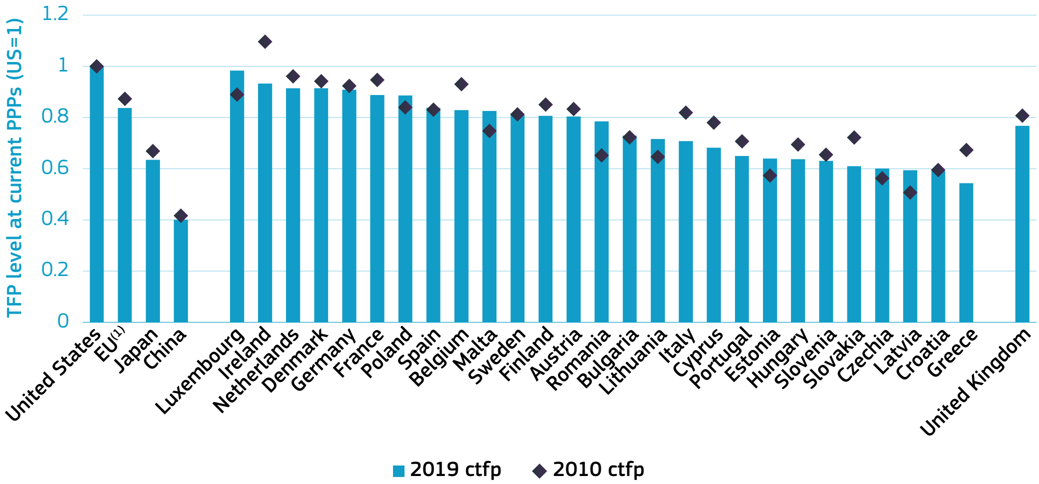
Figure 4.1-5: **Total factor productivity, 2010 and 2019**



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Source: The Penn World Table version 10.0.

Note: EU[1] is computed by DG Research and Innovation - Common R&I Strategy and Foresight Service - Chief Economist Unit as weighted average based on nominal GDPP

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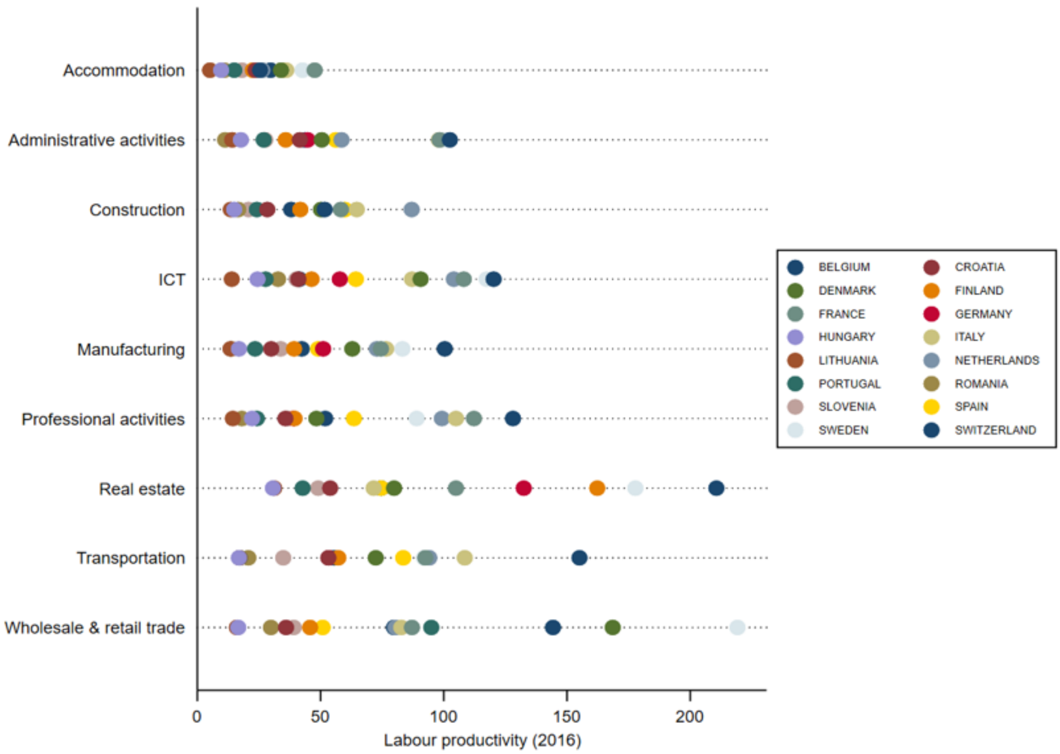
Country level aggregates of productivity hide a vast heterogeneity of productivity levels within countries, across firms and sectors. This implies that the aggregate productivity level of a country does not only depend on its sectoral composition, but also on the underlying productivity distribution across firms. Figure 4.6 depicts such wide variation of productivity levels across European countries and sectors. Looking at unweighted overages, the accommodation and administrative sectors are the least productive, while the wholesale and retail trade sector is the most productive. Countries specialise in different sectors, showing to be more productive in areas where other nations are instead conspicuously less productive.

To understand the current European drivers of productivity, we perform an econometric exercise using country-sector-year data from CompNet's 7th Vintage and country-year data from the World Bank and Eurostat databases (see Box 4.2 for more details).

Figure 4.1-6: Cross-country-sector labour productivity heterogeneity



Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit own elaboration based on CompNet's 7th vintage dataset.
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Box 4-2: Computing the contribution of human capital to labour productivity in the EU

Firstly, we define a Cobb Douglas production function with a Human Capital term $Y=A \times K^{z} \times (H \times L)^{1-z}$ where Y represents the produced output, A is the level of efficiency in the use of the inputs (TFP), K is the physical capital, L is the work force and H is the human capital (cost of human capital) embedded in the workforce. The output elasticity of capital (labour) is indicated by z (1-z). By dividing the production function by L and taking the logs of the components, we obtain a formula for labour productivity, which can be estimated by implementing a simple OLS regression:

$$Log\left(\frac{Y}{L}\right) = z \times log\left(\frac{K}{L}\right) + (1 - z) \times log(H) + log(A)$$

Hence, we regress labour productivity on capital intensity, human capital stock, and some proxies of TFP such as allocative efficiency (measured by the OP gap[8]), concentration (measured by the Herfindahl-Hirschman Index - HHI), credit availability (measured by the share of unconstrained firms), research and development investments (measured as share of GDP) and degree of corruption (measured with the Worldwide Governance Indicators of the World Bank).

Table 1 shows the marginal effects of the different drivers of labour productivity using sector-country-year level data from 1999 to 2017 for 18 EU member states. To compute such estimation a panel regression model with fixed effects is employed.

8 A developed by Olley and Pakes (1996), by computing the extent to which firms with higher productivity have a larger market share. The OP gap is computed as the covariance of the change in productivity and firm size with respect to the mean.

Table 4.1-1: Regression results

VARIABLES	(1) Productivity	(2) Productivity	(3) Productivity
Capital Intensity	0.100*** (0.00926)	0.114*** (0.0134)	0.122*** (0.0130)
Human Capital	0.562*** (0.0223)	0.423*** (0.0364)	0.410*** (0.0335)
Credit Access	0.143*** (0.0246)	0.0814*** (0.0178)	0.0576*** (0.0155)
Concentration	0.374 (0.240)	0.452* (0.245)	0.588*** (0.188)
Allocation	0.672*** (0.0306)	0.584*** (0.0431)	0.543*** (0.0427)
R&D Investments	0.174*** (0.0189)	0.165*** (0.0112)	0.162*** (0.00998)
Control of Corruption	0.0622** (0.0295)	0.0951*** (0.0168)	0.103*** (0.0169)
Constant	1.108*** (0.0872)	1.574*** (0.115)	1.615*** (0.109)
Observations	5,250	5,227	5,132
R-squared	0.888	0.975	0.982
Country FE	YES	YES	YES
Sector FE	YES	YES	YES
Year FE	YES	YES	YES
Country × Sector FE	NO	YES	YES
Sector × Year FE	NO	NO	YES

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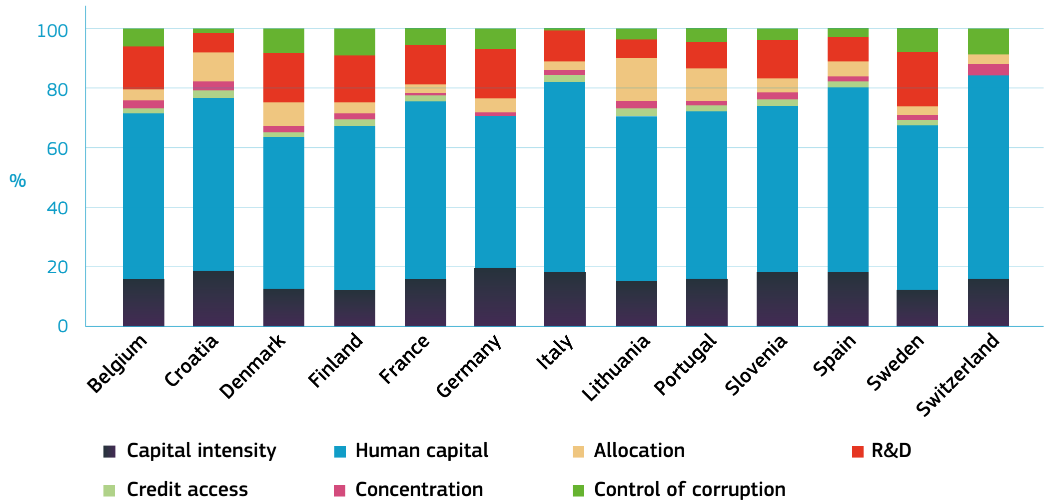
Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit's own elaboration based on CompNet's 7th vintage dataset, World Bank and Eurostat data. Note: robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Using the estimated marginal effects of Table 4.1-1, we construct the relative contribution of each observed driver toward labour productivity, as shown in Figure 4.1-7.

Human capital is the most crucial contributor toward labour productivity, followed by physical capital and R&D investments. On average it accounts for around 50% of the explained variation in labour productivity across European countries. Research and development investments account for around 15% of the explained variation in labour productivity. Physical capital accounts for around another 15% of the explained variation, while credit access, market concentration, allocative efficiently and government corruption jointly account for the remaining part (see Figure 4.1-7).

Figure 4.1-7: **Explained contribution to labour productivity (2016)**



Source DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit's own elaboration based on CompNet's 7th vintage dataset, World Bank and Eurostat data.
Notes: The contribution shares to labour productivity are derived from the regression estimate of Table 1, column 3
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Box 4-3: Intangible Capital and Labour Productivity Growth – A Cross-Country Sectoral Growth Accounting Approach - Felix Roth (University of Hamburg)

Figure 4.1-8 displays the results of an econometric cross-country sectoral growth accounting (CCSGA) approach. The estimation approach at the sectoral level is developed by Roth in the Horizon 2020-funded GLOBALINTO project (Roth and Sen 2021) and resembles an extension of the author's earlier work at the country level as developed within the FP7-funded INNODRIVE project (Roth 2022, Roth 2020 and Roth and Thum 2013). Figure 4.1-8 is based on the following model specification:

$$Q_{c,j,t} = A_{c,j,t} K^{a}_{c,j,t} R^{\beta}_{c,j,t} L^{y}_{c,j,t} \varepsilon_{c,j,t} \tag{1}$$

where $Q_{c,j,t}$ is real value added, $K_{c,j,t}$ is the tangible capital stock, $R_{c,j,t}$ is the intangible capital stock, $L_{c,j,t}$ is labor, $A_{c,j,t}$ is TFP and $\varepsilon_{c,j,t}$ is the error term in country c in sector j at time t.

Dividing both sides of the equation by labour, and taking the logarithm and the first differences of both sides and modeling TFP growth with the help of Nelson-Phelps-type control variables yields the following equation[9]:

$$(\text{In } q_{c,j,t} - \text{In } q_{c,j,t\text{-}1}) = c + gH_{c,t} + mH_{c,t} \frac{(q_{max,t} - q_{c,t})}{q_{c,t}} + \text{n } (1 - ur_{c,t}) + \text{p}\textstyle\sum_{i=1}^{k} X_{i,c,t} + \mu_t$$
$$+ \text{ a } (\text{In}k_{c,j,t} - \text{In}k_{c,j,t\text{-}1}) + \beta \, (\text{In}r_{c,j,t} - \text{In}r_{c,j,t\text{-}1}) + \text{u}_{c,j,t}{}^{9} \tag{2}$$

where c captures a constant, $H\_(c,t)$ captures the innovation capacity, $H_{c,t} \frac{(q_{max,t} - q_{c,t})}{q_{c,t}}$ represents a catch-up term, the term $(1\text{-}ur_{c,t})$ accounts for business cycles and $X_{i,c,t}$ refers to control variables i that might effect TFP growt in a country at time t. μ_t are time-fixed effects. I derive equation (3) by differentiating in equation (2) for three distinct intangible capital dimensions: i) computerized information (ci), ii) innovative property (ip) and iii) economic competencies (ec):

$$(\text{In } q_{c,j,t} - \text{In } q_{c,j,t\text{-}1}) = c + gH_{c,t} + mH_{c,t} \frac{(q_{max,t} - q_{c,t})}{q_{c,t}} + \text{n } (1 - ur_{c,t}) + \text{p}\textstyle\sum_{i=1}^{k} X_{i,c,t} + \mu_t$$
$$+ \text{ a } (\text{In}k_{c,j,t} - \text{In}k_{c,j,t\text{-}1}) + \beta \, (\text{In}ci_{c,j,t} - \text{In}ci_{c,j,t\text{-}1}) + \gamma \, (\text{In}ip_{c,j,t} - \text{In}ip_{c,j,t\text{-}1}) +$$
$$+ \, \delta \, (\text{In}ec_{c,j,t} - \text{In}ec_{c,j,t\text{-}1}) + \text{u}_{c,j,t} \tag{3}$$

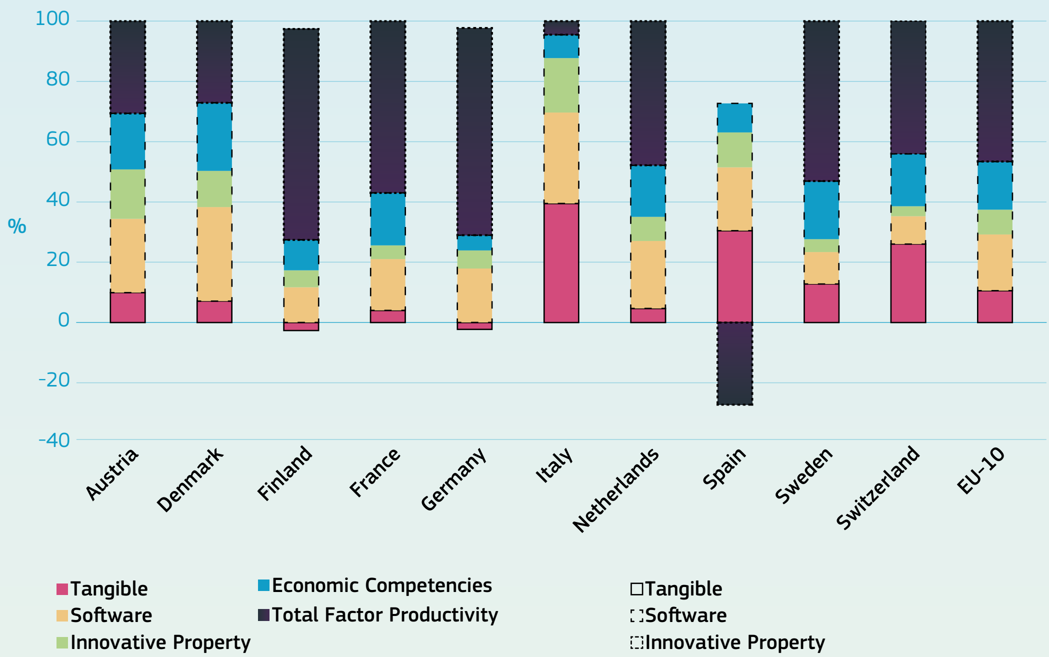
where $(\ln ci_{c,j,t} - \ln ci_{c,j,t\text{-}1})$, $(\ln ip_{c,j,t} - \ln ip_{c,j,t\text{-}1})$ and $(\ln ec_{c,j,t} - \ln ec_{c,j,t\text{-}1})$ are the intangible capital services growth for computerised information (including software), innovative property (including research and development and design and other product developments) and economic competencies (including advertisement, market research and branding, vocational training and organizational capital).

Figure 4.1-8 clarifies three facts. First, on average in the industries of the market economy of the EU-10 countries (Austria, Denmark, Finland, France, Germany, Italy, the Netherlands, Spain, Sweden and the UK), TFP (47%) and intangible capital deepening of the three combined intangible dimensions (43%) explain the main share of labour productivity growth. Tangible capital deepening (10%) only plays a minor role. Second, among the three dimensions of intangible capital, software plays the dominant role (19%), followed by economic competencies (16%) and innovative property (8%).

9 where: $u_{c,j,t} = (ln\varepsilon_{c,j,t} - (ln\varepsilon_{c,j,t\text{-}1})$

Third, the sources of growth show very heterogonous patterns within industries of the market economy of the individual EU10 countries. Whereas intangible capital deepening plays the dominant role in the industries of the market economy in Austria, Denmark, Italy and Spain[10], TFP plays the dominant role in Finland, France, Germany, Sweden and the United Kingdom. In the Netherlands, intangible capital deepening and TFP are equally important.

Figure 4.1-8: Cross-country sectoral growth accounting results for three intangible capital dimensions, 1995-2017



Science, Research and Innovation Performance of the EU 2022

Source: Roth and Sen 2021, Stehrer et al. 2019.

Notes: Figure 4.1-8 displays the cross-country sectoral growth accounting results as displayed in regression 4 in Table 4 in Roth and Sen (2021). It is based on the estimates of equation 3 in Box 4.3 using a random-effects robust VCE estimator and 1 897 sectoral observations for the market economy in the EU-10 from 1995-2017. EU-10 includes the United Kingdom.

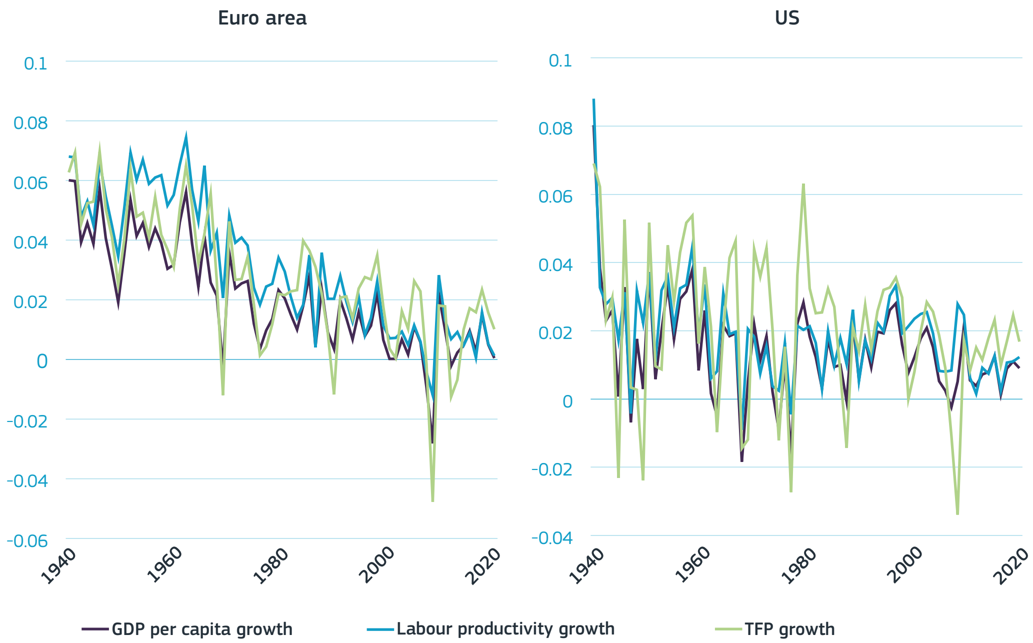
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-1-8.xlsx

10 The negative TFP growth rate in Spain resembles weaker technological progress and innovation. Reasons might be increased rigidities in labour, product and capital markets, as well as negative reallocation effects towards less productive sectors.

3. The EU productivity paradox of the digital era

In 1987, Robert Solow famously stated: 'You can see the computer age everywhere but in the productivity statistics.' Indeed, theoretically, the development of digital technologies should strengthen productivity growth. Yet, despite the information technology (IT) revolution, productivity growth has been diminishing, and then stagnating, over the previous decades.

Figure 4.1-9: Productivity growth slowdown, 1950-2019



Science, Research and Innovation Performance of the EU 2022

Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit's own elaboration based on the Long-Term Productivity Database.

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-1-9.xlsx

A sizable part of the literature on this productivity paradox, or Solow paradox, has attempted to answer the question: **why are digital technologies not leading to higher productivity growth?**

- **Measurement error:** Different authors have argued that some of the observed productivity slowdown is attributable to the difficulties to measure productivity in a service economy, heavily relying on intangibles (McGrattan 2020, Haskel and Westlake 2017, Popović 2018, Syverson, 2017).

- **Long-lag argument:** The productivity implications of a new technology are only visible with a long lag (Triplett 1999). It takes time for new technologies to diffuse and become adopted. This particularly applies to ICT, which requires costly organisational changes and employees' upskilling (Arvanitis 2004, Maliranta and Rouvinen 2004, Brynjolfsson, Rock and Syverson 2019).

- **From micro to macro:** Firm level data shows how the introduction of digital technologies boosts productivity (Hubbard 2003, Bartel et al. 2007). These increases, however, translate into limited impact on aggregate productivity growth, likely due to co-occurring dynamic and competitive effects such as organisational factors, the availability of skills, firm dynamism and polarisation (Pilat 2005).

- **Decline of technical change embodied in capital:** The stagnation of productivity growth is linked to the reduction in the possibilities to achieve productivity growth via capital-embodied technical change (Schubert and Neuhäusler 2018). In this line of research, Castellani et al. (2019) explain the higher levels of productivity of US firms, when compared to EU firms, with the higher capacity to translate R&D into productivity gains of US firms, while EU firms achieve productivity gains more through capital-embodied technological change. The authors argue that such transatlantic differences may be related to the different industrial structures in the US and the EU, with the US economy being disproportionally characterised by high-tech industries, which present higher returns from R&D, and the EU relying more on medium- and low-tech industries, which rely more on capital-embodied technical change.

- **ICT is not plug and play:** Turning investment in ICT into higher productivity is not straightforward. It consistently requires complementary investments and changes in human capital, managerial practice and way of doing business (Pilat 2005, Arvanitis 2004, Maliranta and Rouvinen 2004). Brynjolfsson et al. (2019) show how digital transformation turns out to be particularly difficult for non-frontier firms, with non-trivial adjustments costs, organisational changes, and new skills required, potentially leading to negative returns during the process of adjustment and experimentation.

- **Increasing productivity polarisation:** There is an increasing divergence among OECD countries, industries and firms in the uptake of digital technologies. While a few leading firms push the technological frontier forward, many laggard firms cannot keep up (Calvino et al. 2018, Berlingieri et al. 2017). Andrews et al. (2016) argue that such uneven uptake and diffusion of new technologies throughout the economy is an important source of the productivity slowdown. Sorbe et al. (2019) identify in the features of digital technologies a driver of such polarisation: less productive firms find it harder to attract workers with the right skills to help them adopt digital technologies efficiently, amplifying a cycle that is self-enforcing.

- **Declining business dynamism:** In the last decades, OECD countries have faced declining business dynamics (entry and exit of firms), an increase of zombie firms (firms that would typically exit in a competitive market), as well as an increase in resource misallocation (Criscuolo et al., 2014, McGowan and Millot 2017a, McGowan and Millot 2017b). The lack of exit from the market of less productive firms has generated a drag on aggregate productivity growth.

- **Secular stagnation argument:** In contrast with the long-lag hypothesis, a parallel branch of research argues that most of the economy has already benefitted from the internet and web revolution during the early nineties. According to Gordon (2015), current productivity growth is not unusually low. Instead, productivity growth in the period 1930-1980 was unusually high (thanks to general purpose technologies, including electricity, the internal combustion engine, the telephone, wireless, chemical engineering, and the conquest of infectious diseases). Furthermore, Popović (2018) and Gordon (2015) identify other structural factors, such as education, socioeconomic decay and national debt, as explanations for the productivity slowdown.

Most of the presented explanations of the productivity paradox are complementary and are each not sufficient on their own to explain the paradox, yet jointly able to provide a nuanced understanding of the reasons behind the pattern of subdued productivity growth.

4. The productivity challenge posed by COVID-19

The COVID-19 pandemic has impacted the economy, industries, firms and individuals in very diverse and uneven ways. The effects of some of such disparities are likely (and to a certain extent already have) to lead to serious consequences on the productive capacity of nations. Indeed, if social distancing and lockdowns have propelled the adoption of digital technologies, then firms and households that could not adjust to the new situation have taken the lion share of the costs.

To deal with the necessary restrictive measures, leader firms accelerated the uptake of available digital technologies, shifting working practice from face-to-face to digital. On the other hand, smaller and laggard firms have found such a transition more difficult due to lack of skills, awareness of digital tools and organisational stiffness. This may further widen the productivity gap between leading and laggard firms, particularly in a situation where business dynamism is declining and market cleansing is slowed down through government support to zombie firms.

The impact of the pandemic has also been unequal by sector, with winners and losers. The hospitality sector was among the hardest hit, while digital companies flourished. At the same time, larger companies had more liquidity to perform the necessary adjustments to deal with the pandemic, while smaller firms ran into liquidity problems more quickly (Riom and Valero 2020, Canton et al. 2021). Interestingly, being the low productivity sectors the most affected by COVID-19 (accommodation, restaurants and household services), the reallocation of activity across sectors generated by the pandemic has partially offset the within firm negative effect on aggregate productivity in the short term (Bloom et al. 2021, OECD 2021a).

Digitalised firms were better able to absorb the COVID-19 shock thanks to their higher capabilities to employ digital solutions and teleworking (Andrews et al., 2021). Yet, it is still unknown if a permanent and widespread shift to teleworking would positively affect productivity. Initial studies find a positive effect of teleworking, while pointing out that this effect

Read more in Chapter 12 – Part 2 on 'Productivity growth after the pandemic: understanding long-term trends to tackle the COVID-19 challenges' (Francesco Manaresi, Ilaria Goretti, Chiara Criscuolo, OECD)

Selective review of the policies that can mitigate the long-term effects of the pandemic's unprecedented demand-and-supply shock that has generated a strong push towards the digitalisation of firms, as well as a threat of further productivity divide. Indeed, the ability of firms to invest in digital and intangible assets has been very heterogeneous, with investments in firm digitalisation driven by the already more digitalised firms.

is likely momentary. The long-term impact of teleworking on productivity will instead be dependent on the type of task performed, with some task more effective if done online and other face to face (Barrero et al. 2021; Bloom et al. 2021; Criscuolo et al. 2021; Taneja et al. 2021). Teleworking productivity enhancements could take place thanks to the reduction of logistics costs for long-distance collaboration, and the execution of repetitive tasks that do not need complex human interactions, whereas productivity losses could derive from less productive, large team meetings, reduced informal interaction and face-to-face contact necessary for innovative activities, more difficult managerial oversight, employee strain associated with isolation and telework-fatigue, as well as reduced team spirit.

Support measures related to productivity were broadly effective in alleviating liquidity shortages for productive firms, while being associated with mild negative selection effects (Demmou and Franco 2021). Evidence from European countries showcase that a substantial part of the support was allocated to firms in the middle of the productivity distribution (Altomonte et al., 2021). Furthermore, firms that were financially vulnerable or over-indebted (zombies) before the COVID-19 outbreak were not more likely to be recipients of public support (Harasztosi et al., 2021; Bighelli et al. 2021). Yet, protracted support may hamper reallocation going forward. Prompt emergency support was effective in also avoiding the exit of highly productive firms from the market as a result of severe lockdowns and containment measures at the onset of the pandemic. But the maintenance of such support could hamper the process of resource reallocation, allowing unproductive firms to stay in the market for unfair reasons.

Regarding the long-run productivity implications of COVID-19, worrying signals come from the impact on human capital. Indeed, school closures aggravated existing inequalities with scarring effects on youth and low-income students. Substitutive online teaching methods failed as a perfect substitute of in-presence teaching, leading to a negative impact on learning outcomes, particularly for individuals from poorer socioeconomic backgrounds (Maldonado and Witte 2020, Cacault et al 2021, Di Pietro et al 2020).

Shop closures worsened the employment situation particularly for women, youth, low-income and low skilled workers (ILO 2021; OECD, 2021b, Bartik et al 2020,) as not all kind of jobs can be done remotely from home (Dingel and Neiman 2020). This phenomenon, compounded with the increases in school dropouts (Fernald and Ochse 2021), can decisively affect the long-term productivity capacity of the workers of the future.

5. Conclusions: productivity, prosperity and innovation

Research and innovation are key engines to foster Europe productivity growth, competitiveness and socio-economic outcomes. Human capital combined with R&D investments drives companies' ability to create, absorb and diffuse innovation. Innovation friendly institutions with easy access to finance and low corruption lower the entry cost of innovation, while increasing the innovation capacity of firms and countries.

Productivity can be an ally toward the achievement of the twin transition, providing the necessary resources to invest in new green and digital technologies necessary to tackle the societal challenges of the modern era. Productivity growth entails more (equal) output with the same (or fewer) resources. Such an improvement in the efficiency of production systems is necessary to reduce the impact of production on the planetary boundaries. At the same time, productivity is not a solution to all our problems, as political consensus is necessary to direct its fruits toward desirable outcomes.

The productivity slowdown of the last decades is a worrying phenomenon, likely explained by low technological diffusion, high human capital and organisational uptake costs for laggard firms and declining business dynamism. Efforts directed at easing the access to productivity enhancing technologies should be enacted thought the EU to increase competitiveness while reducing inequality.

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CHAPTER 4.2

BUSINESS DYNAMISM

KEY FIGURES

17.5 %
churn rate of EU businesses

3 times
more scale-ups in the US than in Europe

11.8 %
of EU active firms are high-growth firms

38 %
of high-growth start-ups operate in the ICT sector

98
enterprises became unicorns in 2021 in Europe

KEY QUESTIONS WE ARE ADDRESSING

- What is the latest evidence on business dynamism in the EU and how did COVID-19 impact EU firms' entry and exit rates?
- How does the EU perform in terms of start-up, scale-up and unicorn firms as compared to US and other international competitors? What are the main barriers firms face in their scale-up processes?
- Is the EU entrepreneurial ecosystem well equipped to face the challenges of the digital era?

KEY MESSAGES

What did we learn?

- Business dynamism is declining in the EU, raising concerns about the implications for innovation and economic growth.
- The EU keeps lagging behind its main international competitors in terms of number of start-up and scale-up firms.
- The number of EU unicorns is increasing, but still below the level of our main competitors.
- Women are significantly underrepresented in the EU entrepreneurial landscape.

What does it mean for policy?

- Fast-growing firms are essential to the EU digital and green transition. The EU's performance in terms of start-ups, scale-ups and unicorn firms is improving, but efforts are still needed to improve the overall framework conditions for innovative companies to thrive.
- Increasing the diffusion of innovative ideas and new innovations is essential for the EU's recovery. Innovative enterprises were able to better adapt to the COVID-19 shock, confirming their essential role as drivers of economic productivity and growth.
- A significant gender gap is still to be tackled. The empowerment of women entrepreneurs remains a key policy objective to unleash the EU's untapped growth potential.

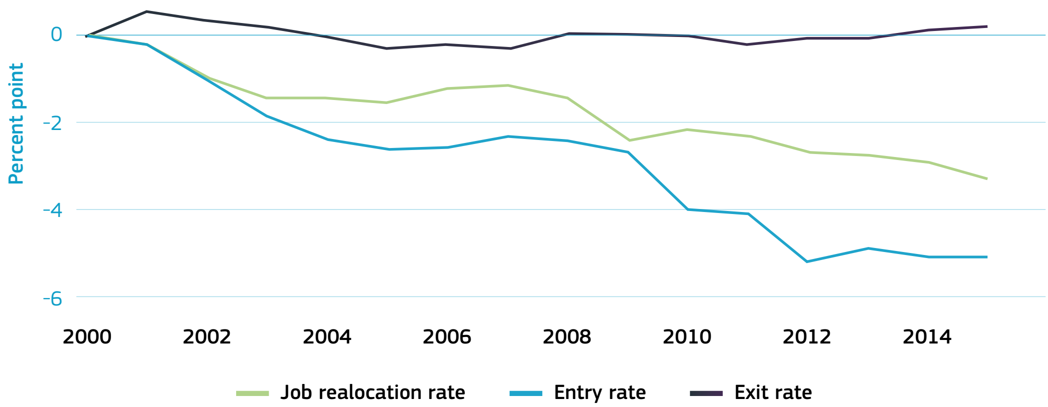
Business dynamism is considered a key driver of aggregate productivity growth. Business dynamism is typically defined as the process through which businesses are born, expand, contract and eventually fail and exit the market (Decker et al., 2018). Overall, there is a wide consensus in the economic literature on the contribution of high-productive firms to aggregate productivity and growth. Through the Schumpeterian process of 'creative destruction', old and less-productive firms make space to new and more productive enterprises, thereby contributing to a more efficient allocation of resources from low-productivity to high-productivity activities (Decker et al, 2016; Bijnesn and Konings, 2018). Haltiwanger et al. (2015) investigated the beneficial effects of business dynamism in the US economy, providing evidence of a higher contribution of high-growth enterprises to job creation, output and aggregate productivity growth. Criscuolo et al. (2014) highlighted the prominent role of young innovative firms in driving the process of creative destruction, while Bravo-Biosca (2016) showed that the positive correlation between a more dynamic firm distribution and higher productivity growth appears to be an empirical regularity observed across different countries.

1. Declining business dynamism: basic facts and potential drivers

Declining business dynamism is a well-established fact. Creative destruction is one of the key drivers of overall productivity growth. In the last decades, there has been a prolific discussion in the academic literature on the declining trend in business dynamism in the US and other economies, in an attempt to identify causes and policy remedies. Economic research documented several aspects related to declining business dynamism (e.g. De Loecker et al., 2021; Markiewicz and Silvestrini, 2021; Akcigit and Ates, 2021). Decker et al. (2016) discuss the pervasive decline in firm dynamics experienced by the US economy in the last decades, noticing that since 2000 the trend has been accompanied by a decrease in the number of high-growth young firms. Haltiwanger et al. (2014) investigated business dynamism in the US high-tech sector, showing that the secular stagnation in US entrepreneurship dynamics also applies to the high-tech industry in the post-2000 period. Furthermore, several studies addressed the issue from a cross-country perspective, finding interesting similarities between the US and other economies. In this regard, a first important contribution is that of Bartelsman et al. (2005) finding similar patterns of business churning across different OECD countries. A further interesting cross-country investigation was provided by Criscuolo et al. 2014, which documented the decline in business dynamism by comparing firm-level data across 18 OECD countries. Bijnesn and Konings (2018) used Belgian data to study the trend in business dynamism, finding patterns similar to the US experience despite the structural differences between the two economies.

Entry and job reallocation rates have been declining across different economies. The birth rate of new firms is typically considered an important indicator to assess the degree of job creation and, thus, economic growth. Unproductive incumbents are pushed out of the market by new entrants (or more productive firms), thereby increasing efficiency and competitiveness, as well as stimulating innovation and the adoption of new technologies. Similarly, evidence on job reallocation rates, which measures the simultaneous level of job creation and destruction in an economy,

Figure 4.2-1: **Average trends in job reallocation, entry and exit rates in selected OECD countries, 2000-2015**



Science, Research and Innovation Performance of the EU 2022

Source: OECD DynEmp3 database, June 2020.
Note: The figure reports average within-country-sector trends of job reallocation, entry and exit rates, based on data from 18 countries: AT, BE, BR, CA, CRI, DK, ES, FI, FR, HU, IT, JP, NL, NO, NZ, PT, SE and TR. Each point represents average cumulative change in percentage points since 2000.
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-1.xlsx

is also a useful indicator to capture the evolution of business dynamism over time. Figure 4.2-1 shows that both indicators have experienced a steady decline over time. Entry rates and job reallocation rate have decreased by 0.2 and 0.35 percentage points, respectively, over the period 2000-2015 (Calvino et al., 2020). Furthermore, **the decline in firm entry rates is not homogeneous across countries and sectors:** telecommunications, IT, and scientific R&D[1] reported the strongest decline over the reference period (Calvino et al., 2020).

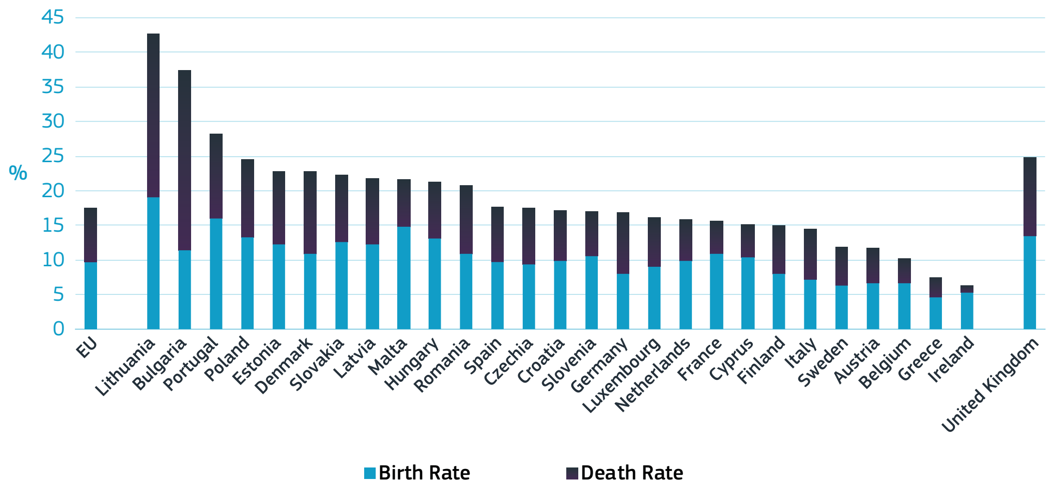
Firms' birth rates are quite heterogeneous across EU countries. Figure 4.2-2 displays the churn rate (measured as birth rates plus death rates) of the EU's business economy in 2018, and across Member States. Focusing on birth rates only, a quite heterogeneous pattern is observed across EU countries. Greece had the lowest share of newly born enterprises in 2018 (about 4.7 %), followed by Ireland (5.3 %) and Sweden (6.3 %).

The highest birth rates were reported in Lithuania (19.0 %) and Portugal (16.0 %), while other countries such as Croatia, Spain and the Netherlands performed close to the EU average (9.7 %). Regarding the share of EU enterprises exiting the market, **in 2008 the average death rate in EU was 7.8 %.** Bulgaria and Lithuania reported the highest death rates (26 % and 23.7 %, respectively). Portugal, Denmark and Poland followed with a share ranging between 11.2 % and 12.1 %. Among the EU countries showing death rates below average, Belgium, Greece and Ireland reported the lowest, with a share well below 5 %.

Understanding the reasons behind declining business dynamism remains a high priority on the policy agenda. A large and growing body of empirical and theoretical works on the decline in business dynamism has proposed several culprits. According to Karahan et al. (2016), the **demographic shifts** followed by the end of the baby-boomer

1 Here defined according to the ISIC v4 classifications, and corresponding to the activities under Section M – Division 72

Figure 4.2-2: Churn rate (birth rate plus death rate) per country, 2018



Science, Research and Innovation Performance of the EU 2022

Source: Eurostat [online data code bd_9bd_sz_cl_r2]
Note: Data for business economy except activities of holding companies.
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-2.xlsx

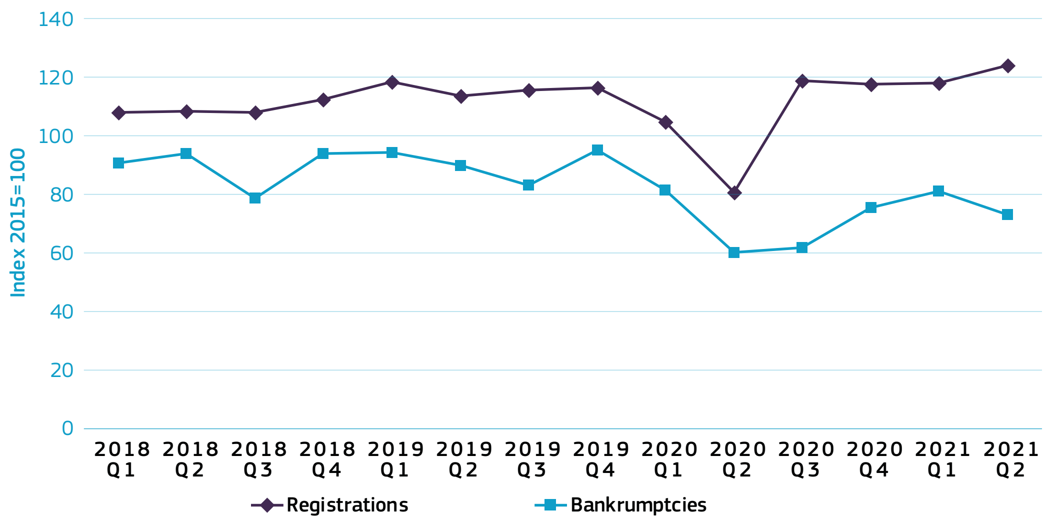
generation have been associated with an increase in labour costs that has negatively affected firms' entry rate. Decker et al. (2018) propose declining responsiveness to shocks as a potential candidate explaining the fall in business dynamism. They argue that the slowdown in factor reallocation is not the result of structural changes in the economy, but rather the outcome of a **declining marginal responsiveness** of firms to idiosyncratic shocks due to increased adjustment costs (Decker et al., 2018). Akcigit and Ates (2021) identify **the decline in knowledge diffusion and ideas implementation** as another potential culprit. Their argument stems from the consideration that innovation plays a leading role in determining productivity growth, but it is not sufficient alone to boost productivity if new technologies are not adequately diffused in the economy. A high level of knowledge diffusion enables laggard firms to learn from market leaders, thereby making it possible for them to catch up on their productivity gap. Akcigit and Ates (2021) argue that the level of knowledge diffusion and ideas implementation in the US economy has been declining over time, making it more difficult for new firms to enter the market, leading to a reduction in entry rates. Yet, De Loecker et al. (2021) argue that the **combination of increasing mark-ups and changes in market structure** leads to a fall in business dynamism.

2. Business dynamism in Europe and the COVID-19 crisis

Soon after the outbreak of the pandemic in the second quarter of 2020, the number of business registrations in the EU fell significantly. Although it is still not possible to entirely assess the overall effects of the COVID-19 pandemic on businesses, preliminary data clearly shows that the lockdown measures have produced a massive change in the way of doing business (see Chapter 1 – COVID-19, recovery and resilience). Figure 4.2-3 displays the number of business registrations in the EU over the period 2018 Q1-2021 Q2. A significant drop in the number of registrations (almost -20% compared to the values of 2015) occurred after the adoption of the first lockdown measures. The sharp decrease in the number of business registrations is particularly worrisome as it could imply missed opportunities in terms of innovation and growth (Fareed and Overvest 2021)[2]. Nevertheless, business registrations started to increase again in the third quarter of 2020 and kept increasing to pre-pandemic levels in the first half of 2021 (Figure 4.2-3).

The number of business bankruptcies has decreased after the outbreak of the COVID-19 pandemic. Figure 4.2-3 also displays business bankruptcies in the EU over the period 2018 Q1-2021 Q2. The number of firms filing for bankruptcies has fallen by more than 30% after the outbreak of the pandemic (2020 Q2) as compared to

Figure 4.2-3: Business registrations and business bankruptcies in the EU(1), 2018 Q1-2021 Q2 (seasonally and calendar adjusted)



Science, Research and Innovation Performance of the EU 2022

Source: Eurostat [online data code STS_RB_Q]

Note: (1)Industry, construction and market services (except public administration and defence; compulsory social security; activities of membership organisations)

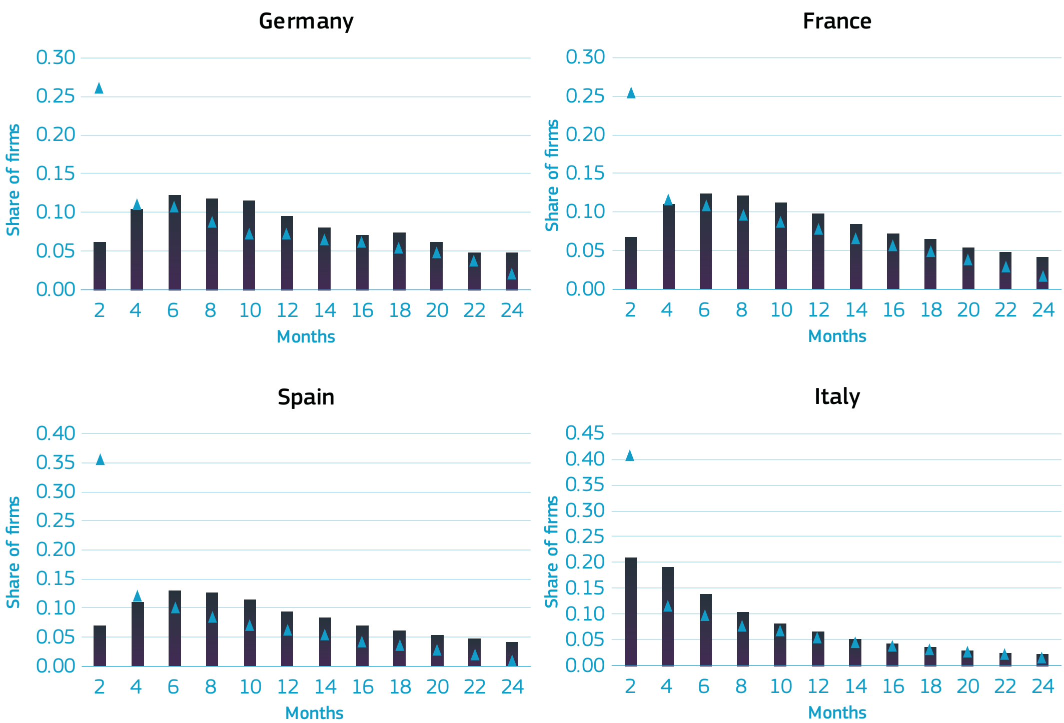
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-3.xlsx

2 Slowdown in business dynamics during the COVID pandemic | VOX, CEPR Policy Portal (voxeu.org)

end-2019. This trend is presumably partially due to the massive policy support provided by national governments and through the EU's programmes. As matter of fact, the COVID-19 pandemic called for unprecedented counteracting policy measures. Gourinchas et al. (2020) estimate that the effects of COVID-19 on firms' survival would have been way more disruptive without the massive policy support mobilised to sustain the economy during the different phases of the pandemic.

Policy measures supporting firms' liquidity mitigated the effects of the pandemic on corporate defaults. In its *Financial Review* of November 2020, the ECB provided evidence of the impact that support measures had on corporate liquidity distress horizons[3]. Figure 4.2-4 looks at four large EU countries, showing that supporting measures have had a stronger impact in Italy and Spain compared to France and Germany. Without policy support, about 40% (Italy) and 36% (Spain) of firms would have been unable to service their liabilities within two months of the COVID-19 shock, against the nearly 25% reported for both Germany and France. **The presence of liquidity buffers were crucial to prevent European firms from entering into severe liquidity distress** (Archanskaia et

Figure 4.2-4: Share of companies that would have faced liquidity distress after the first lockdown with and without policy support



Science, Research and Innovation Performance of the EU 2022

Source: ECB, Financial Review, November 2020 based on Eurostat, Eurosystem Household Finance and Consumption Survey, Bureau van Dijk – Orbis database

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-4.xlsx

3 'The corporate liquidity distress horizon indicates how long a company would be able to service its current liabilities as they fall due, given its cash holdings and the projected cash inflows and outflows, taking into account the reduced turnover since the outbreak of the pandemic and assuming that liabilities would not be rescheduled.', ECB (2020).

al., 2022). With the first peak of the COVID-19 pandemic, the share of European firms incurring financial distress in the absence of liquidity buffers was around 70%. On the contrary, the share of firms in liquidity distress dropped by 30-40 percentage points when liquidity buffers were deployed (Archanskaia et al., 2022).

The COVID-19 shock has the peculiar characteristic of also potentially endangering viable firms. The shock induced by the pandemic affected the entire economy, possibly also hitting those firms that would have remained viable under other types of disturbances (Laeven et al., 2020). Without the large-scale government support put in place during the different lockdowns, liquidity squeezes connected with a fallout in turnover would have easily turned into insolvency problems, thereby forcing otherwise viable firms to exit the market (Laeven et al., 2020).

Nevertheless, concerns remain on government support keeping unviable businesses afloat, thereby stifling the restructuring process. The support measures issued in response to the pandemic helped to counteract the disruptive effects on the EU economy. Nevertheless, economies in post-lockdown are and will be facing the important challenge of ensuring a smooth phasing out of the support measures, in order to avoid disruptive effects on the economy as a whole (Blanchard et al., 2020). Furthermore, government support may also be used by unviable firms. The specific nature of the COVID-19 crisis makes distinguishing between illiquid and insolvent firms particularly difficult (Laeven et al., 2020). In a recent study, Cross et al. (2021) investigate whether the process of bankruptcies in France was distorted in 2020. They find no significant change in the drivers of bankruptcies, suggesting that the risk of impairing the cleansing effect is not high. As such, the phasing out from the support measures poses the challenge of ensuring business continuity for viable firms with potentially higher debt due to the COVID-19 shock, and progressively reducing the support reaching non-viable entities (Cros et al., 2021).

The presence of zombie firms[4] in the economy is a potential driver of weak productivity performance. The term 'zombie firms', first used by Caballero et al. (2008), is typically used to denote older firms with prolonged difficulties in meeting their interest payments that are still active, although they should already be out of the market (Andrews et al., 2017). There exist three main channels through which zombie firms are found to affect aggregate labour productivity growth (McGowan et al., 2017). First, zombie firms typically exhibit lower levels of labour productivity compared to other firms. Second, zombie firms may crowd-out investment, thereby limiting non-zombie enterprises' access to financial resources. Third, zombie firms are found to hinder the efficient allocation of resources throughout the economy, preventing new and more productive firms from entering the market (McGowan et al., 2017; Andrews et al., 2017; Banerjee and Hofmann, 2020; Laeven et al., 2020).

The share of zombies firms has risen in the last decades. Andrews et al. (2017) undertake a cross-country analysis, showing that the share of zombie firms has increased over the period 2003-2013. Banerjee and Hofmann (2018) found similar evidence across different definitions of zombie firms, showing that the increasing trend may be due to the fact that firms tend to remain in the status of zombie firms longer, rather than exiting the market. Building on this evidence, Banerjee and Hofmann (2020) show that the share of zombie firms across economies has risen since the late 1980s, partially also due to the reduced financial pressure reflected by the low interest rate environment. Looking at EU countries only,

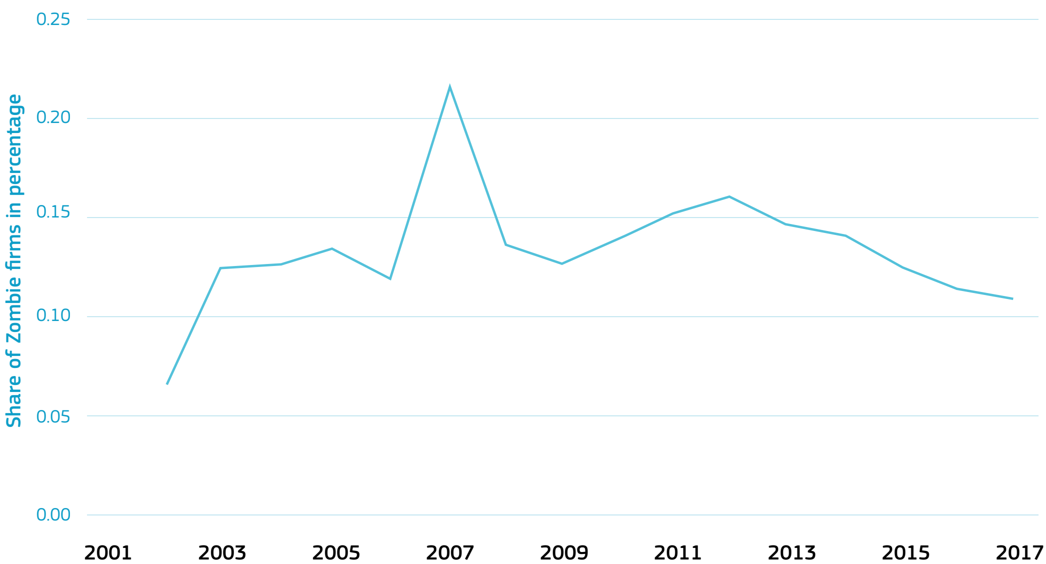
4 Zombie firms are defined as firms aged at least 10 years and with an interest coverage ratio smaller than 1 over three consecutive years.

the share of zombie firms has increased over 2002-2017. Excluding the peak reported in the years of the global financial crisis, the share of zombie firms in the EU has increased from about 6.6% in 2002 to 15.4% in 2012 (Figure 4.2-5). Since 2012, the proportion of non-viable firms in the EU economy has started to decrease. Nevertheless, the share remains well-above the 2002 value, with 10.7% of firms classified as zombie firms in 2017.

The share of zombie firms differs across EU countries. In 2016, the proportion of non-viable firms in the EU ranged between 22.3% in Portugal to slightly less than 3% in Denmark. After Portugal, France, Lithuania and the Netherlands reported the highest shares (respectively 16.2%, 15.2% and about 5.1% of zombie firms), whereas Belgium and Italy accounted for the smallest shares, with 6.1% and 6.9% respectively (Figure 4.2-6).

The way the COVID-19 crisis will keep affecting entry-exit dynamics remains uncertain. Although there exists general consensus on the fact that as less productive firms exit the market, new more productive firms come in, thus driving economic growth (Hopenhayn, 1992), debates remain on how this process is affected by major economic disturbances (Hall, 1995; Caballero and Hammour, 1994). On the one hand, creative destruction may be accelerated by crises, as a severe economic disturbance would amplify the efficient reallocation of resources accelerating entry-exit dynamics in favour of more productive enterprises. On the other hand, shocks and crises could also determine a destructive-destruction process, i.e. market exits by firms would destroy productive resources that would ultimately translate in economic stagnation (Baden-Fuller, 1989). Muzi et al. (2021) carry out a cross-country analysis, finding evidence of a strong negative

Figure 4.2-5: Share of zombie firms[1] in the EU, 2002-2017



Science, Research and Innovation Performance of the EU 2022

Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit, based on CompNet 7th Vintage, accessed in October 2021

Note: [1]Zombie firms are identified as those entities with interest payments exceeding operational profit for three years, and presenting a lack of high labour growth.

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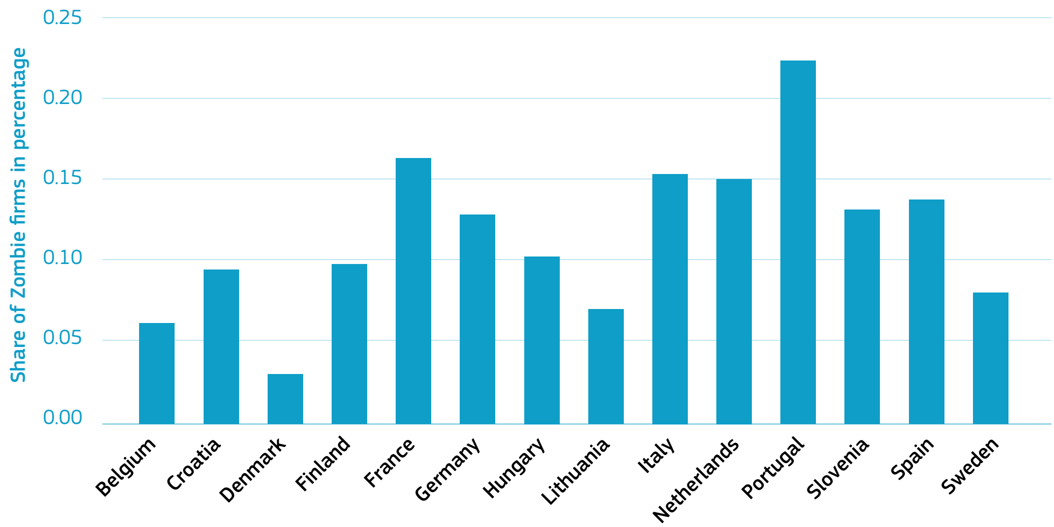
Figure 4.2-6: Share of zombie firms[1] for selected Member States, 2016



Science, Research and Innovation Performance of the EU 2022

Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit, based on CompNet 7th Vintage, accessed in October 2021

Note: [1]Zombie firms are identified as those entities with interest payments exceeding operational profit for three years, and presenting a lack of high labour growth.

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-6.xlsx

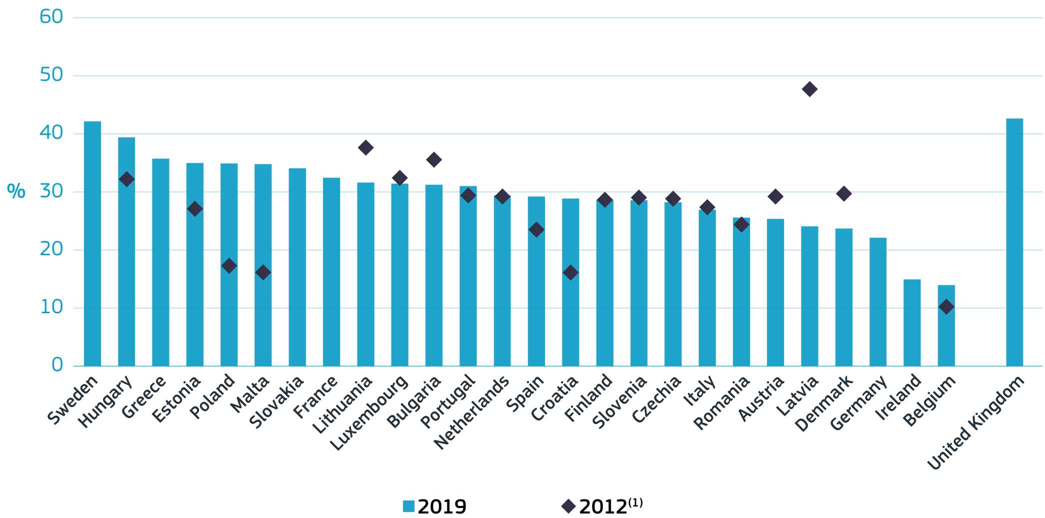
relationship between productivity and firm exit rates during the COVID-19 crisis. Nevertheless, these findings do not allow researchers to clearly discern whether there is a process of cleansing out of unproductive firms at play, or if the crisis is also forcing productive firms to exit the market (Muzi et al., 2021).

Firm exit rates are concentrated in particular industries. Crane et al. (2020) found that firm exit rates were relatively higher for small firms operating in those industries that were affected the most by the lockdown measures. Muzi et al. (2021) also report interesting results concerning other determinants of firm exit rates. First, they found that innovative firms are less likely to leave the market. This result confirms that **innovation, and especially the ability to innovate as market conditions change, represents a key determinant of a firm's survival.** Second, they found evidence of a negative correlation between digital presence and the probability of permanently exiting the market (Muzi et al., 2021). This finding is in line with recent evidence showing a massive increase in the adoption of digital technologies following the outbreak of the COVID-19 crisis (see Chapter 5.3 – ICT sector and digitalisation), and confirms how technology and innovation have helped firms to cushion the negative impact from the pandemic.

3. The EU scale-up gap

Start-ups and scale-ups[5] represent a key driver of economic growth and job creation, playing a critical role in fostering innovation. Start-ups and scale-ups foster aggregate investment activities, in particular those in intangible assets (EIB, 2019). Start-ups and scale-ups companies[6] report significantly higher investment levels per employee than older firms. Furthermore, **they are also catalysts for innovation.** More than 70% of start-ups and scale-ups companies interviewed in the survey indicate the main innovative aspects of their business as the offering new products or services, as well as new delivery modes. However, start-ups and scale-ups also carry new ideas when it comes to developing new ways of generating revenues from products and services sold, and to branding and advertisement strategies implemented on the market (EIB, 2019).

Figure 4.2-7: Share of start-ups up to 5 years old in total employer enterprises by country, 2012 and 2019



Source: Eurostat (online data code: bd_9fh_sz_cl_r2)
Note: (1)Data in 2012 not available for FR, DE, EL, IE, SK, SE, UK. (2)Data for CY is not available.
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-7.xlsx

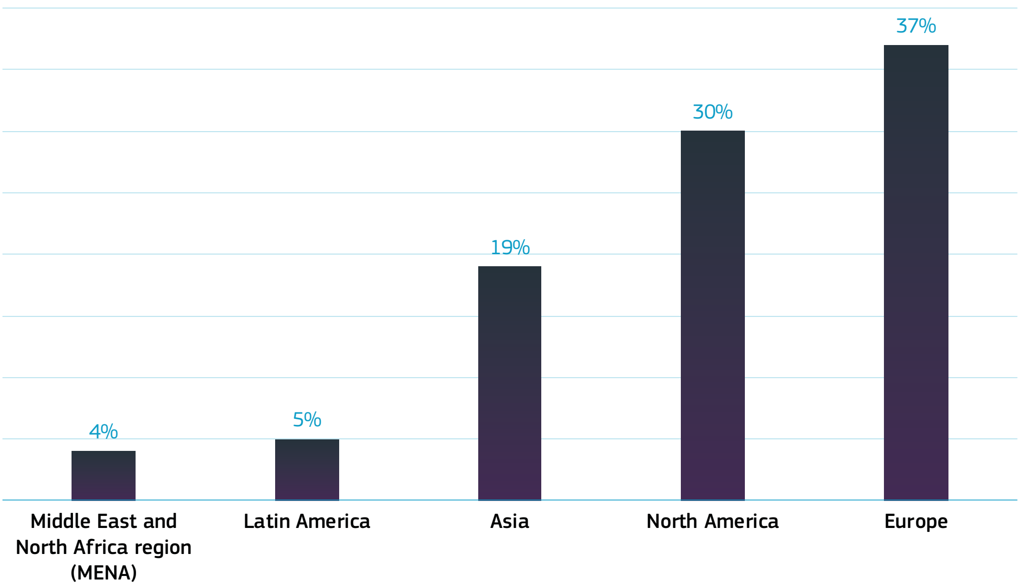
5 Please note that diverging data and definitions (as well as a number of different methodologies) are typically adopted to define start-up and scale-up companies. As such, it is extremely challenging to provide a comprehensive overview of the European landscape, using a unique definition.

6 Here, defined as firms younger than 10 years old and with high growth potential. The definition excludes, for instance, young businesses that do not intend to grow beyond their solo founder or that already reach a wide geographical market (EIB, 2019).

In 2019, the share of start-ups[7] in EU ranged between about 14% (Belgium) to about 42% (Sweden). Compared to 2012, the number of start-ups increased in several countries, notably in Belgium, Croatia, Estonia, Hungary, Malta, Poland, Portugal, Romania and Spain. Croatia and Poland are the Member States that experienced the largest increase over the period considered, with the share of start-ups almost doubling compared to 2012. On the contrary, Latvia experienced a significant contraction in the number of young enterprises, reporting almost 50% less start-ups than in 2012, followed by Denmark with a fall of 20%.

The EU aims at creating a fertile innovation ecosystem so as to play a key role in both the green and digital transition. Innovative start-ups play a pivotal role in addressing the challenges of the twin transition. Andrews et al. (2014) found strong evidence of resource reallocation towards patenting firms. Additionally, both the EU's industrial strategy and SME strategy[8] for a sustainable and digital Europe acknowledge the importance of supporting innovative start-ups as key drivers of economic growth.

Figure 4.2-8: Share of emerging start-up ecosystems by world region, 2020

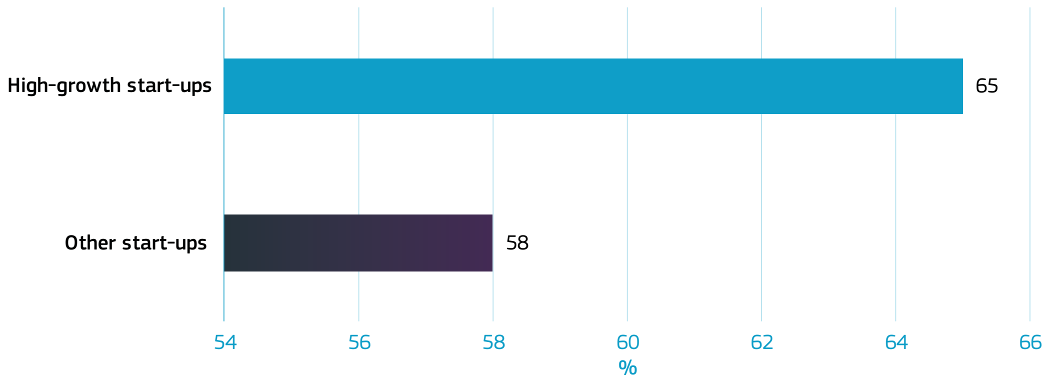


Science, Research and Innovation Performance of the EU 2022

Source: Startup Genome, 2021
Note: Emerging ecosystems are defined as ecosystems at the early-stage of their growth
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-8.xlsx

7 Here defined as enterprises up to 5 years old
8 communication-industrial-strategy-update-2020_en.pdf (europa.eu)

Figure 4.2-9: Share of new-to-the-world innovators in EU-28



Science, Research and Innovation Performance of the EU 2022

Source: EIB (2020) based on EIBIS Start-up and Scale-up Survey 2019, firms sampled from Crunchbase.
Note: Baseline is all start-ups that stated an innovative aspect in EU + UK.
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-9.xlsx

The EU keeps lagging behind its main international competitors in terms of start-up ecosystems[9]. The main objective of a start-up ecosystem is to support companies in their launch and growth phases. When looking at the global start-up ecosystem ranking, North America keeps dominating the international scene, hosting 50% of Top 30 ecosystems in the world. Asia follows with 27%, after having outranked Europe between 2019 and 2021.

Nevertheless, the EU's performance is improving and the EU is performing relatively well in creating emerging start-up ecosystems[10]. In 2020, the EU was in the lead in terms of emerging ecosystems, accounting for 37% of global emerging start-up ecosystems, followed by North America and Asia, with a share of 30% and 19%, respectively (Figure 4.2-8).

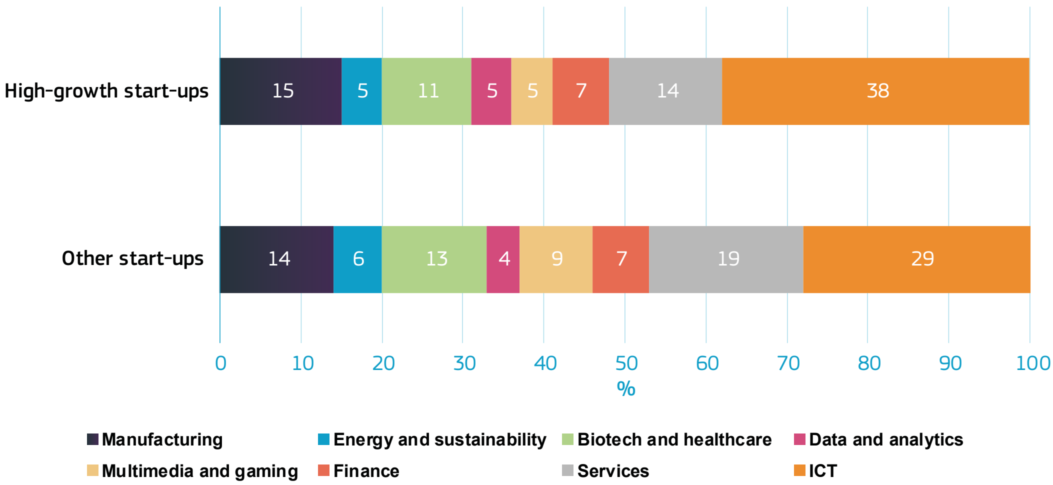
Building effective ecosystems for innovative start-ups to grow and scale remains a high priority of the EU's agenda. A distinctive feature of high-growth start-ups is their ability to innovate. According to data collected by the EIB, 65% of high-growth start-ups[11] in Europe report that the most innovative aspect of their business was the creation of innovations previously unknown to the market (against 58% of lower-growth start-ups) (EIB, 2020) (Figure 4.2-9). **The latter aspect makes innovative start-ups essential players for the EU's economic growth**. As carriers of disruptive ideas, high-growth start-ups have the potential to introduce game-changing innovations to the market, thereby creating new economic opportunities that increase EU competitiveness at the global level (EIB, 2020).

9 A start-up ecosystem is defined as a cluster of start-ups (and related entities) which pool together resources and reside within a 100-kilometre radius from a central point (Startup Genome, 2021).
10 Emerging ecosystems are defined as ecosystems at the early-stage of their growth (Startup Genome, 2021).
11 High-growth start-ups are defined as firms less than 10 years old reporting an average turnover growth higher than 60% over the last three years in the EIB Start-up and Scale-up Survey 2019.

High-growth start-ups typically operate in highly innovative sectors. The largest share of high-growth start-ups is registered in innovation-enabling sectors (EIB, 2020): 58 % of high-growth start-ups in Europe operate in the ICT sector, against 29 % of start-ups with lower growth rates. Other sectors in which there is a good presence of high-growth innovative start-ups are the manufacturing and services sectors, with 15 % and 14 % of active innovative enterprises (Figure 4.2-10). Furthermore, the share of high-growth start-ups adopting innovative technologies is typically higher than that of other start-ups and SMEs in general (EIB, 2020): 53 % of high-growth start-ups adopt cognitive technologies (such as big data or artificial intelligence), compared to 40 % of start-ups with lower growth and 11 % of SMEs (see Chapter 5.3 - ICT sector and digitalisation).

The number of EU scale-ups has increased in recent years, but the gap with the US remains. On average, there are three times more tech scale-ups in the US than in Europe (Mind the Bridge, 2019). Despite the contraction experienced with the outbreak of the coronavirus, European fast-growing companies showed a good degree of resilience to the COVID-19 shock[12]: after a 20 % contraction in the level of scale-up investment, in 2021 the European scale-up landscape has been able to almost double the investment value reported in 2019 (European Scaleup Monitor, 2021).

Figure 4.2-10: **Share of high-growth and other start-ups per economic sector**



Science, Research and Innovation Performance of the EU 2022

Source: EIB (2020) based on EIBIS Start-up and Scale-up Survey 2019, firms sampled from Crunchbase.

Note: Baseline is all start-ups that stated an innovative aspect in EU + UK. Sector classification based on EIBIS Start-up and Scale-up Survey 2019

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12 See also, Coad et al. (2022) for a discussion on the COVID-19 effects on high-growth enterprises in Europe. Additionally, Coad et al. (2022b) find evidence that R&D investors are more likely to be pessimistic about investment plans as a consequence of the COVID shock.

European scale-ups[13] are strongly concentrated in few countries, notably UK, France which account for about 50 % of total scale-ups in Europe (European Scaleup Monitor, 2021). In 2021, UK remained the leading country in terms of scale-up performance, counting around 33 % of the European scale-up force. London maintained its record as Europe's scale up capital, with 145 scale-up companies. Paris followed with 50 fast-growing firms, accounting for 17 % of total scale-ups in France. Berlin ranked third, with 25 scale-ups (Figure 4.2-11).

The European scale-up landscape is dominated by companies operating in digital and tech industries. Around 57 % of European scale-ups is active in the computer software-industry (57.1 %). Banking, insurance and financial services sector ranks second with 12 %, while 7.5 % of European scale-ups firms operate in the field of biotechnology and life-sciences (European Scaleup Monitor, 2021).

Availability of staff is one of the main barriers identified by innovative start-ups. Difficulties in hiring staff with the appropriate skills is reported as one of the main constraints to start-ups' growth (EIB, 2020). This is particularly relevant for high-growth start-ups, which indicate the lack of skilled personnel as a main barrier to success in 34 % of the cases, against 24 % of start-ups with lower growth rates (Figure 4.2-13). In particular, high-growth start-ups appear to experience particular difficulties in recruiting staff with appropriate technical skills (43 %), while 20 % do not find personnel with the right qualifications or experience (EIB, 2020). The scarce availability of skilled personnel is reported as a major issue by 66 % of EU start-ups, against 45 % of American ones. The gap is striking also when looking at EU scale-ups (72 % against 60 %) (Figure 4.2-13) (see Chapter 4.3. – Skills in the digital era).

Figure 4.2-11: Top Scale-up countries and cities in Europe, 2021

Source: European Scaleup Monitor, 2021

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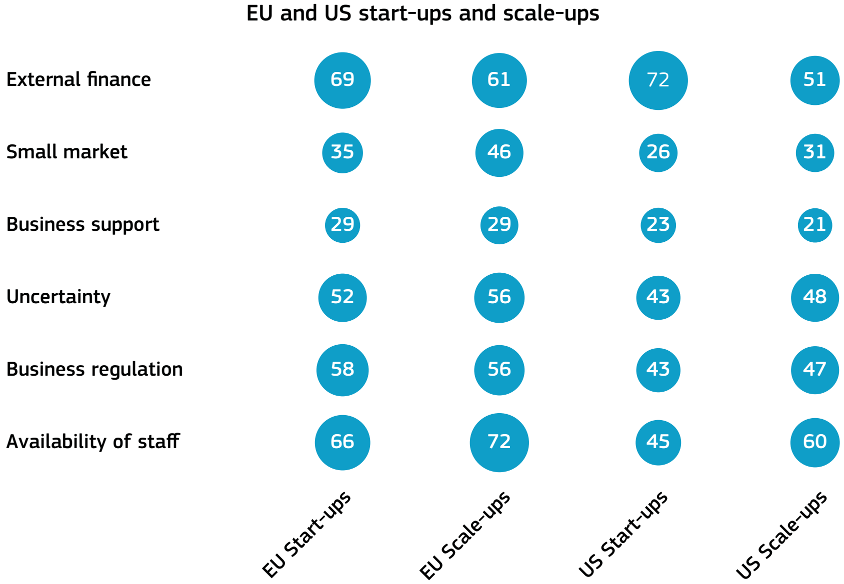
13 Here defined as young fast-growing companies (10 years old or younger) that have received at least EUR 1 million within the past 10 years (January 2011 - December 2020) (European Scaleup Monitor, 2021).

Figure 4.2-12: Start-ups and scale-ups obstacles to success – EU vs US



Science, Research and Innovation Performance of the EU 2022

Source: Ambrosio et al. (2021) based on EIB Investment Report 2019/2020, authors' calculations

Note: Data refers to the question 'To what extent is each of the following an obstacle to the success of your business?'. Relative difference is calculated by: $(scale\_up_{\_EU} - start\_up_{\_EU}) - (scale\_up_{\_US} - start\_up_{\_US})$

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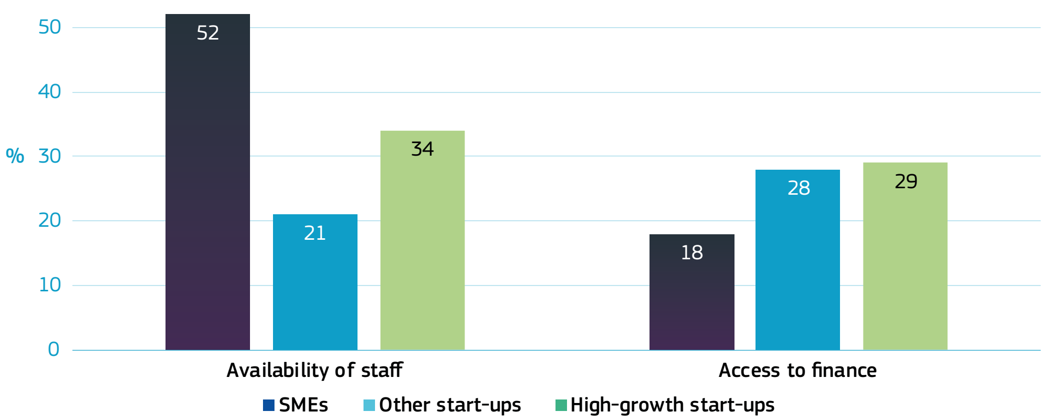
Figure 4.2-13: Share of enterprises experiencing 'availability of staff' and 'access to finance' as a main barrier to growth



Science, Research and Innovation Performance of the EU 2022

Source: EIB (2020) based on EIBIS Start-up and Scale-up Survey 2019, firms sampled from Crunchbase.

Note: Baseline is all in EU + UK

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About one in three start-ups indicates limited access to finance as the main constraint to growth (EIB, 2020). This applies equally to high-growth and low-growth start-ups (29 % and 28 %, respectively), while 18 % of European SMEs report barriers to external financing as a major issue (Figure 4.2-13). The lack of external finance contributes to explain the significant scale-up gap between the EU and the US. Europe significantly lags behind the US in terms of venture capital investment, and the gap increases as start-ups get older (EIB, 2020) (see Chapter 7.1 - Financing innovation: access to finance).

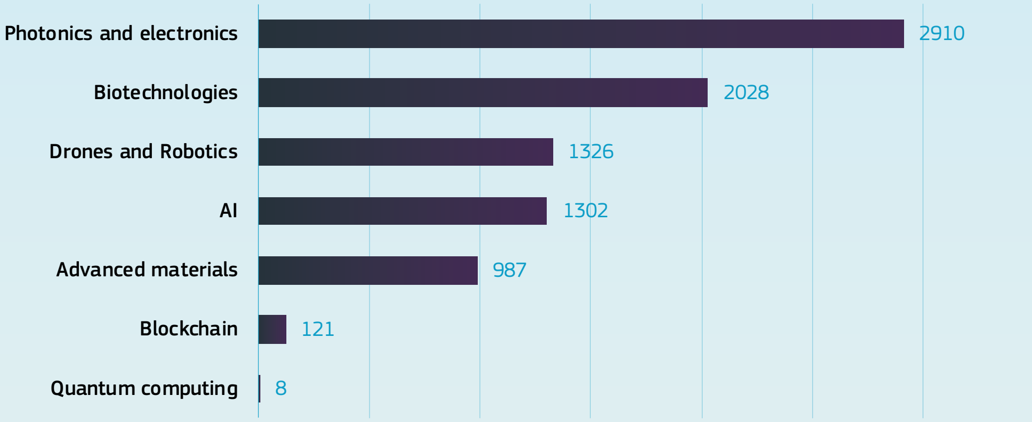
Other structural barriers potentially hindering EU companies' scale-up process include **a still fragmented EU internal market**, which could potentially explain why many start-ups and scale-ups in the EU typically operate only in their home country, and a **heterogeneous business regulation** across Member States (EIB, 2019). In the EU 56 % of scale-ups mention business regulation as one of the main obstacles to success, against 47 % in the US (Figure 4.2-12). This would call for a more homogeneous legal framework, able to promptly adapt to the pace of technological developments (DigitalEurope, 2021).

Box 4.2-1: Deep technologies

According to Boston Consulting Group (BCG) and Hello tomorrow (2021), **deep technologies are defined as novel technologies offering significant advances over those currently in use**. Deep technologies are typically identified along three dimensions: impact, time, and capital needed. In a study carried out in 2019, BCG and Hello tomorrow identified almost 8 700 deep-tech start-ups worldwide. These companies are anticipated to a have a significant impact on different UN Sustainable Development Goals (SDGs). In particular, 51 % of the deep-tech start-ups surveyed in the study predict they will impact the goal related to good health and well-being, 50 % on the goal related to industry, innovation and infrastructure, and 28 % consider their businesses will likely significantly contribute to mitigating the environmental spillovers of human activities. **Nevertheless, deep technologies typically take time to be fully deployable on the market**. The time to develop a commercially viable application varies across sectors (for instance, an average of 4 years is needed to develop deep technologies in the biotech industry, and 2.4 years for a start-up based on blockchain technologies) (BCG and Hello tomorrow, 2021). Furthermore, given the complexity of the products and services produced by these types of firms, significant financing resources are necessary for them to develop and scale.

Deep-tech start-ups mainly operate in seven fields worldwide. About 33.5 % of the deep-tech start-ups identified are active in the field of photonics and electronics (2 910 start-ups) (Figure 4.2-14). Biotechnologies and drones and robotics follow with 2 028 and 1 326 firms, respectively. AI ranks fourth, accounting for about 15 % of the deep-tech start-ups identified (BCG and Hello tomorrow, 2019)

Figure 4.2-14: Number of Deep-tech start-ups worldwide per technological field



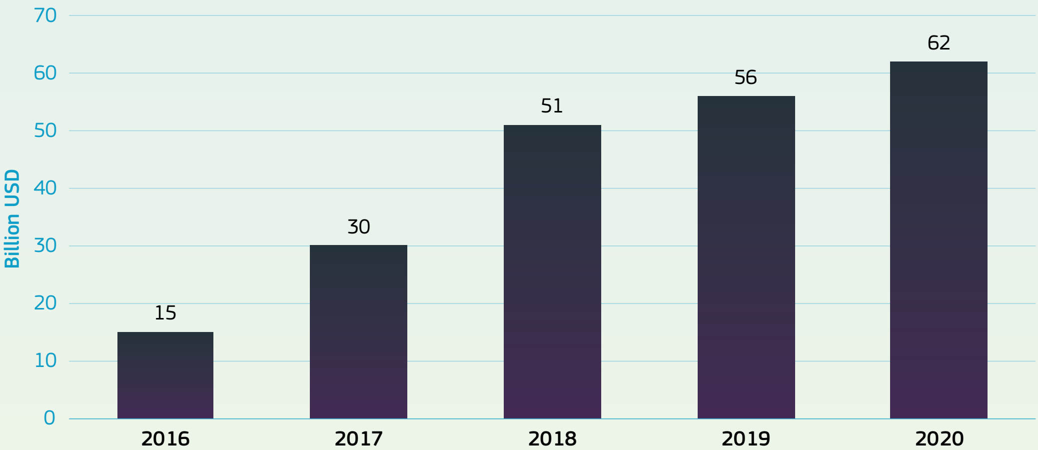
Science, Research and Innovation Performance of the EU 2022

Source: BCG Center for Innovation Analytics; BCG and Hello Tomorrow analysis (2019)

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-14.xlsx

Deep-tech investments world-wide increased significantly over 2016-2020. In 2020, the level of global investments in deep-tech stood at over USD 60 billion (Figure 4.2-15). Funding needs differ considerably depending on the type of technology. Developing a first prototype in biotech is estimated to cost on average USD 1.3 million, while the costs of developing a first prototype in blockchain is about USD 200 000 (BCG and Hello tomorrow, 2021). Additionally, deep-tech investment is unevenly distributed across sectors. In 2020, about two-thirds of deep tech investments was raised by ventures in AI and synthetic biology (BCG and Hello tomorrow, 2021b).

Figure 4.2-15: Deep-tech investments worldwide, 2016-2020



Science, Research and Innovation Performance of the EU 2022

Source: Capital IQ; Crunchbase; Quid; BCG Center for Growth and Innovation Analytics; BCG and Hello Tomorrow analysis

Note: investments include private investments, minority stakes, initial public offerings and M&A

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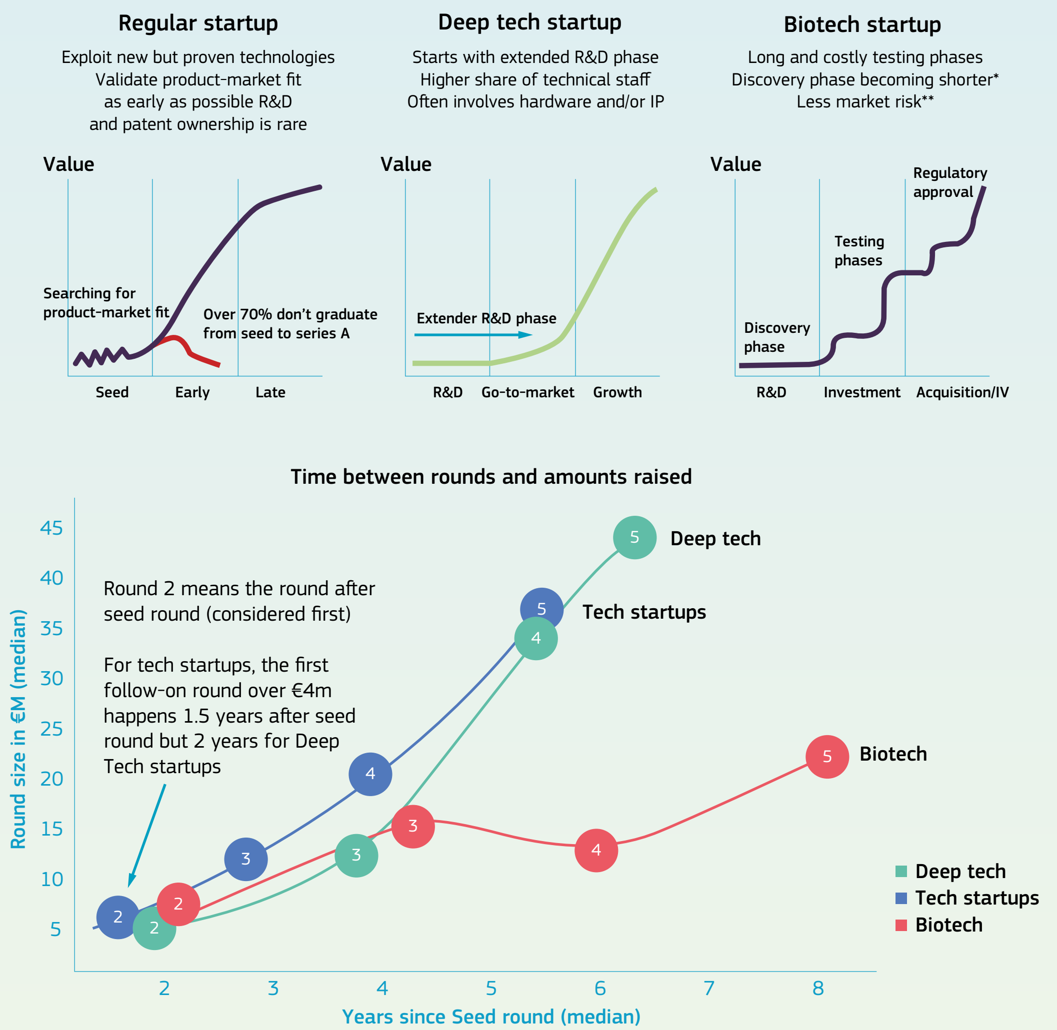
Private investment in deep-tech from corporate investors is on the rise. Between 2016 and 2020, deep-tech private investments coming from corporate investors increased from USD 5.1 billion to USD 18.3 billion. Furthermore, private investment in Europe has experienced a faster growth than China and US, reporting a CARG of 49 %, against the 34 % and 28 %, respectively (BCG and Hello tomorrow, 2021b).

A deep-tech start-up typically takes more time to become fully operational on the market. As shown in Figure 4.2-16, for regular tech start-ups it typically takes 1.5 years after the seed round to raise follow-on capital. This takes longer for deep-tech firms, typically needing about two years (Dealroom, 2021).

Figure 4.2-16: Differences and time between rounds and amount raised for tech start-ups, deep-tech start-ups and biotech-start-ups



Source: Dealroom - 2021: the year of Deep Tech (2021)

Note: Data refer to 1 700 qualified European start-ups that raised a seed round > EUR 200 000 between 2010 and 2015 and closed a 2nd round of at least EUR 4 million.

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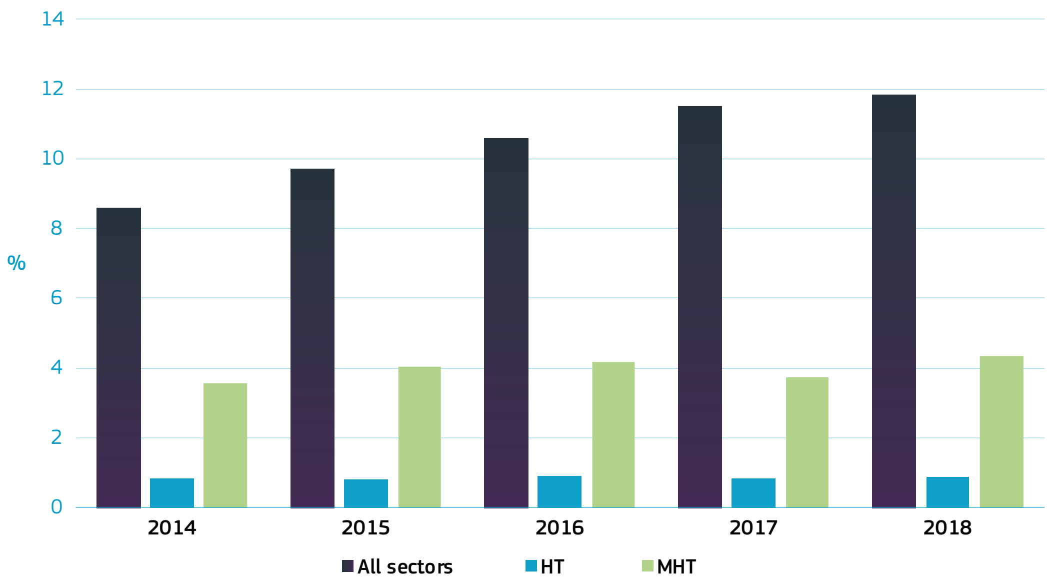
The untapped potential of European deep-tech is still significant. As noted by Dealroom (2021), many European deep-tech companies are strongly interlinked with academia and heavily rely on public support. An important step to unlock the European growth potential is to foster the entrepreneurial culture within European universities, strengthening the link between academia and the business sector. Europe hosts world-class universities and research centres. In order to reduce the commercial and technological divide between Europe and frontier runners (such as China and US), it is essential to strengthen the relationship between academic production and commercialisation. Furthermore, successes like BioNTech demonstrate the importance of providing promising companies with significant support at early stage. In this regard, government intervention is needed to mobilise financing, which is a pre-condition to keep attracting top talents in Europe and from the rest of the world (Dealroom, 2021).

Figure 4.2-17: Share of high-growth enterprises[1] in EU per sector, 2014-2018



Science, Research and Innovation Performance of the EU 2022

Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit, based on Eurostat [online data code : bd_9pm_r2_1]

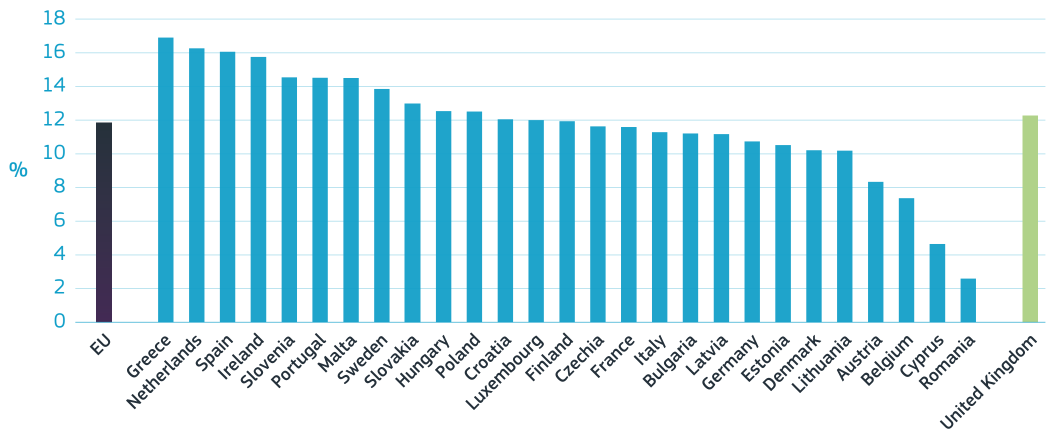
Note: [1]High growth enterprises measured in employment (growth by 10 % or more).

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-17.xlsx

On average, slightly less than 12 % of companies in EU are high-growth enterprises. The number of high-growth enterprises[14] in the EU has steadily increased over the period 2014-2018 (Figure 4.2-17), but only slightly more than 5% of these enterprises operate in high-tech[15], and medium-high tech[16] sectors.

There exist inter-country differences across the EU in terms of high-growth enterprises. Some EU Member States perform well above the EU average (with a share of around 12 %): Greece, Ireland, the Netherlands, Portugal and Spain report a share of high-growth enterprises of around 16 %. On the contrary, for Austria, Belgium, Denmark, Estonia, Germany and Lithuania we observe a share around 10 %, while Cyprus and Romania perform significantly below the EU average with respectively 4.6 % and 2.5 % of active high-growth enterprises (Figure 4.2-18).

Figure 4.2-18: Share of high-growth enterprises(1) in EU Member States, 2018



Science, Research and Innovation Performance of the EU 2022

Source: Eurostat [online data code : bd_9pm_r2_1]
Note: (1)High growth enterprises measured in employment (growth by 10 % per year or more).
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-18.xlsx

14 All enterprises with average annualised growth greater than 20 % per annum, over a three year period should be considered as high-growth enterprises. Growth can be measured by the number of employees or by turnover.

15 High-technology sectors include: firms involved in the manufacture of basic pharmaceutical products and pharmaceutical preparations (C21); manufacture of computer, electronic and optical products (C26); manufacture of air and spacecraft and related machinery (C30.3)

16 Medium-high-technology sectors include: firms involved in the manufacture of chemicals and chemical products (C20); manufacture of weapons and ammunition (C25.4); manufacture of electrical equipment (C27); manufacture of machinery and equipment n.e.c. (C28); manufacture of motor vehicles, trailers and semi-trailers (C29); manufacture of other transport equipment (C30) excluding the building of ships and boats (C30.1) and excluding manufacture of air and spacecraft and related machinery (C30.3); manufacture of medical and dental instruments and supplies (C32.5).

Box 4.2-2: The fully-fledged European Innovation Council (EIC) – Investing in Sustainable Start-ups and Scale-ups, Women Innovators and Business Leaders and European Deep Tech

Prior to the launch of the fully-fledged EIC in March 2021, the EIC pilot and its enhanced version were designed to prepare the ground for the full integration of the predecessor instruments and services, such as the SME instrument, FET Open & Proactive, to arrive at the three main funding instruments that now constitute this unique European initiative. As part of Horizon Europe, the EIC Pathfinder, EIC Transition and the EIC Accelerator funding schemes will ensure Europe's competitiveness when it comes to deep-tech start-ups as well as building an investment pipeline of sustainable scale-ups made in Europe. Furthermore, the EIC is taking action on its ambition to invest in a balanced and diverse European innovation ecosystem by fostering female entrepreneurship and business leaders from all over the EIC community.

The 2021 EIC's Impact Report[17] showed the first successes of the EIC and included 5 500 pilot Accelerator projects (including those from SME Instrument) and 408 pilot Pathfinder projects (including those from FET).

EIC Accelerator companies already attracted EUR 9.6 billion in follow on investments, primarily from venture capital, but also from corporates, national promotional banks and others.[18] Overall, they reached a valuation of around EUR 50 billion, including 91 centaurs (with a company valuation of over EUR 100 million) and four unicorns (with a company valuation of over EUR 1 billion).

Figure 4.2-19: The three EIC funding instruments

1. EIC PATHFINDER

For a advanced high-risk research on breakthrough technologies

2. EIC TRANSITION

For transforming the most promising research results into innovation opportunities

3. EIC ACCELERATOR

For ambitious and innovative companies to develop and scale uo cutting-edge innovations

Science, Research and Innovation Performance of the EU 2022

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-19.xlsx

17 https://eic.ec.europa.eu/news/european-innovation-council-impact-report-2021-key-numbers-eic-performance-2021-11-24_en

18 Investment data in cooperation with Dealroom

Figure 4.2-20: The EIC unicorns

4 Unicorns

CELLINK A BICO COMPANY

BIOARCTIC

SWORD HEALTH

infarm

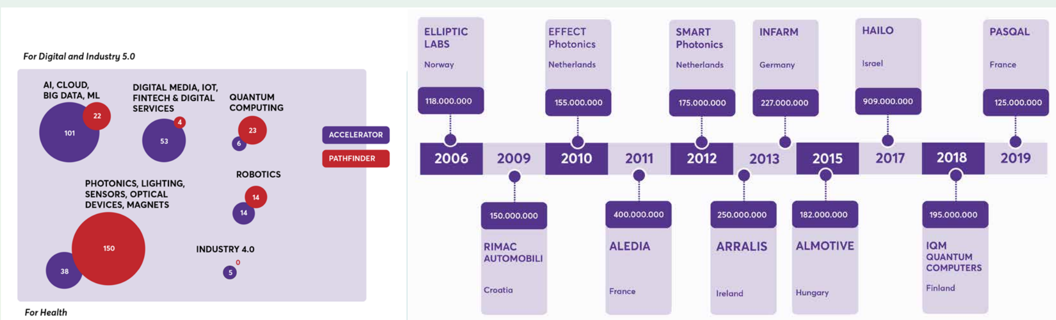
Science, Research and Innovation Performance of the EU 2022

Source: Dealroom
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-20.xlsx

The EIC's Impact Report 2021 also revealed that EIC companies are well positioned to feed into current investor appetites for digital, green and health investment opportunities:

Figure 4.2-21 below shows the EIC's digital portfolio for both Accelerator and Pathfinder, and includes trending areas such as cloud computing, magnets, fintech and quantum computing. Digital centaurs also contributed to a significant rise in value of the overall EIC portfolio of companies.

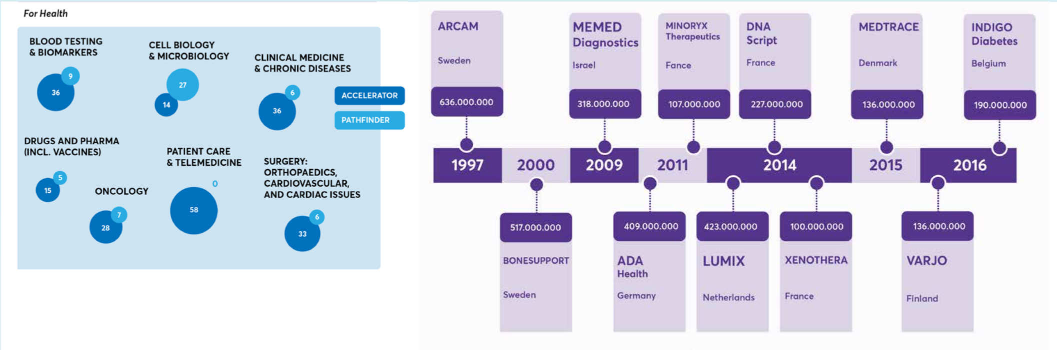
Figure 4.2-21: EIC digital portfolio and EIC digital centaurs



Science, Research and Innovation Performance of the EU 2022

Source: EIC 2021
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-21.xlsx

Figure 4.2-22: EIC health portfolio and EIC health centaurs



Science, Research and Innovation Performance of the EU 2022

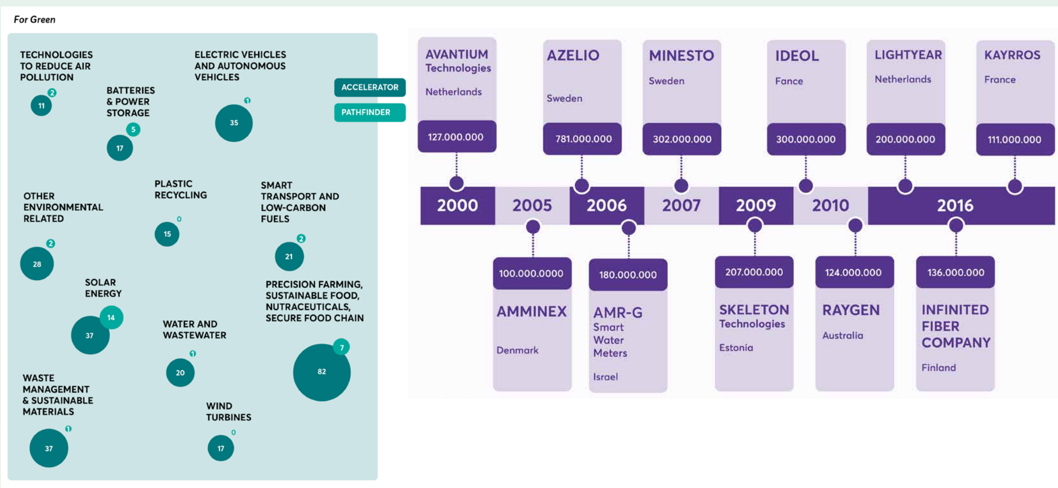
Source: EIC 2021
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-22.xlsx

The EIC's health portfolio and its associated centaurs are also positioned in promising areas, albeit the pandemic is likely to change its entire composition in the years to come.

The EIC's green portfolio is one of its kind and combines some of the most pioneering companies and projects to target and reach the market for sustainable investing. The portfolio is diverse and wide ranging and includes sustainable food companies as well as sustainable materials innovators.

For 2022, EIC Accelerator funding of EUR 1.16 billion is earmarked for start-ups and SMEs to develop and scale up high-impact

Figure 4.2-23: EIC green portfolio and EIC green centaurs



Science, Research and Innovation Performance of the EU 2022

Source: EIC 2021
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-23.xlsx

and disruptive innovations. Its blended finance option provides equity (or quasi-equity such as convertible loans) between EUR 0.5 million and EUR 15 million through the EIC fund, with grants of up to EUR 2.5 million. Moreover, about EUR 537 million in Accelerator funding will go towards breakthrough innovations as part of a call dedicated to Open Strategic Autonomy and technologies in line with the Fit for 55 strategy.

EIC Pathfinder is committed to investing in European deep techs with a high risk and high potential for scientific and technological breakthroughs. Pathfinder multi-disciplinary research teams, worth EUR 350 million in 2022, are working towards the future basis for innovations and the investment opportunities of tomorrow. Research teams can apply for up to EUR 3 million or EUR 4 million in grants.[19] According to the EIC's 2021 Impact report, EIC pilot Pathfinder projects have generated over 800 innovations so far (tracked by Innovation Radar). The majority of pilot Pathfinder projects include SMEs or other commercial partners that are also more likely to generate patents as part of their business plans. Moreover, the Pathfinder has led to a large number of scientific impacts (high impact publications). Together with the EIC's Programme Managers, who pro-actively support the innovation potential of their portfolio projects, the EIC strives to bring these breakthroughs closer to the market.

The new EIC Transition Instrument is investing EUR 131 million in 2022[20] to turn research results into innovation opportunities. This will be implemented in cooperation with the European Research Council (ERC), who will contribute with proof-of-concept projects, and the European Institute of Innovation and Technology (EIT). Together the EIC, EIT and the ERC will build business cases for mature technologies and for specific applications.[21] Furthermore, the EIC will continue its commitment towards increasing the number of women-led start-ups in 2022 and the years to come and can already report its first success: Of those awarded funding in 2020, over 20% have a female CEO, a doubling of the previous level.

19 The bulk of the funding is awarded through open calls with no predefined thematic priorities, while EUR 167 million is allocated to tackle six challenges: carbon dioxide and nitrogen management and valorisation; mid-long term, systems-integrated energy storage; cardiogenomics; healthcare continuum technologies; DNA-based digital data storage and alternative quantum information processing, communication, and sensing.

20 EUR60.5 million for three Transition Challenges: green digital devices for the future; process and system integration of clean energy technologies; and RNA-based therapies and diagnostics for complex or rare genetic diseases.

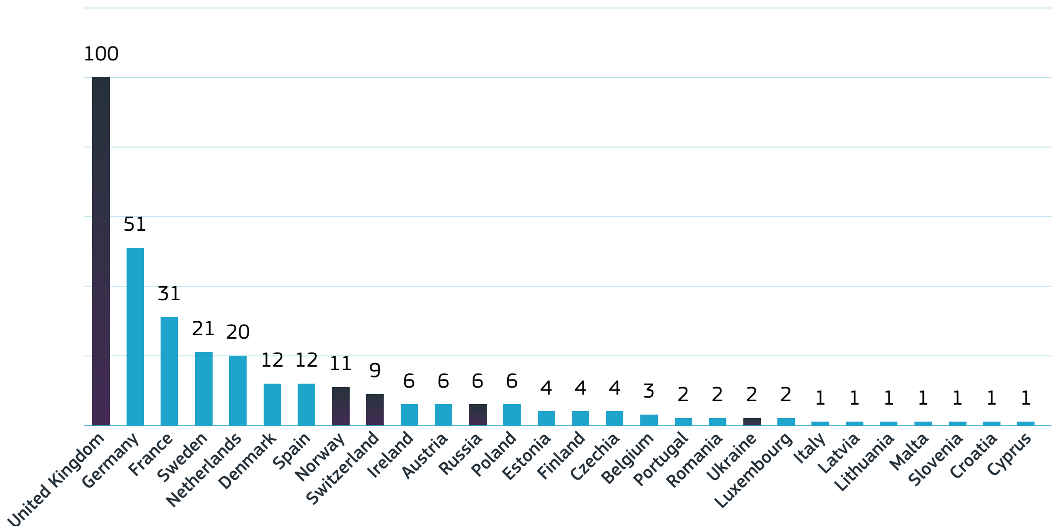
21 Consortia can apply for EUR 2.5 million grants (or more if justified).

4. In need of unicorns ?

Unicorn companies[22] are typically fast-growing start-ups operating at the edge of the innovation frontier. Besides playing an important role in boosting aggregate economic productivity and job creation, unicorns also act as catalyst for innovation. One of the key characteristics of a unicorn company is a quickly adaptable business model, which allows the company to promptly react to changes in market and innovation trends (Casnici, 2021). In monitoring unicorns it is thus useful to investigate emerging trends in the innovation landscape, as this type of company typically swiftly adopts and are themselves carriers of cutting-edge technologies.

The number of European unicorns grew significantly in 2021. According to the latest available data, the number of unicorns founded in Europe increased by almost 44% in 2021, jumping from 223 at the end of 2020 to 321 by November 2021. Between November 2021 and now, 98 new unicorns were founded in Europe (Atomico, 2021). This trend confirms that the European entrepreneurial landscape is strengthening, significantly improving its ability to create new and fast-growing innovative actors. **Nevertheless, many of the unicorns founded in Europe tend to move their headquarters elsewhere.**

Figure 4.2-24: **Geographic distribution of unicorns in Europe, up to 2021**



Science, Research and Innovation Performance of the EU 2022

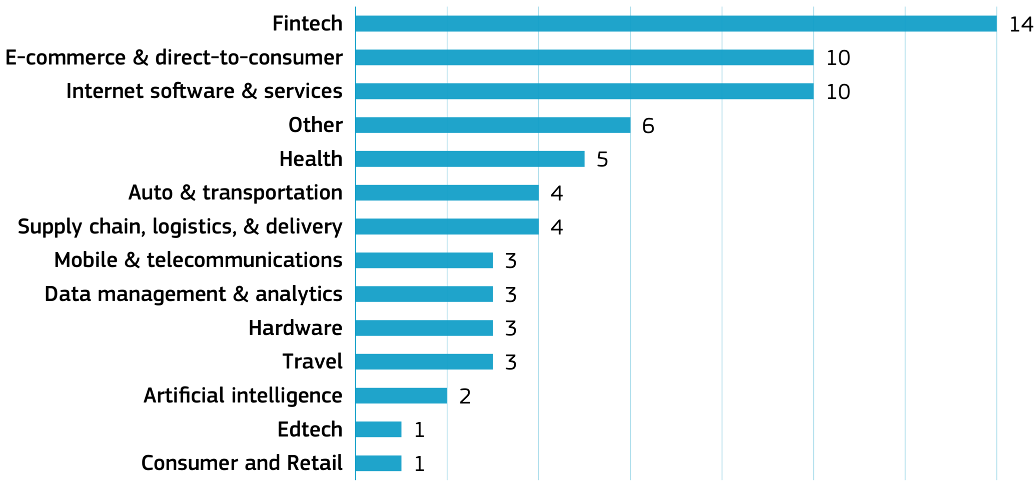
Source: Atomico (2021) based on Dealroom data
Note: Data refers to the number of unicorns founded in each country
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-24.xlsx

22 A unicorn start up is a privately owned company which manages to reach a valuation of $ 1 billion (currently about EUR 867.14 million) or more.

There exist considerable differences in the distribution of unicorns across European countries. The UK keeps leading the European landscape in terms of founded unicorn companies, with a total of 100. When looking at the EU Member States, Germany accounts for the largest share of unicorns founded in the EU (51). France has the second highest number of founded unicorns (31), followed by Sweden (21) and the Netherlands (20). Latvia and Cyprus both saw the creation of one unicorn in 2021, with Printful (Latvia) and Nexters Group (Cyprus) reaching unicorn status in May 2021 (Atomico, 2021).

EU unicorns are mostly active in the financial and digital sector. The Fintech sector accounts for about 20% (14) of the EU-headquartered unicorns (Figure 4.2-25), as a result of the large investments injected in this sector over the past ten years (Testa et al., 2022). The ICT-software sector reports 20 unicorn firms (10 unicorns active in the e-commerce industry, and internet software and services, respectively). The health and transportation industries follow with 5 and 4 unicorns, respectively.

Figure 4.2-25: **Sectorial distribution of EU unicorn firms, up to November 2021**



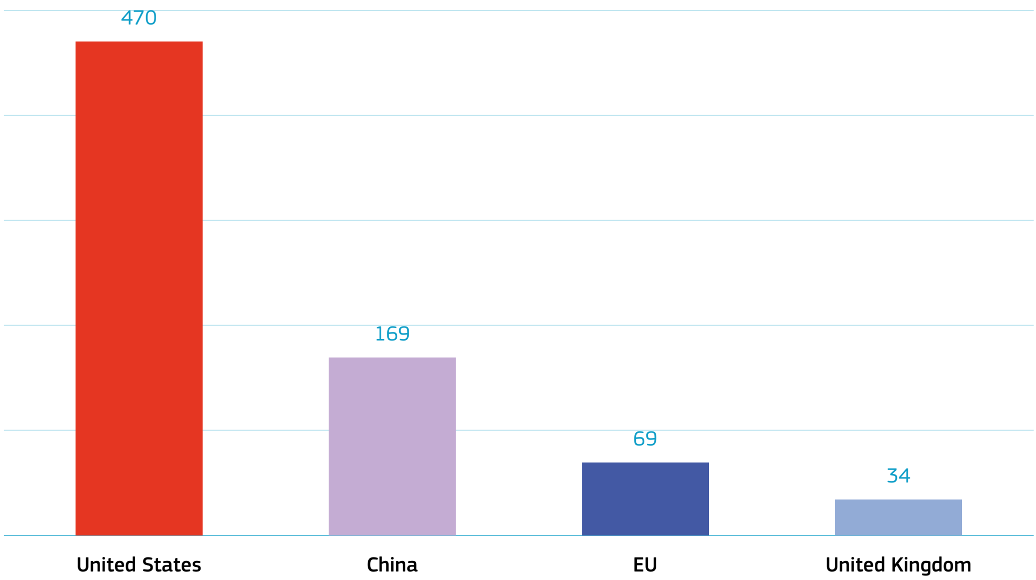
Science, Research and Innovation Performance of the EU 2022

Source: CBInsights, updated up to Nov 2021
Note: Data refers to unicorn companies headquartered in the EU.
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-25.xlsx

Despite the rapid increase in the number of European unicorns, the EU still underperforms as compared to other major economies. The EU's limited ability to scale start-ups into major companies is also reflected by the lower number of unicorn firms compared to our main competitors.

In 2021, the US reported almost seven times more unicorns than Europe, while China outperformed the EU by a factor more than two (Figure 4.2-25). By the end of 2021, there were 742 companies worldwide with unicorn status. Of those, more than 60 % (470) are based in the United States, more than one fifth in China (or 169), and about 9 % (69) are in the EU. Furthermore, EU unicorns are typically older than US and Chinese ones. On average, it takes about 10 years for an EU unicorn to reach the USD 1 billion valuation, against the eight and five years reported by US and China (Testa et al., 2022). One of the main reasons behind the differences between the EU and the US is the significant difference in capital markets between the two economies, which calls for the creation of a more efficient capital ecosystem able to raise the necessary funding for EU firms to scale-up (see Chapter 7.1 - Access to finance: the importance of equity and venture capital).

Figure 4.2-26: Number of unicorns across world regions per headquarter, up to August 2021



Science, Research and Innovation Performance of the EU 2022

Source: CBInsights, updated up to Nov 2021

Note: Figure 4.2-26 reports the number of unicorns headquartered in the different geographical regions.

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5. Entrepreneurial ecosystems in the digital age

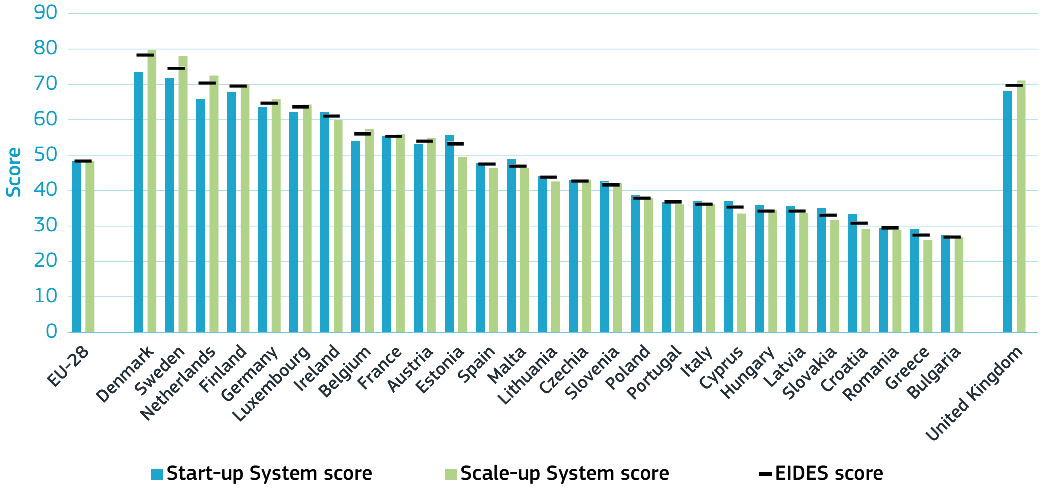
Entrepreneurship is essential for creating jobs, boosting innovation and increasing growth. Along with the concept of creative destruction, Schumpeterian growth theory outlays the idea that innovation and, thus, long-term growth is generated by entrepreneurial investment (e.g., R&D, training, equipment purchases) (Aghion and Howitt, 1992). There exists a large body of economic literature linking entrepreneurial activity to economic growth. Central to this literature is the consideration that economic growth cannot be explained only by looking at the inputted factors of production, but also strongly hinges on the profit opportunities created by the entrepreneurial process (Prieger et al., 2016). In this regard, the literature coined the term 'productive entrepreneurship' to indicate any entrepreneurial activity that contributes to producing additional output (Baumol 1993; Bosma et al., 2018). Although there is a large consensus on the positive relationship between entrepreneurship and growth, the channels through which this relationship works are still debated. Wennekers and Thurik (1999) identified **three main channels through which entrepreneurship can drive economic growth, namely innovation creation, innovation diffusion and competition**. Nevertheless, the link between entrepreneurial activities and economic performance also depends on the institutional environment. An increasing number of studies have attempted to uncover such a complex system of interlinkages, broadly referred to as the 'entrepreneurial ecosystem' (Bosma et al., 2018; Aution and Cao, 2019; Content et al., 2020).

Today entrepreneurial ecosystems are critical for the digital transition. The reorganisation of our societies and the changes in the way of doing business following the harnessing of digital technologies create new opportunities for entrepreneurs, and calls for the adoption of innovative business models and practices (Autio and Cao, 2019). In this context, entrepreneurial ecosystems can play a prominent role in unlocking the opportunities coming from the digital transition (Autio et al., 2020). Furthermore, according to Autio et al. (2019), entrepreneurial ecosystems specialise in fostering digital start-ups, thereby making entrepreneurial ventures a driver for the digital transition (Autio et al., 2020).

EU countries perform very differently in terms of having a digitalised framework conditions for entrepreneurship. The European Index of Digital Entrepreneurship Systems (EIDES) measures both physical and digital conditions for stand-up, start-up and scale-up ventures in the EU Member States, plus the UK. The average performance of EU countries has improved in the last three years (Autio et al., 2020). Figure 4.2-27 reports the result of the 2020 EIDES scores. Denmark, Sweden, the Netherlands, Finland, Germany, Luxembourg and Ireland are leading in terms of their digitalised framework conditions for entrepreneurship.[23] Denmark and Sweden appear as leaders also when sub-indices (stand-up, start-up and scale-up indices) are considered, while the Netherlands ranks as third for the stand-up and scale-up systems, and fifth in terms of start-up systems.

23 Countries can be divided into four groups according to their EIDES score: 1) leaders, with a score above 60; 2) followers, with an score between 60 and 45; 3) catchers-up, with a score ranging between 45 and 35; and 4) laggards, with a score lower than 35.

Figure 4.2-27: EIDES score by country, 2020[1]



Source: Autio et al., 2020 based on EIDES 2020

Note: [1]Countries can be divided into four groups according to their EIDES score: 1) leaders, with a score above 60; 2) followers, with an score between 60 and 45; 3) catchers-up, with a score ranging between 45 and 35; and 4) laggards, with a score lower than 35.

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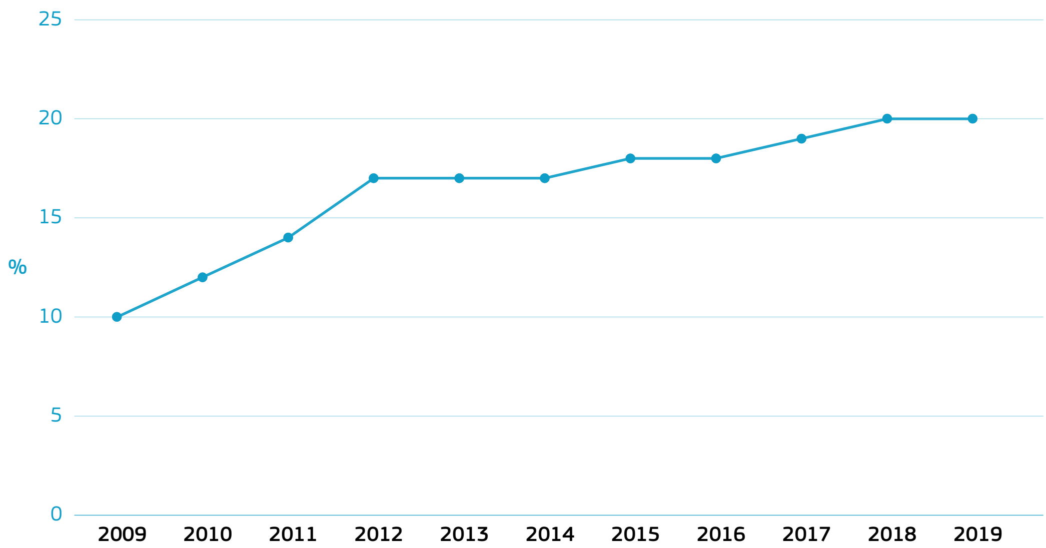
Germany and Luxembourg score respectively sixth and seventh in the three sub-indices, whereas Ireland ranks eighth. A second group, with an average score 16 points lower than the leader group identified as followers, comprises of Belgium, France, Austria, Estonia, Spain and Malta. Lithuania, Czechia, Slovenia, Poland, Portugal, Italy, and Cyprus follow as catching-up countries, while Hungary, Latvia, Slovakia, Croatia, Romania, Greece and Bulgaria are lagging behind, with an EIDES score ranging between 26.9 (Bulgaria) and 34.4 (Hungary and Latvia) (Autio et al., 2020).

6. The EU entrepreneurial gender gap

The number of women founding start-ups is increasing worldwide, but a gender gap still remains. Inclusiveness is a critical feature for entrepreneurship. Excluding one or more societal groups from the entrepreneurial ecosystem would result in untapped growth opportunities in terms of job creation, innovation and productivity. Figure 4.2-28 reports the evolution of the share of global start-ups with a female founder over the period 2009-2019. The data shows an increasing trend over time: overall the share of female funded start-ups almost doubled, increasing from 10% in 2009 to 20% in 2019.

Figure 4.2-28: Share of start-ups with a female founder, 2009-2019



Science, Research and Innovation Performance of the EU 2022

Source: Crunchbase (2019)
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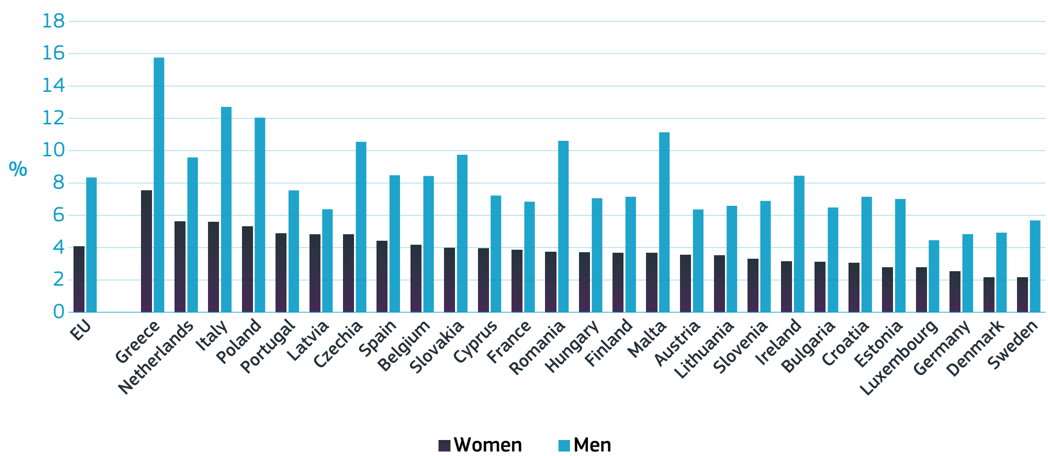
Europe shows lower female entrepreneurial activities compared to other regions in the world. The rate of early-stage women entrepreneurial activity (i.e. the share of women aged between 18 to 64 years old who are either nascent entrepreneurs, or are owners of a business[24]) in Europe is 5.7%, against a world average of 11% (GEM, 2021). European women perform poorly when compared to men across the different stages of the business creation process.

The entrepreneurial gender gap persists also within EU Member States. When looking at entrepreneurial intentions (i.e., intentions of starting a business), the gender gap is particularly striking in Norway (4.9% for women vs. 10.3% for men) and Poland (2.8% vs. 7%), whereas in Luxembourg (10.7% vs. 11.5%) and Latvia (15.9% vs. 19%) the divergences are less pronounced (GEM, 2021). As regards female entrepreneurial activity in businesses less than 3.5 years old, Italy (0.9% vs. 2.9%), Luxembourg (5% vs. 10.9%) and Slovakia (8.9% vs. 18.8%) report the highest divergences, followed by Spain (4.8% vs. 5.6%) and Germany (4.3% vs. 5.1%) (GEM, 2021). The gap is even more pronounced when considering established businesses (more than 3.5 years old), with most countries showing differences close to or exceeding 100% (GEM, 2021). An alternative way to look at the entrepreneurial gender gap is to focus on female and male self-employment rates[25] (Figure 4.2-29). In 2020, the number of female entrepreneurs were half that of men (4% against 8%). Sweden, Slovakia, Romania, Poland and Malta present the highest gender gaps in terms of

Figure 4.2-29: Female entrepreneurship rates across EU Member States, 2020



Source: Labour Force Survey (2020), [online data code: lfsa_esgan2_1]
Note: The entrepreneurship rate is measured as the number of self-employed women as a proportion of total active population aged 15 to 64.
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24 I.e. entrepreneurs in the process of starting a business but have not paid wages for more than three months, and owners of businesses that are older than three months but younger than 42 months (GEM, 2021).

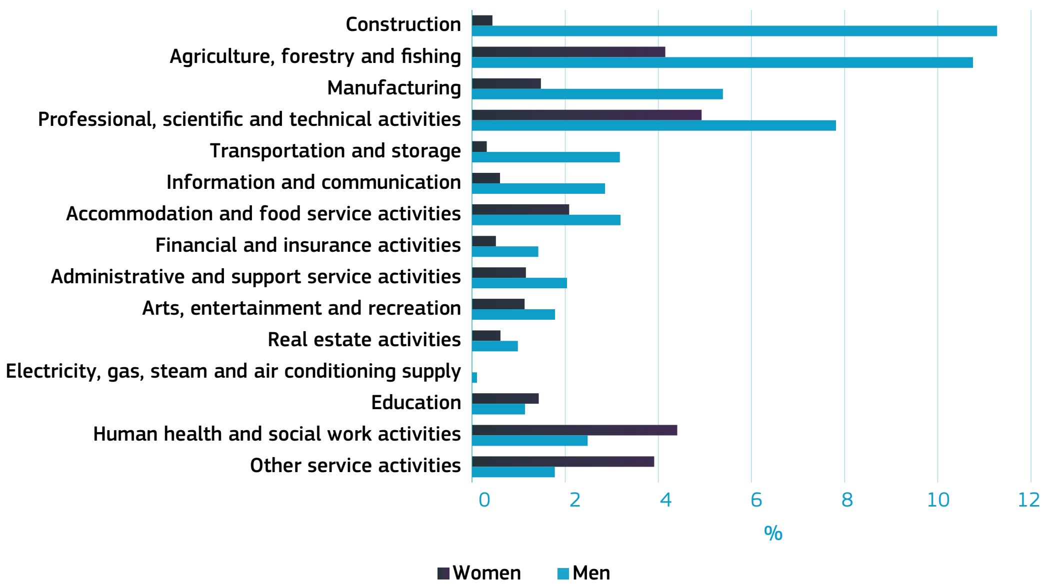
25 Self-employment is one of the most common proxies used to measure entrepreneurial activities.

self-employed women and men, whereas Luxembourg, Latvia, and Germany show the smallest discrepancies.

A potential reason for the EU entrepreneurial gender gap is the presence of a sectorial gender segregation. Female entrepreneurs in the EU are mostly found in economic sectors typically characterised by a lower level of entrepreneurial activities. Typically fast-growing sectors (such as construction, manufacturing, professional, scientific and technical activities, as well as information and communication) are dominated by male entrepreneurs. Such a gap is particularly striking for the construction and manufacturing industries, with a share of male entrepreneurs of respectively 10% and 5%, against less than 1% and 1.5% of female entrepreneurs, respectively. On the contrary, self-employed women mostly operate in the health and social work sector (4.4% women against 2.5% men), and in other service sectors including washing and cleaning textile products, hairdressers, as well as well-being services[26] where the proportion of female entrepreneurs is twice that of males (4% against 2%).

Furthermore, the EU still struggles to improve its performance in terms of female patent applications, and falls behind its main international competitors. The share of female patent applications filed under the Patent Cooperation Treaty (PCT) to the European Patent Office (EPO) did not increase much over 2008 to 2018 (Figure 4.2-31). Furthermore, the EU's performance remains significantly below that of other international economies. China and South Korea are at the top of the ranking, with 31.6% and 30.6% respectively of female patent applicants in 2018.

Figure 4.2-30: **Distribution of female entrepreneurs by industry, 2020**



Science, Research and Innovation Performance of the EU 2022

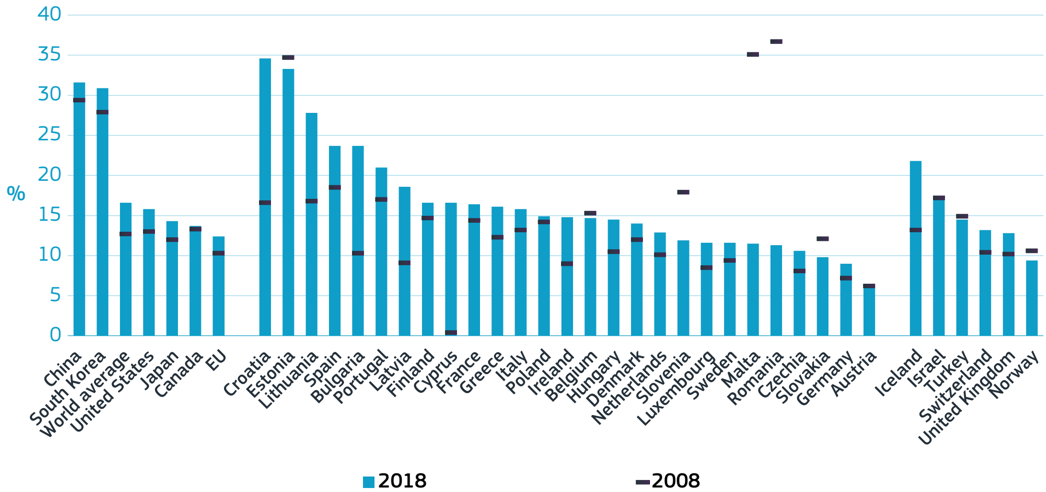
Source: DG Research and Innovation - Common R&I Strategy and Foresight Service - Chief Economist Unit, based on Labour Force Survey (2020), [online data code: lfsa_esgan2_1]]

Note: The entrepreneurship rate is measured as number of self-employed women as proportion of total active population aged 15 to 64.

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-30.xlsx

26 E.g. medical massage and therapy, and activities related to health, fitness and body-building clubs and facilities.

Figure 4.2-31: Share of female applicants on patent applications filed under PCT to the EPO, 2008 and 2018



Science, Research and Innovation Performance of the EU 2022

Source: DG Research and Innovation - Common R&I Strategy and Foresight Service - Chief Economist Unit based on Science-Metrix using data from EPO PATSTAT database.

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-2-31.xlsx

The US follows with 15.8%, which is slightly below the world average (16.6%). The EU is significantly behind, reporting only a 12.4% share (Figure 4.2-31). In addition, the EU also shows significantly inter-country differences. In 2018, Croatia reported the highest share of female patent applicants (34.6%), followed by Estonia and Lithuania (33.3% and 27.8%, respectively). Croatia was also among the Member States showing the highest increase over 2008 to 2018 (Figure 4.2-31). Similarly, most of the Member States improved their performance over the same time span, ending up above the EU average. The important exceptions were Slovenia, Malta and Romania, which experienced a significant reduction in the share of female patent applications, dropping below 12% (Figure 4.2-31).

7. Conclusions: fuelling business dynamism in EU

In order to reverse the sluggish trend in productivity growth, the EU has to accelerate the development and diffusion of innovative ideas and inventions in support of EU enterprises with high-growth potential. The EU can count on a vibrant start-up ecosystem, and needs to increase its efforts to create a fertile innovation landscape for firms to scale-up and grow. Although still lagging significantly behind US, the European scale-up landscape shows considerable potential and has proved to be able to quickly react to the challenges posed by COVID-19. **Innovative enterprises showed better adaptation capacities to the shock, confirming the role of innovation as key ingredient for economic resilience**. Furthermore, since November 2021 European unicorns have increased by more than 40%, confirming that the role of Europe as global tech player is increasing.

The improved EU performance in terms of fast-growing companies is of key relevance in the aftermath of the COVID-19 pandemic. High-growth firms not only have the potential to speed-up the recovery, but are also essential for progress in the green and digital transition. Nevertheless, challenges remain (notably, the presence of skill bias, limited access to finance and fragmented regulatory framework), which call for continuous actions to improve the EU framework conditions for innovation.

Empowering women entrepreneurs remains a top priority. The EU has always promoted diversity as a key ingredient for a thriving economy. The European challenge to unleash its growth potential also needs solutions to ensure better female representation within the EU entrepreneurial landscape. Currently, the EU suffers from a significant entrepreneurial gender gap, which results in missed opportunities in terms of innovation, employment and growth. In renovating its commitment to reverse this trend, the European Commission presented the *EU Gender Equality Strategy 2020-2025* in March 2020, setting out EU policy objectives to create a gender-equal Europe. This includes actions to strengthen European women's economic empowerment, e.g. the creation of an enabling environment for women's economic activities, facilitating access to finance through innovative investment schemes targeting women entrepreneurs and female-led businesses.

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CHAPTER 4.3

SKILLS IN THE DIGITAL ERA

KEY FIGURES

56 %
of the EU population has basic or above-basic digital skills

23 %
of EU enterprises have provided ICT training to their personnel

34 %
of online job postings in the EU mention communication, collaboration and creativity skills

20 %
increase in the share of high-skilled jobs in the EU from 2002 to 2020

12 %
decrease in the share of middle-skilled jobs in the EU from 2002 to 2020

KEY QUESTIONS WE ARE ADDRESSING

- How is technological change and digitalisation affecting the job market?
- What skills are required in the digital era?
- How does the European population perform in terms of digital skills?

KEY MESSAGES

What did we learn?

- Skill-biased technological change is driving structural changes in skills requirements in both the EU and the US. The share of highly skilled jobs has risen, that of middle-skilled jobs has diminished, and that of low-skilled jobs remained steady.
- In the digital era, the job market presents more jobs requiring non-routine, abstract, analytical and social skills. Skills in high demand are, in addition to technical and ICT skills, the ability to communicate, to work in teams, collaborate and be creative, and the capacity to work effectively with computers.
- In the EU, there is a strong heterogeneity of skills levels across countries, urban and rural areas, and age groups.

What does it mean for policy?

- Reskilling policies for low- and middle-skilled workers will be crucial for sustainable and inclusive economic growth.
- Lifelong learning activities will become increasingly important to keep workers' skills aligned with evolving job market demands and to support longer working lives.
- In the digital era, education and training policies should increase their emphasis on developing non-cognitive skills that complement digital skills, such as social intelligence, collaboration, creativity and adaptability.

1. Skills in a digital world and global trends

The digital transformation is changing the skills requested and rewarded by the labour market. Research confirms that some jobs are being displaced by automation and the nature and tasks of others is changing, while new jobs are emerging as the digital revolution unfolds (e.g. Acemoglu and Restrepo, 2019). To ensure an inclusive digital transition, it is important to understand what types of skills and tasks will be best rewarded in the digital economy, while at the same time identifying the distributional changes that the labour market may face, and which workers risk being displaced by technological change.

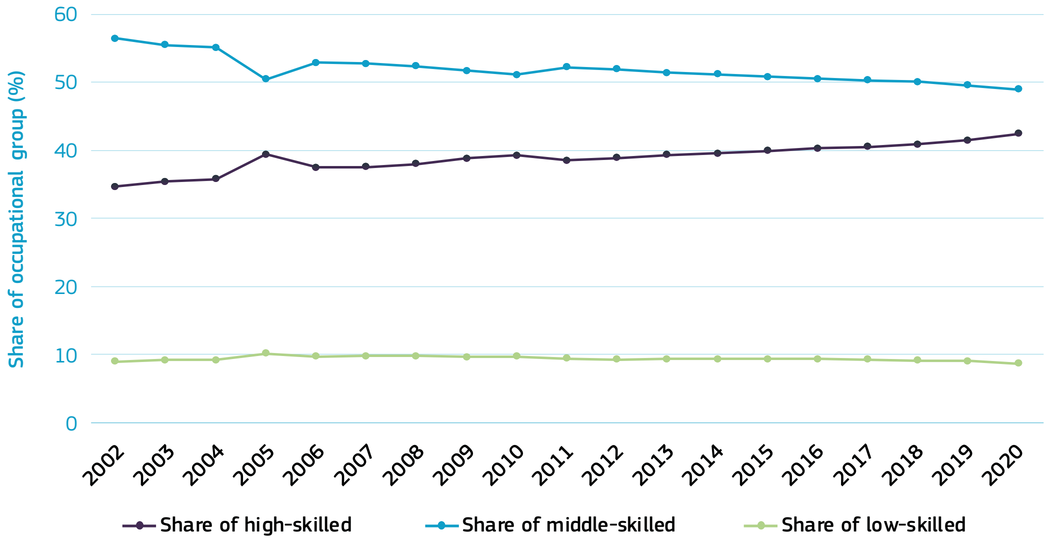
Technology is often described as substituting for less-skilled workers and complementing high-skilled workers, generating skill-biased shifts in labour demand. Technological change is rarely neutral towards the different production factors: it typically changes the proportions in which production factors such as capital, less-skilled labour and high-skilled labour are demanded. Many new technologies increase the complexity of tasks and jobs and therefore raise the skill requirements of jobs. If the increase in demand for higher-skilled individuals outpaces the growth in their supply through the education system, this may put upward pressure on the skills wage premium (Tinbergen, 1974, 1975). As a result, imbalances in the demand and supply of different groups of workers, exacerbated by technological change, can cause a rise in wage inequality[1]. So far, nevertheless, there is little evidence of a structural rise in wage inequality in Europe over the last two decades, possibly as a result of policies and other factors counteracting the rise in inequality[2].

In the EU and the US, the proportion of high-skilled occupations has increased, the proportion of middle-skilled occupations decreased, and the proportion of low-skilled occupations remained steady over the last two decades (see Figures 4-3-1 and 4-3-2). In the EU, the share of high-skilled occupations (out of total employment) increased by 7 percentage points between 2002 and 2020, growing from 35 % to 42 %, especially in market services. The share of low-skilled occupations remained steady at around 10 %. In contrast, the share of middle-skilled occupations plummeted by around 7 percentage points, from 56 % in 2002 to 49 % in 2020. Sector-wise, these job losses were particularly concentrated in agriculture and manufacturing (OECD, 2021). The US presents a similar picture, with the share of high-skilled occupations increasing by 4 percentage points from 2002 to 2020, the share or low-skilled occupations staying almost steady and the share of middle-skilled occupations decreasing by 5 percentage points.

1 See Katz and Murphy (1992), Card and Lemieux (1994), Acemoglu (1998), Autor, Katz and Krueger (1998), Chennells and Van Reenen (1998), Machin and Van Reenen (1998), Card and DiNardo (2002), Goldin and Katz (2010), Acemoglu and Restrepo (2020).

2 See e.g. Filauro and Fischer (2021) and Vandeplas (2021)

Figure 4.3-1: **Structural changes in skills requirements[1] in the EU, 2002-2020**



Science, Research and Innovation Performance of the EU 2022

Source: DG Research and Innovation – Common R&I Strategy and Foresight Service – Chief Economist Unit based on Eurostat data. Online data code: LFSA_EGISED

Note: [1]Following the International Labour Organization (ILO) (2007) methodology, high-skilled occupations include jobs classified under the ISCO-08 1-digit codes 1, 2 and 3. Middle-skilled occupations include jobs classified under the major groups 4, 5, 6, 7 and 8. Low-skilled occupations include jobs classified under group 9.

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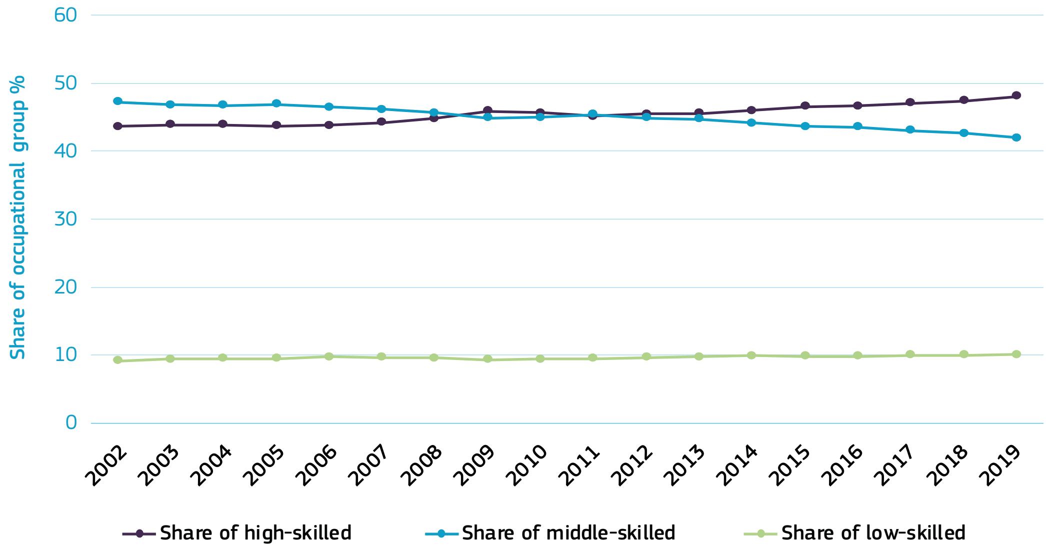
Figure 4.3-2: **Structural changes in skills requirements[1] in the United States, 2002-2019**



Science, Research and Innovation Performance of the EU 2022

Source: DG Research and Innovation Common R&I Strategy and Foresight Service – Chief Economist Unit based on ILO data

Note: [1]High-skilled occupations include jobs classified under the ISCO-08 1-digit codes 1, 2 and 3. Middle-skilled occupations include jobs classified under the major groups 4, 5, 7 and 8. Low-skilled occupations include jobs classified under group 9. In the ILO-USA classification, ISCO code 6 is not presented separately but is merged with ISCO code 9. Data refer to the US.

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A major driver of these observations, as proposed by the literature, has been routine-biased technical change. A commonly used classification of job tasks discerns three major types of tasks:

- *Non-routine abstract tasks*. Activities that require problem solving, intuition, persuasion and creativity. Such tasks are complementary to digital technologies and are mostly performed in professional and managerial jobs.
- *Non-routine manual tasks*. Activities that require situational adaptability, in-person interaction, yet few formal education requirements. Such tasks are harder to automatise; a non-exhaustive list of them may be food preparation and serving, cleaning and janitorial work, maintenance, security and driving.
- *Routine tasks*. Activities that can be easily codified into a series of instructions to be executed by a machine.

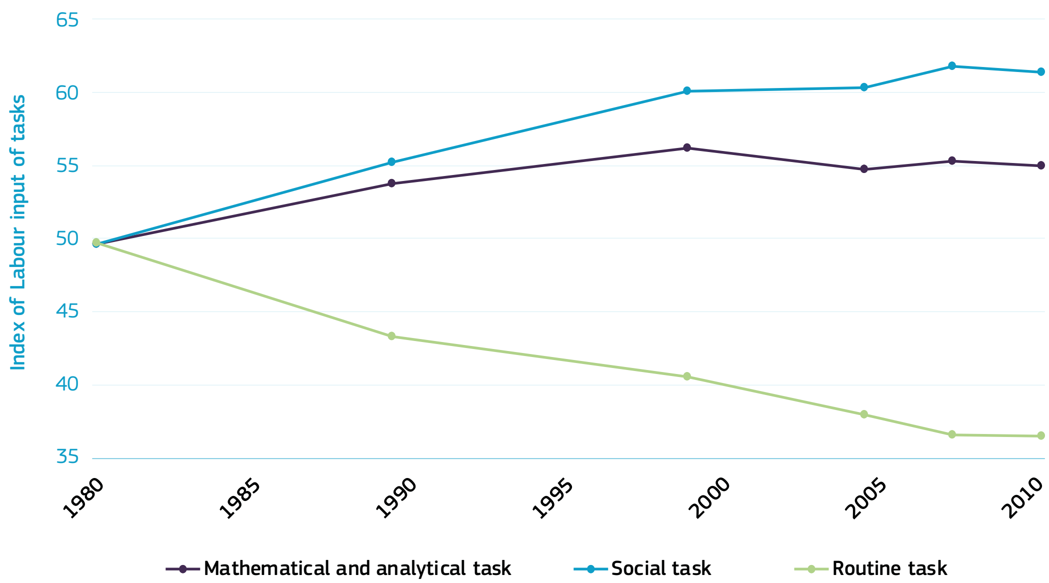
Routine-based tasks that take place in structured environments and require little social interaction are more likely to be automated (or outsourced) (Acemoglu and Autor, 2011; Acemoglu, 2012; Autor, 2015). Acemoglu and Autor (2011) hypothesise that non-routine abstract tasks most often require skills at the high end of the skills distribution, that non-routine manual tasks are usually situated at the low end of the skills distribution, and that routine tasks are characteristic of many middle-skilled jobs, such as clerical and production jobs. Empirical studies nevertheless suggest that the routine content of jobs is highest in occupations in ISCO 1-digit categories 8 (plant and machine operators) and 9 (elementary occupations), in other words the occupations with the lowest skill requirements (see e.g. Marcolin et al., 2019; Cirillo et al., 2021). Work by Graetz and Michaels (2018) also suggests that low-skilled workers are more likely to be displaced by automation than middle- and high-skilled workers. The routine task content and hence the risk of automation is lowest for high-skilled occupations, and these have seen the strongest expansion over the last two decades. Interestingly, even though occupation structures are de-routinising, the task content within jobs may not follow the same trend. Indeed, Bisello et al. (2019) found that (in the EU) jobs with more social-task content are expanding relative to the rest, but that this is in contrast with a decline in the number of social tasks people actually do in those (and other) jobs. Freeman et al. (2020) find that (in the US) social skills go up on aggregate, and that most of this is due to internal changes. Automation has been found to raise labour productivity, raise total factor productivity (TFP) and lower output prices, while redistributing labour away from lower-skilled to higher-skilled workers (Graetz and Michaels, 2018).

These observations highlight the fact that technological change does not happen in a vacuum. As Fernández-Macías and Hurley (2017) argue, economic factors (e.g. business cycle-related developments), policy decisions and institutional variables (e.g. wage-setting systems) have contributed to dynamics in skills demand over recent decades. Oesch and Piccitto (2019) also point to the large impact of wage-setting institutions and trends in skills supply (through changes in educational attainment and migration) on changes in skills demand. Acemoglu and Restrepo (2022) argue that changes in labour supply are driving automation and therefore skills demand. Notably, they found that automation and robot adoption has been particularly widespread in industries most affected by a scarcity of manual workers as a result of demographic ageing.

Non-cognitive skills are increasingly important in the digital economy, as tasks requiring social skills are less easily performed by technology (Morandini et al., 2020). Deming (2017) and Deming and Kahn (2017) find a growing complementarity between cognitive skills and social skills in the labour market, including in STEM jobs. US-based data suggest that when jobs are decomposed into the skills they require, with a distinction between non-routine analytical tasks, social skills, routine skills and high/low maths-intensive skills, routine tasks are on a declining trend, while non-routine analytical and social tasks are on an increasing trend (see Figure 4.3-3).

Adaptability is also set to be a major determinant of worker resilience. Cedefop's European skills and jobs survey (ESJS) in 2014 surveyed about 49 000 adult employees in the European Union, revealing that around 43% of EU employees experienced a recent change in the technologies they use at work, and that 26% thought that their skills would be outdated by 2019 (Cedefop, 2018). The ESJS also underlined that skills requirements are swiftly evolving in highly skilled jobs such as ICT, health, business and engineering related occupations. Even if these are less likely to see displacement by technology, continued participation in adult learning to update skills will also be key for workers in these occupations.

Figure 4.3-3: Task polarisation in the United States, 1980-2012



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Source: Deming (2017), Replication data for 'The Growing Importance of Social Skills in the Labor Market' on Harvard Dataverse

Note: The index of labour input of tasks is constructed using O*NET task measures and a method developed by Autor, Levy and Murnane (2003).

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The growing importance of non-cognitive skills is also underlined by recent OECD work identifying which skills are most in demand. The OECD analysis identifies shortages and surpluses for specific types of knowledge, skills and abilities[3] by combining information on employment and wage dynamics by occupation from 2004 to 2013/14 with information on the skills requirements within that occupation (OECD, 2017). The analysis of skills needs suggests that abstract reasoning and soft skills (e.g. active listening, active learning, critical thinking, judgment and decision making) are in high demand in the EU as well as in the US, while manual and routine skills (e.g. operation and control, equipment maintenance, repairing and monitoring) seem to be in surplus already (see Figure 4.3-4). Based on the OECD analysis, shortages of qualified/skilled personnel seem more pressing for the EU than for the US. In the knowledge domain, not surprisingly, IT comes out as a domain in high demand, as do education and psychology, while demand for mechanics and building and construction seems to have declined. In the abilities domain, verbal, reasoning and quantitative abilities are most in demand, while endurance, physical strength and balance/coordination have become less important.

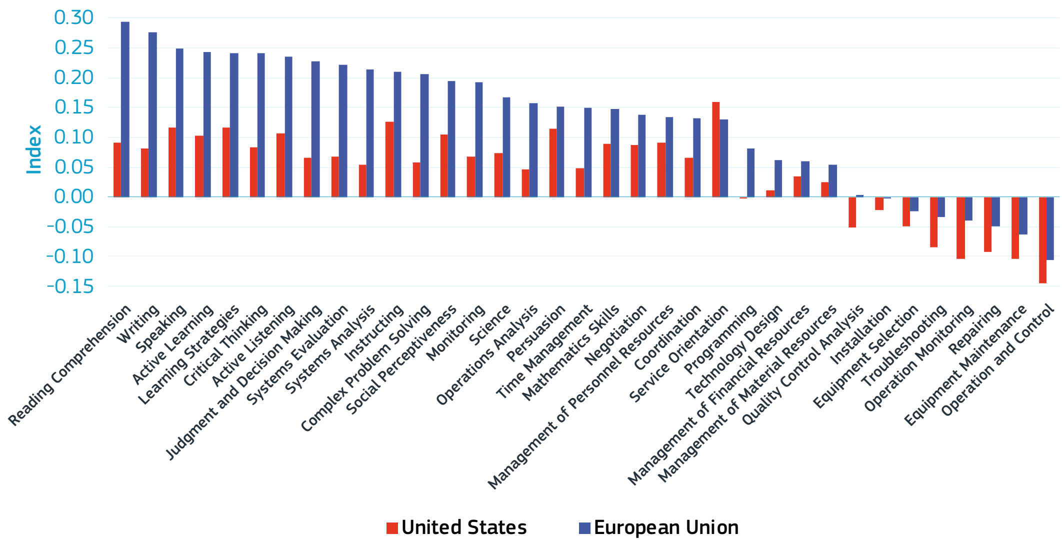
In the aftermath of the COVID-19 pandemic, skills shortages in the EU are at an all-time high and risk creating a drag on recovery. According to the European Business and Consumer Survey, more companies than ever report in 2022 that their growth or investment is held back by labour shortages. In the European Investment Bank's most recent Group Survey on Investment and Investment Finance (EIBIS survey), a lack of skills is the barrier to investment most often reported by firms (EIB 2021). In particular, 79% of firms in Europe report being held back by the scarcity of workers with the right skills. The figure is higher for more innovative firms, digital and climate-focused firms and SMEs. Through the Network of Eurofound Correspondents, labour shortages in sectors linked to the transition to a climate-neutral economy have been reported for 15 Member States (Eurofound 2021). The percentage of enterprises with hard-to-fill vacancies for ICT specialists has been steadily increasing, from 3% of all enterprises in 2012 to 5% in 2021, or from 40% of enterprises that tried to recruit ICT specialists in 2012 to 55% in 2020[4]. The ManpowerGroup Talent Shortage survey also finds that talent shortages are more pressing than ever, with 69% of employers reporting difficulties in filling vacancies in 2021, as compared to 58% in 2019[5]. Shortages are more frequently reported by firms in the EU than in the US and China according to the ManpowerGroup survey. This aligns with findings by Anderson and Wolff (2020), who highlight a more serious shortage of artificial-intelligence skills in the EU when compared to the US and China. They argue that the European Union produces fewer master's and PhD graduates in computer science and artificial intelligence and that it struggles to transform theoretical research into applied research that produces algorithms ready for practical commercial use.

3 While abilities are defined as 'enduring individual attributes that influence performance at work', skills are 'developed capacities that facilitate learning and performance', which include, inter alia, basic and transversal skills. Knowledge types relate to general work domains, such as business, engineering, psychology and so on.

4 Cf. ESTAT's survey on ICT use in enterprises, variable code ISOC_SKE_ITRCRN2

5 ManpowerGroup Talent Shortage survey

Figure 4.3-4: **Need for skills in the EU and United States, 2015**



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Source: OECD Skills for Jobs database

Note: Positive values indicate skill shortage while negative values point to skill surplus. The larger the absolute value, the larger the imbalance.

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Skills shortages can negatively affect labour productivity by constraining investment and slowing down the process of innovation and diffusion of new technologies (Vandeplas et al., 2019). Studies confirm that company investment in employee training has a positive impact on productivity. The impact on productivity is generally larger in magnitude than the impact on wages[6]. Individuals nevertheless stand to gain significantly from having better skills as it improves employability prospects and access to quality jobs.

For Europe at large, persistent skills shortages come at economic and social costs (Brunello and Wruuck, 2019). The incidence of labour shortages was already on the rise before the pandemic. This was also because of demographic trends: the working-age population has been shrinking all over the EU. The pandemic has exacerbated these shortages at least transitorily as it hampered education and training activities and had different impacts across sectors, and thus influenced the sectoral composition of labour demand.

6 See Konings and Vanormelingen (2015) for a study using Belgian data; Colombo and Stanca (2014) for a study using Italian data; Dearden et al. (2006) for a study using UK data; and Almeida and Carneiro (2009) and Martins (2021) for two studies using Portuguese data.

Sectors with a high proportion of non-essential contact-intensive jobs saw a stronger contraction in demand, while sectors with a high proportion of teleworkable jobs were considerably more resilient. The pandemic is also likely to have temporarily reduced the responsiveness of the labour supply to sectoral changes in demand through policy support measures and by imposing barriers to inward mobility and migration.

Policy can help mitigate skills shortages through adequate investment in education and training by strengthening skills intelligence, making labour markets more inclusive and facilitating migration. Higher skills levels and a stronger capacity to adapt to changing labour market conditions are crucial to equip workers to successfully navigate the digital transition and to ensure inclusive growth going forward. Preparing a highly skilled workforce, without leaving anyone behind, requires adequate and efficient investment in education and training from an early age and throughout life. As the duration of working lives is expanding while the pace of change in the labour market appears to be accelerating, high quality initial education is a precondition but not sufficient to equip workers adequately for the labour market: providing sufficient up- and reskilling opportunities to workers to update their skills and flexibly move into expanding sectors is key (Gratton and Scott, 2016). Education and training programmes and policies should be kept up-to-date by strengthening skills intelligence and gathering insights on emerging labour market needs in close collaboration with stakeholders, not least employers. Labour markets that are more inclusive can draw on a broader labour supply and a wider variety of skills. Facilitating migration already helps to address skills shortages in the short run.

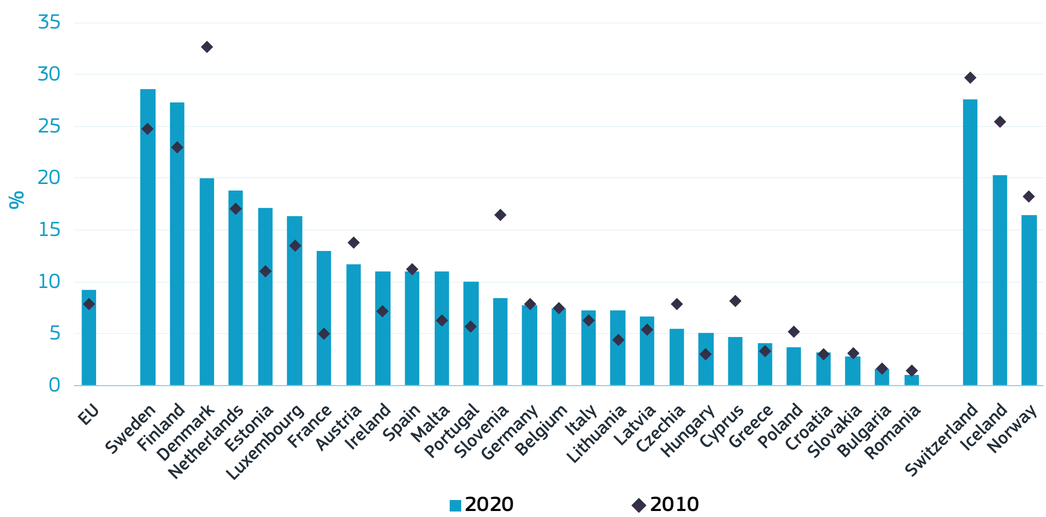
At the EU level, several initiatives have already been taken to address skills shortages, and more are underway. In 2020, the Commission proposed a renewed Skills Agenda, with 12 actions set to expand opportunities for people to train, especially in view of the green and digital transition. The agenda aims to catalyse investment in adult learning by public and private entities[7]. It highlights the need for collective action, mobilising all stakeholders to work together, identify skills needs and invest in the development of skills, including through the Pact for Skills. It interlinks with other policy initiatives such as the European Education Area, which promotes innovative and inclusive education at all levels, and the European Research Area, which promotes upskilling and reskilling, especially in academia. The Digital Europe programme invests particularly in the development of advanced digital skills. More recently, the revised EU Blue Card Directive aims to facilitate attracting high-skilled migrants to the EU. The Commission proposal on individual learning accounts proposes to provide each individual, independent of their working status, with a training entitlement and to reinforce the institutions that enable people to undertake training. The proposal on micro-credentials proposes a European approach to certification of upskilling and reskilling experiences and to support cross-border recognition. The Commission also recently proposed a European strategy for universities to strengthen the EU dimension of higher education and research and to empower universities as key actors of change in the green and digital transition. The Commission proposal on learning for environmental sustainability recommends that Member States support educators to also use new tools and materials to teach for environmental sustainability, including in digital settings.

7 https://ec.europa.eu/social/BlobServlet?docId=22832&langId=en

Adult participation in training increased across most EU countries over 2010-2019, but slid back in 2020. On average, the proportion of adults aged 25-64 participating in learning rose from 8% in 2010 to 11% in 2019, but deteriorated to 9% in 2020 (see Figure 4.3-5). The pandemic is likely to be the main culprit, as training and learning activities were severely hampered by social distancing measures and widespread school closures. In 2020, Sweden topped the EU ranking with 29% of its adult population having engaged in learning in the four weeks preceding the survey, closely followed by Finland and Denmark. Slovakia, Bulgaria and Romania show the lowest figures, with only 1% of the adult population in Romania having engaged in learning activities.

Given the shift toward a digital and learning economy, stronger engagement in lifelong learning would make the workforce more resilient and ready for transformational change. Pronounced cross-country differences in engagement in continuous learning risk exacerbating existing cross-country disparities. Furthermore, even within countries, adults with lower levels of education and skills engage less actively with adult learning activities (OECD, 2019). A key reason for this participation gap is that adults with low skill levels find it more difficult to identify their learning needs and hence are less likely to seek out training opportunities (Windisch, 2015). Participation rates also vary along the spatial dimension: while the participation rate in cities in the EU

Figure 4.3-5: Adult participation in learning[1], 2010 and 2020



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Source: Eurostat (online data code: SDG_04_60)

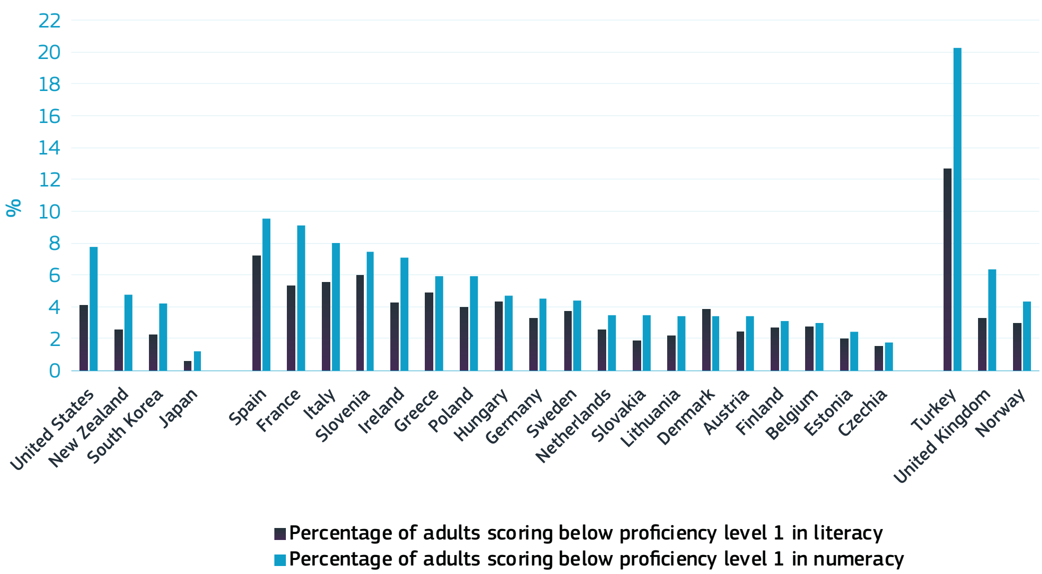
Note: [1]Share of people aged 25 to 64 who stated that they received formal or non-formal education and training in the four weeks preceding the survey

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-3-5.xlsx

was 11.5 % in 2020, it dropped to 8 % in towns and suburbs, and to 7 % in rural areas. Skill-biased technological change risks widening existing spatial inequalities. Therefore, policies that address disparities, and provide additional support to vulnerable regions and individuals through investments in infrastructure, local economic development and skills development, are necessary to ensure inclusive growth and avoid a deterioration in social tensions, political divide and unrest.

Ensuring a strong foundation of basic and transversal skills for all, while leaving no one behind, is key to enabling adults to engage in up- and re-skilling later in life. These foundational skills (such as literacy and numeracy) are acquired in initial education and training and are indispensable to further learning. Between 2011 and 2017, the OECD surveyed adults aged 15-65 in nearly 40 countries around the world and tested their foundational skills (literacy, numeracy and problem-solving) (Survey of Adult Skills, Programme for the International Assessment of Adult Competencies - PIAAC). Japan is the best-performing country, with only around 1 % of adults having very low literacy and numeracy skills (around 1 % for both). Spain is the EU Member State with the worst performance, having around 10% of adults with a very low numeracy level, and 7 % of adults with very low literacy performance (see Figure 4.3-6). A similar picture is obtained for average adult population scores on literacy and numeracy. In almost all countries, the level of numerical proficiency is lower than the level of literacy proficiency. Japan and Finland obtain the highest scores, while Turkey and Italy the lowest (see Figure 4.3-7). The UK and the US score above most EU countries in the centre or south, yet below northern European countries.

Figure 4.3-6: Share of adults with very low literacy and numeracy skills, 2011-2015



Source: Survey of Adult Skills (PIAAC), wave1-3 (2011-2015)
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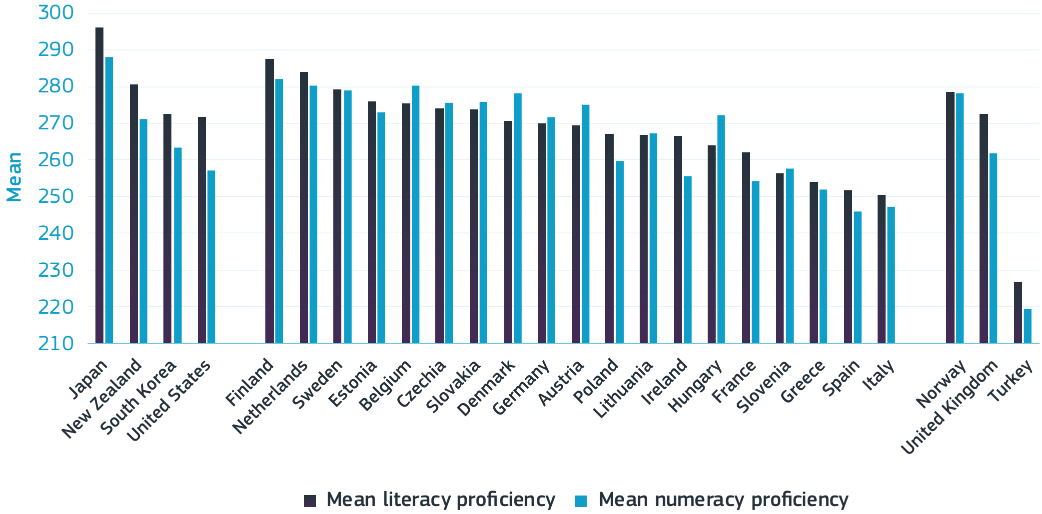
Figure 4.3-7: Average literacy and numeracy proficiency of adult population, 2011-2015

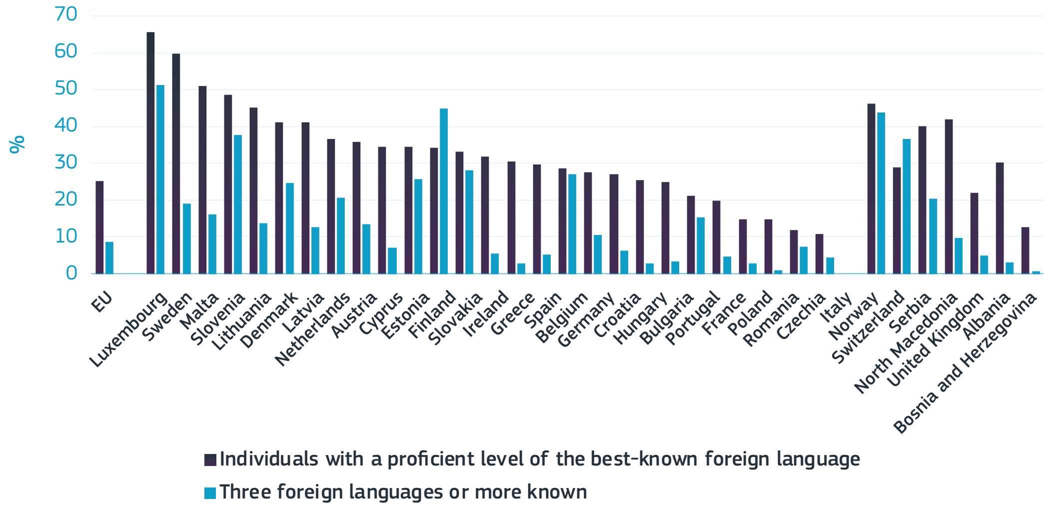


Source: Survey of Adult Skills (PIAAC), wave1-3 (2011-2015)
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-3-7.xlsx

In 2016, on average, 9 % of EU individuals knew more than three foreign languages, while 25 % define themselves as 'proficient'[8] in the foreign language that they know best (see Figure 4.3-8). Italy, Czechia, Romania and Poland are the countries with fewer individuals speaking at a proficient level their best-known foreign language. In Italy, only 11 % of individuals speak proficiently their best-known foreign language, and 12 % in Czechia and 15 % in Romania. Luxemburg and Sweden are the nations with the highest proportion of individuals fluent in a foreign language. The countries that have the highest percentage of the population speaking more than three foreign languages are Luxemburg, Finland and Norway.

8 Proficient' was the highest level in the list (better than 'good' or 'basic' knowledge) and defined as 'I can understand a wide range of demanding texts and use the language flexibly. I master the language almost completely.'

Figure 4.3-8: Share of individuals with foreign language skills, 2016



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Source: Eurostat. Percentage of individuals (age group 25-64) self-reporting knowing three or more foreign languages in 2016. Online data code: EDAT_AES_L21. Percentage of individuals self-reporting their best-known foreign language to be at a proficient level of knowledge. Online data code: EDAT_AES_L31

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2. Digital skills supply in Europe

In an increasingly digitalised world, digital skills are key to allowing people to take part in the labour market, the economy and society more broadly. On average, only 56 % of the EU population aged 16 to 74 had at least a basic level of digital skills in 2019 (see Figure 4.3-9), up from 54 % in 2015. Skills levels vary across gender, age, qualification level and employment status[9]: among women, 54 % have at least basic skills, versus 58 % of men. Among young people (aged 25-34), 74 % have at least basic skills, versus only 24 % for older individuals (aged 65-74) (see Figure 4.3-10).

Among people with low qualifications, only 32 % have at least basic digital skills, as compared to 54 % with medium qualifications and up to 84 % with tertiary qualifications. Among unemployed people, only 44 % have at least basic digital skills.

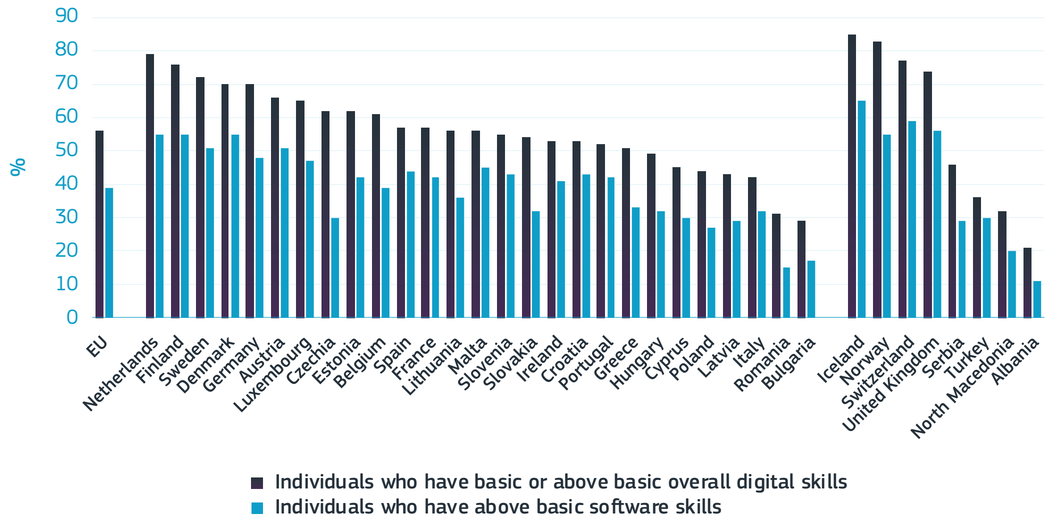
What are digital skills?

The EU digital competence framework 2.2 (DigComp 2.2) distinguishes five areas:

- information and data literacy (e.g. using a search engine and storing information and data);
- communication and collaboration (including teleconferencing and application sharing);
- digital content creation (such as producing text and tables, and multimedia content);
- safety (e.g. using a password and encrypting files, but also being aware of the social and environmental impact of digital technologies);
- problem solving (e.g. finding IT assistance and using software tools to solve problems).
- More details are available in Vuorikari et al. (2022).

9 See ESTAT variable isoc_sk_dskl_i

Figure 4.3-9: Share of Individuals with digital skills, 2019



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Source: Eurostat (online data code: ISOC_SK_DSKL_I)
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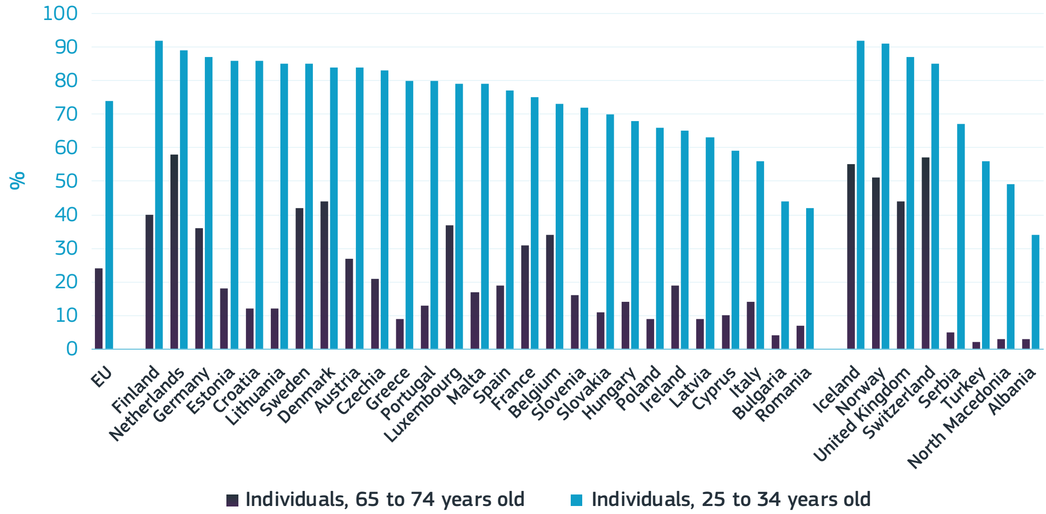
Northern European countries top the ranking with very high levels of overall digital literacy and software programming skills. In 2019, the proportion of adults with at least basic digital skills ranged from 79 % in the Netherlands to 29 % in Bulgaria (Figure 4.3-9). Even for young people, the difference remains wide: in the Netherlands, 89 % of people aged 25-34 have at least basic digital skills as compared to 44 % in Bulgaria (Figure 4.3-10). Furthermore, Dutch individuals in the 65-74 age group have better digital literacy than individuals in the 25-34 age group in Romania, Bulgaria and Italy.

Figure 4.3-10: Individuals who have basic or above-basic overall digital skills by age group (2019)



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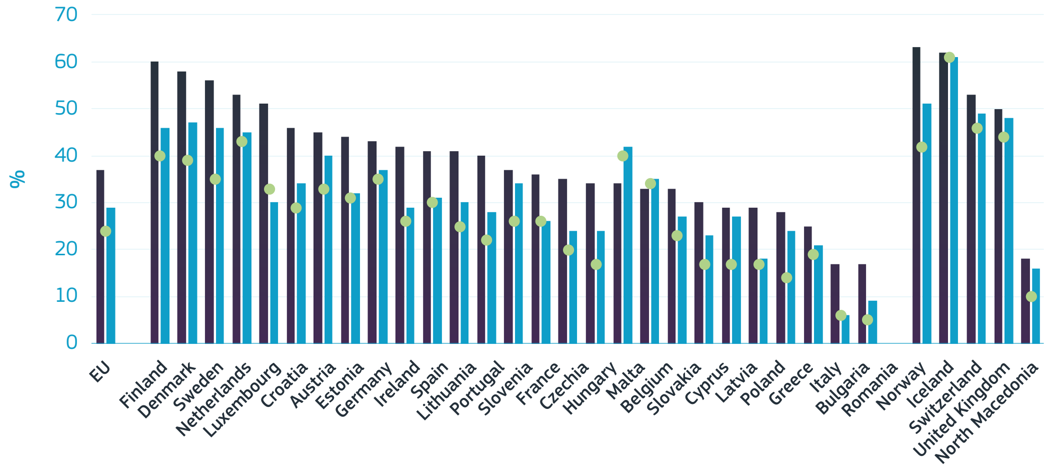
Source: Eurostat (online data code: ISOC_SK_DSKL_I)
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-3-10.xlsx

Individuals living in cities have higher digital literacy than those living in towns, suburbs and rural areas (see Figure 4.3-11). Among individuals living in cities in the EU, 37% hold above-basic digital skills. The proportion is lower for individuals living in towns and suburbs (29%) and for individuals living in rural areas (24%). In some countries, such as Bulgaria and Romania, rural-urban gaps are particularly accentuated, while in other countries, gaps are much smaller. In Belgium, people in rural areas are better equipped with digital skills than people in urban areas. As already mentioned above, these spatial inequalities should be addressed by policymakers to promote inclusive growth and social resilience.

Figure 4.3-11: Share of individuals who have above-basic overall digital skills by urban group, 2019



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Source: Eurostat (online data code: ISOC_SK_DSKL_I)
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-3-11.xlsx

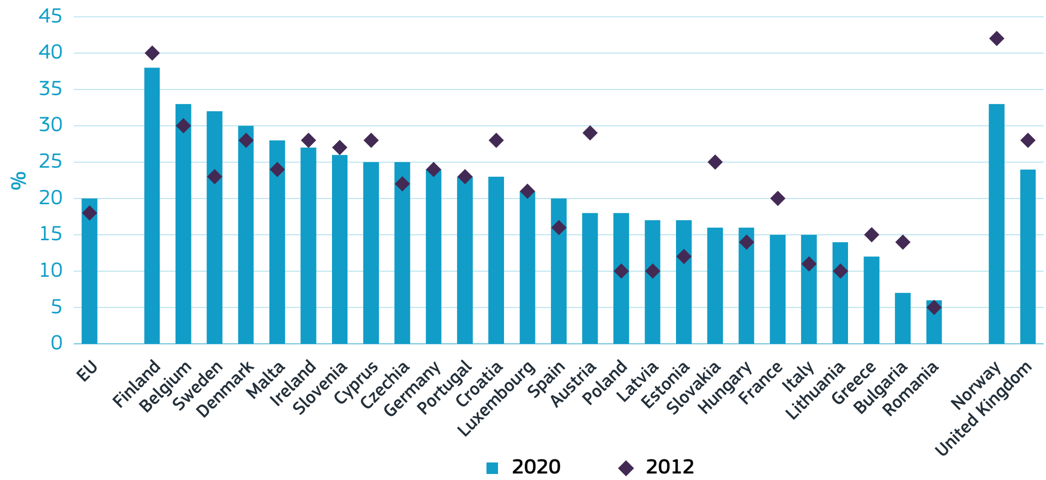
The diffusion of digital technologies drives transformation in the world of work and contributes to the transition towards climate and environmental objectives. New types of jobs are emerging, and routine-based jobs are disappearing. Importantly, digital skills are not employed in ICT sectors only, but are increasingly required in different occupations, and all citizens need at least basic digital skills to participate in society (Carretero et al., 2017). Digital technologies can also be leveraged to drive forward the green transition, for instance to digitalise energy systems, realise sustainable-mobility solutions in urban and rural settings and promote participatory approaches to involving people in shaping the green transition.

Given the rising importance of digital skills in the work environment, more and more firms are training their personnel in ICT skills. Between 2012 and 2019, the percentage of EU firms that provided ICT training to their employees increased by 5 percentage points, growing from 18% to 23%, equivalent to a growth rate of 28 % (see Figure 4.3-12). The country that most trained its workers among the surveyed countries is Norway, with around 44 % of enterprises providing ICT training, followed by Finland, Belgium, Austria and the UK. The country that engaged the least in training provision was Romania with only 6 % of enterprises upgrading workers' ICT skills.

The European Commission has undertaken substantial efforts to support firms and individuals to tackle digital skills gaps. For instance, the Digital Skills and Jobs Coalition was launched by the European Commission in 2016 in tandem with Member States, employers, training providers and other organisations with a view to strengthening digital skills through a multi-stakeholder partnership. As part of the 2020 SME strategy, the European Commission launched a digital volunteers programme, through which skilled mentors from leading companies offer their expertise for the digital transformation of EU SMEs. It has also announced it will roll out digital crash courses for SME employees to become proficient in areas such as AI, cybersecurity or blockchain. Further initiatives are spelled out in the European Commission's Digital Education Action Plan and the Digital Europe programme.

The rise of ICT has not only required workers to reskill, but also changed the tasks performed and number of individuals engaging with computers and software. In the EU, 8 % of individuals reported the content of their job changing because of new software or computer equipment (see Figure 4.3-13). This statistic is very high in countries such as Iceland (22 %), Norway (21 %), the Netherlands (15 %), Denmark (16 %) and Finland (13 %), while very low in countries such as Romania (3 %), Bulgaria (3 %) and Greece (3 %).

Figure 4.3-12: Share of enterprises that provided training to develop/upgrade ICT skills of their personnel, 2012 and 2020



Source: Eurostat (online data code: ISOC_SKE_ITTN2)
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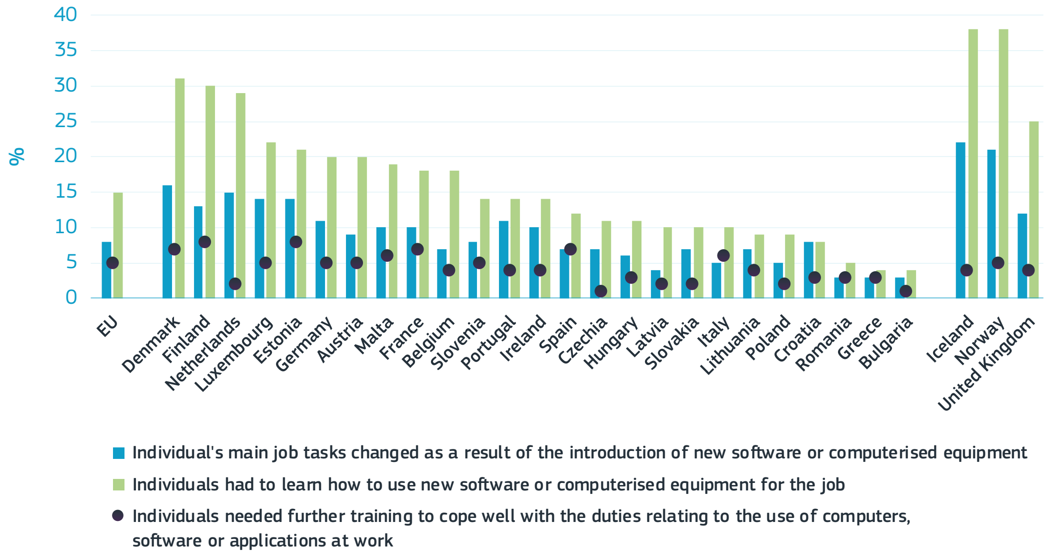
Figure 4.3-13: Individuals who had their skills impacted by ICT, 2019



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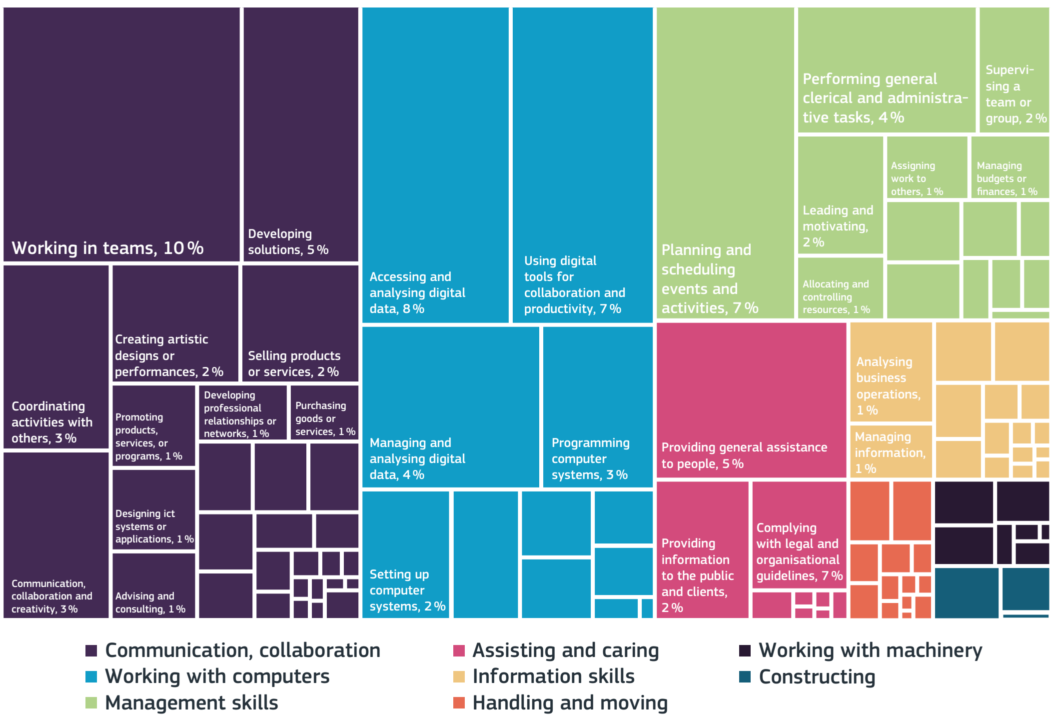
Source: Eurostat (online data code: ISOC_IW_IMP)
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-3-13.xlsx

3. Skills demand in Europe

Analysis by Cedefop suggests that social and digital skills, combined with managerial and analytical competences are among the most frequently requested in online job vacancies in the EU. Cedefop collected millions of online job advertisements in EU countries from thousands of sources, including private job portals, public employment service portals, recruitment agencies, online newspapers and corporate websites over Q3 2020-Q2 2021. The collected data were analysed in terms of their references to specific types of skills, knowledge, attitudes and work values, and language-related skills[10]. While around 45 % of online job posts referred to relevant skills and 36 % to requirements in terms of specific competences or knowledge, only 13 % referred to desirable attitudes and work values and 6 % to language-related skills.

Figure 4.3-14: Percentage of skills type total mention in the EU, Q3 2020-Q2 2021



Source: Cedefop, Skills-OVATE

Note: The image represents the share of total mentions of skills (skills ranking) in millions of online job advertisements in EU countries, collected from thousands of sources, including private job portals, public employment service portals, recruitment agencies, online newspapers and corporate websites.

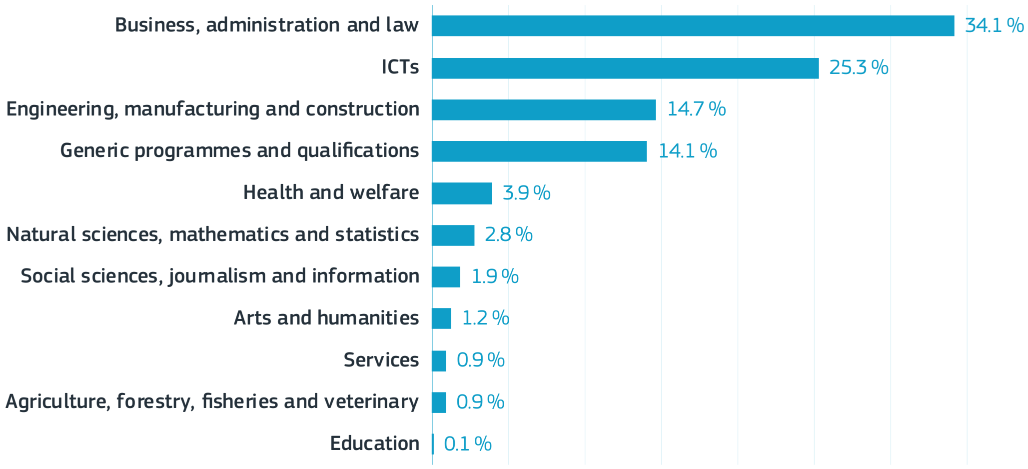
Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-3-14.xlsx

10 Online job advertisements tend to relatively over-represent white-collar (mostly professional) occupations and their attendant skills, compared to manual ones, in terms of occupational structure.

The most requested transversal skills are on the one hand, the abilities to communicate, work in teams, collaborate and being creative, and on the other hand, the capacity to work effectively with computers. Around 34 % of online jobs posted in the EU (from 2020 to 2021) mention communication, collaboration and creativity skills, 28 % mention computer skills and 20 % mention management skills (see Figure 4.3-14). Such trends are in line with our above-mentioned findings on structural changes in skills requirements triggered by the digital transformation: the diffusion of digital and automation technologies increases demand not only for digital skills but also for complementary abstract thinking and social skills. The least requested skills are constructing (0.98 %), working with machinery (1.55 %) and handling and moving (1.8 %).

The most requested knowledge domains are business, law and ICT, closely followed by engineering. Around 34% of online job posted in the EU from 2020 to 2021 mention business, administration and law, 25 % mention ICT competences and 15% mention engineering, manufacturing and construction knowledge (see Figure 4.3-15). A relatively high proportion of vacancies (14%) include only generic qualification requirements. The high demand for ICT-related knowledge suggests that ICT skills are not required exclusively in the science and technology sector, but are required across the entire economy.

Figure 4.3-15: Percentage of knowledge type total mention (EU)



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Source: Cedefop, Skills-OVATE

Note: The image represents the share of total mentions of knowledge (knowledge ranking) in millions of online job advertisements in EU countries, collected from thousands of sources, including private job portals, public employment service portals, recruitment agencies, online newspapers and corporate websites. Period: Q3 2020-Q2 2021

Stat. https://ec.europa.eu/assets/rtd/srip/2022/figure-4-3-15.xlsx

4. Conclusions: skills, labour market and technological change

Digitalisation is affecting the task content of jobs and as a result the skills sought and rewarded in the labour market. Routine tasks have been in decline, while tasks requiring abstract thinking and social skills have expanded. Skills endowments are becoming increasingly linked to stable and high-quality employment outcomes. This risks widening disparities between workers with low and high skills endowments. To ensure an inclusive digital transition, policymakers will need to step up investment in digital skills and infrastructure, particularly for vulnerable workers and regions. Adequate investments should be made in education and skills from an early age, but also, very importantly, for adults. The lengthening of working lives in today's knowledge economy requires a paradigm shift in which individuals dedicate themselves to long-life learning.

In the digital economy, technical and digital skills increasingly need to be complemented by social and communication skills and the capacity to adapt to changing circumstances. Formal and non-formal education and training programmes should cater to digital era needs by considering the complementarities between technical and social skills. The stronger the foundation skills that individuals have, the easier they will find it to upskill and reskill and to adjust to changing circumstances in the labour market.

Digital skills are key for individuals and for employers alike, to support high-quality labour market outcomes and sustainable and inclusive growth, as well as citizens' effective inclusion in a participative and democratic modern society. Nevertheless, skills gaps persist. Employers around the world report that their investments are being hampered by shortages of skilled labour. The demand for ICT specialists has become ever more pressing. But even when it comes to very basic digital skills, skills gaps persist: 44% of EU adults were found to have not even the most basic digital skills. Unfortunately, countries with the largest skills gaps are typically also the countries with the lowest adult participation in learning. This is likely to perpetuate and exacerbate existing disparities and risks worsening social cohesion in the EU. Policymakers need to step up efforts to address these gaps, with extensive support from the EU, and to tackle observed disparities across age groups, countries and regions to successfully construct a resilient, competitive and fair European society.

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