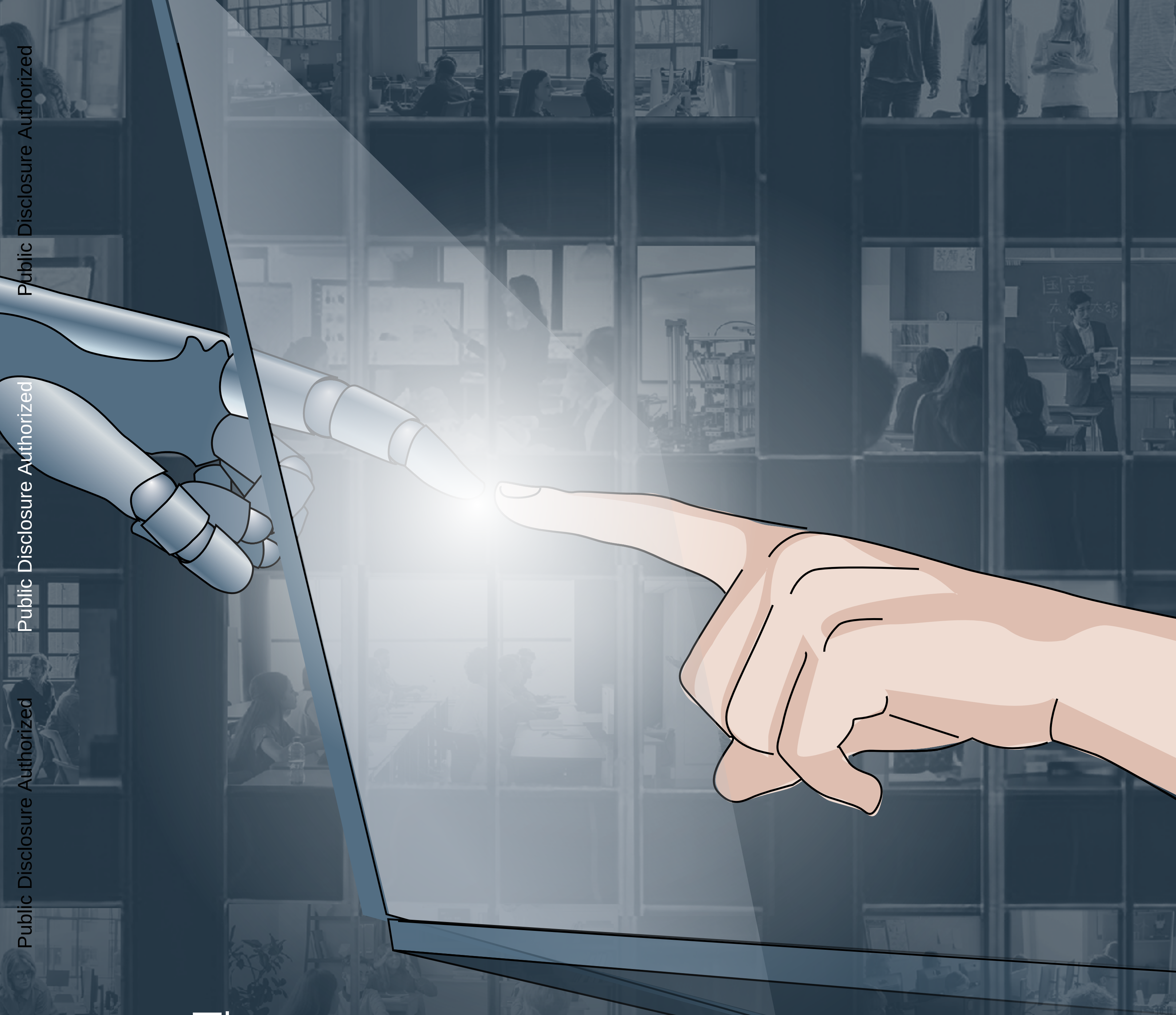

# The FUTURE of WORK

## Implications for Equity and Growth in Europe

Nicolò Dalvit, Rafael de Hoyos, Leonardo Iacovone, Ioanna Pantelaiou, Aleksandra Peeva, and Iván Torre

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# Acknowledgements

The team received valuable support and input from several people throughout the project. Jonathan Stöterau offered ongoing feedback and provided valuable inputs on Active Labor Market Programs (ALMPs), while Piotr Lewandowski played a vital role in analyzing technology exposure. Fabio Montobbio, Jacopo Staccioli, Maria Enrica Virgillito, and Marco Vivarelli helpfully reviewed the existing evidence on technology and labor markets. The analysis of the Italian firm-level data is based on work with Fabiano Schivardi, and was made possible thanks to the collaboration with Giulio Perani, Stefano De Santis, and Silvia Lombardi from the Italian National Institute of Statistics (ISTAT). The team is also grateful for the excellent research assistance of Manfredi Aliberti, Juan Bedoya, and Luca Lorenzini.

The report improved substantially thanks to the comments and suggestions from Maurizio Bussolo, Halsey Rogers, Lars Sondergaard, Siddharth Sharma, Shiro Nakata, Reena Badiani-Magnusson and Harry Patrinos. Gallina Vincelette, Fadia Saadah, Lalita Moorty, Rita Almeida, Cem Mete, and Ilias Skamnelos provided overall support and guidance to the team.

Aarre Laakso's editing and George Maier's design significantly improved the quality of the report. We are grateful to Anna Karpets for her continuous and efficient administrative support throughout the implementation of this project.

# OVERVIEW Technological Progress to Benefit All

*"The notion of thinking about the future as a prediction exercise neglects the fact that the future is a creative exercise—it is something that we are building."*
David Autor

Technological progress is the best expression of human ingenuity—the result of an environment enabling human capital accumulation, innovation, scientific knowledge, and free competition. Technology is the engine of productivity and economic growth and has made possible the unprecedented human wellbeing we enjoy today. But the most relevant and widespread technological progress is disruptive. It triggers what the Austrian economist Joseph Schumpeter named "creative destruction," where old ways are abandoned to give rise to new ones. The process of creative destruction results in winners and losers and often affects established interests. It always generates both positive and negative outcomes.

Firms adopting new technologies must change or adapt their production processes, sometimes reducing the demand for certain types of workers while augmenting that of others. Technology-driven changes in labor demand and its potential effects on wages and employment levels have sprung fear since the Industrial Revolution. Although some of these fears are well grounded, historical evidence shows that, whereas technology has replaced some workers in performing specific tasks, in the medium to long term, technology has also created new tasks, jobs, and occupations for both high- and low-skilled workers (Autor et. al, 2022b).[1]

Over the last 40 years, technological progress and the integration of international markets have had a significant impact on income distribution in rich countries. Jobs in the middle of the skills distribution in high-income countries like the United States (US) and in Europe have been destroyed (Autor et. al, 2022c; Goos et al., 2014). Losing middle-class jobs has increased income disparities, intensifying political polarization on both sides of the North Atlantic.[2] Technological progress will continue for the foreseeable future and could exacerbate income disparities, fueling further political polarization in high-income countries.

This report aims to contribute to our understanding of the relationship between technology, economic growth, and equity by analyzing the impact of technological progress on firm-level productivity, market concentration, and labor market outcomes of workers with different education levels. The analysis focuses on the effects that technology can have in European Union (EU) member states, addressing two main distributional challenges: (i) an increase in market concentration, with a few large and innovative firms hoarding the benefits of technological progress, and (ii) technological progress exacerbating income differences between highly educated and other workers. These two challenges, and the public policies aiming to address them, will shape the future relationship between technological progress, economic growth, and income distribution in Europe.

The first challenge is the impact that technology has on firm performance, market concentration, and economic growth. Technological progress can increase market concentration, expanding the share of national income going to capital and reducing that of labor. Depending on social preferences, an equilibrium characterized by technology-driven higher income inequality could be tolerated if it is considered the price to pay for higher productivity and economic growth. However, ***hollowing the middle***—the loss of jobs at the middle of the skills distribution that has dominated labor markets in high-income countries since the late 1970s—has not come with higher productivity or more growth. Instead, following the great recession of 2008, productivity growth decelerated on both sides of the North Atlantic. This apparent paradox of rising inequality and stagnant productivity during a period of rapid technological progress is explained, at least partly, by an increasing market concentration with a few large, dominant, innovative, and productive "superstar" firms outcompeting smaller, less productive ones (De Loecker et al., 2020)—a process that went along with the fall in the share of national income going to labor and destruction of middle-skills jobs (Autor et al. (2020b); Qureshi, 2018).

[1] Confirming the capacity of technology to create new tasks and jobs, recent work of Autor et. al (2022b) found that 60 percent of occupations in the United States (US) in 2018 did not exist in 1940.

[2] Autor et. al (2020a) and Rodrik (2021) show compelling evidence that the emergence of Trump's populist movement in the US can be traced to the erosion of labor market opportunities for middle-skilled Americans in manufacturing industries caused by trade liberalization. Europe has not been immune to this political process, with the increase in inequality across European regions driving political polarization (Winkler, 2019; Anelli et al. 2019).

Technology also changes the incomes of workers with different skills, posing a second challenge. Over the last 40 years, technology in the firm has typically led to substituting routine tasks while enhancing the demand for higher-skilled workers. Repetitive tasks—manual or cognitive—that follow specific rules that can be codified in instructions are easily automated. Using robots in warehouses to store goods and software to keep track of inventories are examples of routine manual and routine cognitive tasks, respectively, undertaken by current technologies. In addition, technological progress creates new occupations and reduce the duration of job tenure (Bandiera, 2022; Bussolo et al., 2022). Technology-driven, dynamic labor markets introduce important challenges for workers with low skill levels, potentially increasing the wage gaps between highly educated and other workers.

Recent improvements in artificial intelligence (AI) bring the concerns about technology's impact on future labor markets to new levels. Language processing tools driven by "generative pre-trained transformer" (GPT) models have the potential for profound disruptions in the labor market. With these recent AI developments, even nonroutine cognitive tasks such as analyzing data and interpreting different arguments and propositions (what the coauthors of this report are doing here) might soon be performed more efficiently by an AI.

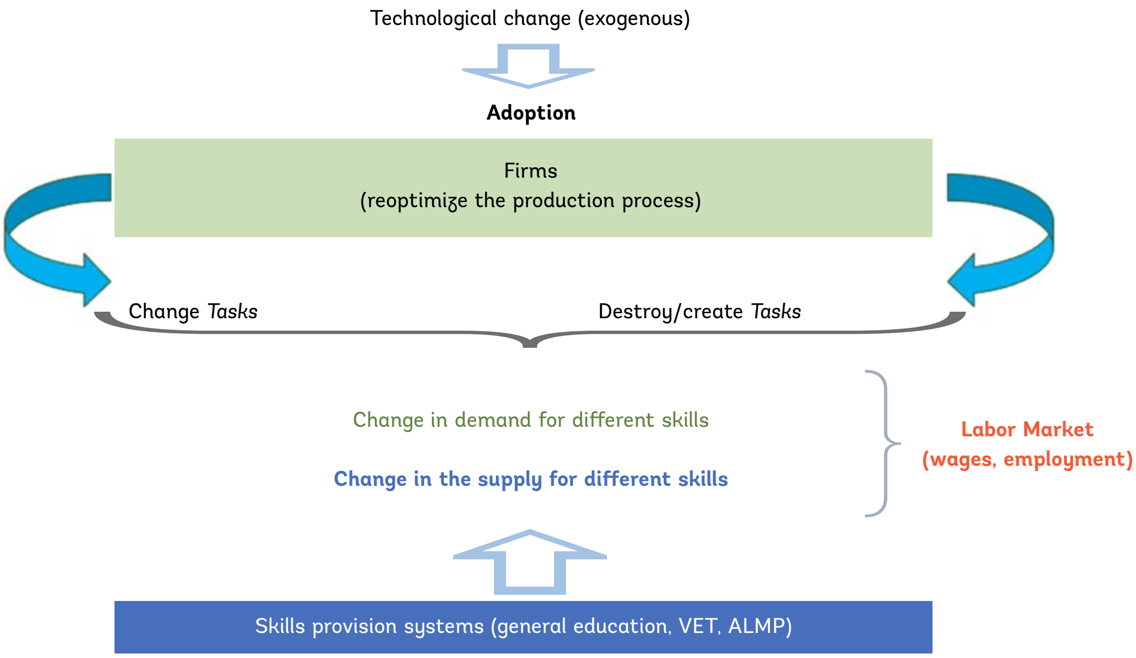
What are the implications of these technological changes for growth and inclusion in Europe? What should EU governments do to make sure technology does not exacerbate income inequality—fueling political polarization? What is the most effective strategy for promoting technology adoption among small firms and avoiding market concentration? What reforms are needed in education systems to provide all future workers (ongoing students) with the necessary skills in a technology-driven labor market characterized by changing tasks and increasing dynamism?

### O.1. A framework linking technology, firms, and labor markets

The development of technology connects to growth and income distribution through companies and labor markets. By increasing productivity, profits, and the size of firms, technology can bring benefits. However, if only a few large firms adopt technology, it can lead to market concentration and reduce the share of national income going to labor. This can cause distributional tensions to worsen.

Technology can also affect how income is distributed among workers with varying levels of education. To better understand how technology and labor markets are interconnected, it is helpful to use a simple framework that considers firms, their production processes, the tasks involved, and the demand for workers' skills. The skills provision system, which includes formal education, vocational education, and short-term training courses or ALMPs, plays a vital role in determining the supply of skills. The interaction between the demand and supply of skills in the labor market ultimately affects the wages and employment of different workers. Figure O.1 illustrates the linkages between technological progress, firms, tasks, skills provision systems, and labor market outcomes as analyzed in this report.

**FIGURE O.1.** **Conceptual linkages between technology, firms, and labor markets**




This study distinguishes between technological progress, which is seen as outside a firm's control, and the firm's implementation of technology. Obstacles to technology adoption can hinder the potential effects of new technologies on productivity and job markets. When a firm adopts new technology, it changes its production process, resulting in the creation, destruction, and modification of tasks (as depicted by the top rectangle and arrows in Figure O.1). This restructuring within the firm affects the demand for workers with different skills (as illustrated in the middle of Figure O.1).

Instead of focusing on the reskilling needs of current workers, our study examines the changes in the education system necessary to equip future workers with essential skills. Specifically, we analyze secondary vocational education and training (VET) systems that offer skills to underprivileged youth in Europe and compare them with the skills required to succeed in an unpredictable, technology-driven, and ever-changing labor market (bottom part of Figure O.1).

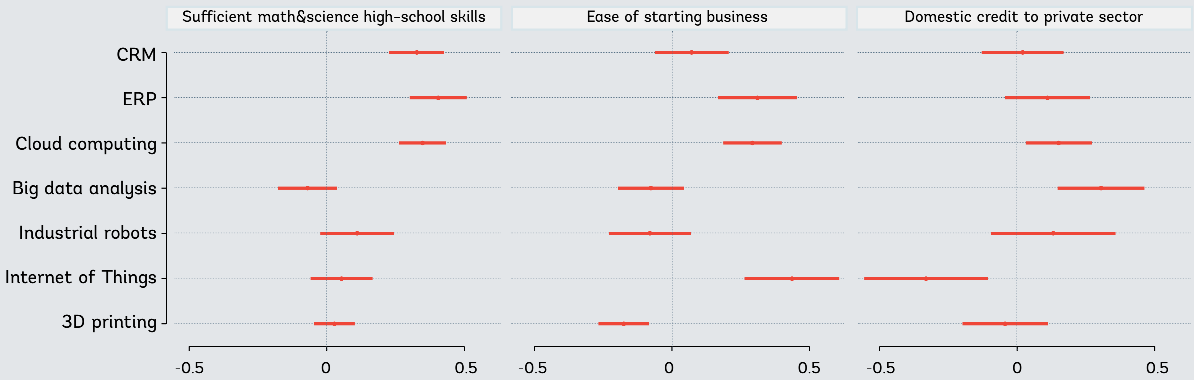
## O.2. There is ample space to promote technology adoption in the EU

A survey by the European Investment Bank (EIB) revealed that 20 percent of firms in the EU use no digital technology, whereas only 12 percent of firms in the US use none (European Investment Bank, 2023). The results also show that larger companies in both the US and the EU are more likely than small companies to adopt new technologies, with no significant difference in adoption rates between large firms in the US and those in the EU (European Investment Bank, 2022). However, small and micro firms in the EU are less likely than their counterparts in the US to adopt technology. For example, technology adoption rates[3] for small firms in the US are 39 percent, whereas they are 31 percent in the EU. For micro firms, the rates are 47 percent in the US and 33 percent in the EU.

[3] Technology adoption rate is the share of firms that have reported using a given technology at the time of the survey. This definition does not report how intensely the technology is used within the firm.

Combining several firm surveys covering 32 European countries over the period 2014–22 and aggregated over region and industry, we identify the determinants of technology adoption. Our results show that larger and more productive firms tend to adopt more technology. We also found that in countries and regions with higher levels of human capital, greater access to financial resources, and business-friendly regulatory frameworks are more likely to adopt new technologies (see Figure O.2).

**FIGURE O.2. Determinants of technology adoption, EU27+**



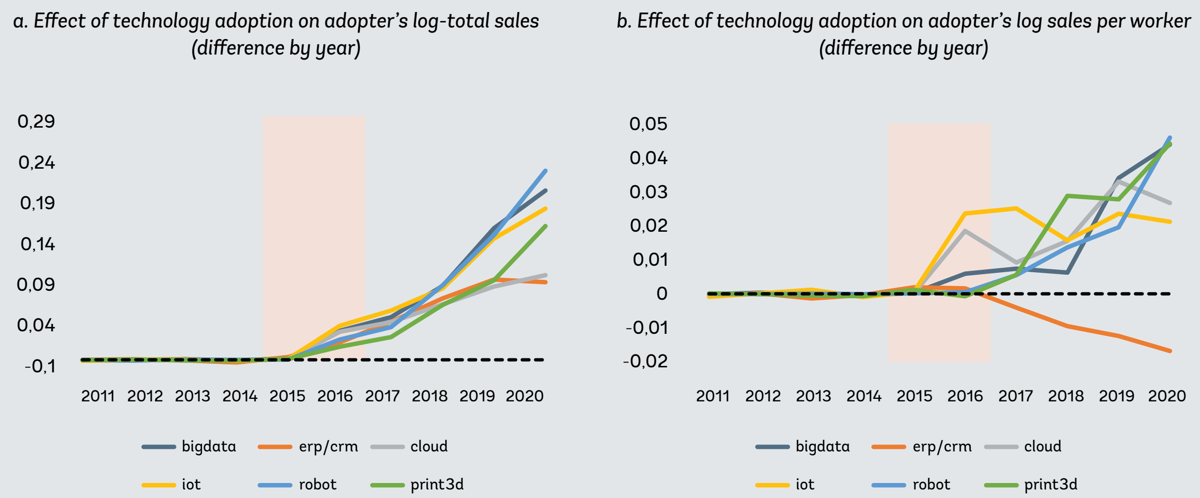

Note: Sufficient math&science high school skills refers to the share of 15-year-olds who are not low-achieving in mathematics or science. The data comes from the Programme for International Student Assessment (PISA), a triennial international survey which tests the skills and knowledge of 15-year-old students. PISA defines low-achieving as failing to reach basic skills level on the PISA scale for core school subjects.

The adoption of technology is greatly influenced by managerial practices. Studies have found that US multinational companies operating in Europe experience greater productivity gains from information and communication technology (ICT) adoption as compared to European firms due to superior management practices. Research has linked low levels of technology adoption in some EU member states to the lack of managerial capabilities (Calvino et al., 2022; Cirillo et al., 2023).

### O.3. Technology increases productivity, market concentration, and the demand for skilled workers

We analyze the effects of technology adoption on productivity and the demand for workers based on an event study comparing output, productivity, tasks performed, and workers employed in Italian firms adopting new technologies versus firms not adopting them. Our results show that adopting new technologies can give businesses an edge over their competitors, letting them expand their operations (Figure O.3, panel a). Firms that embrace new technologies tend to grow faster than those that stick to their old ways. At the same time, our firm-level analysis for Italy shows no evidence that adopting new technologies negatively affects employment. In fact, companies that adopt new technologies tend to see increases in their workforces resulting from their expanding business activities. Furthermore, the total value of sales in companies that adopt new technologies grows faster than their employment, leading to increased productivity (measured as sales per worker) (Figure O.3, panel b). However, if firms adopting new technologies do not experience sales growth, they may reduce their labor demand (due to the change in the production function), which could negatively affect overall employment.

**FIGURE O.3.** **Effects of technology adoption on total sales and productivity**




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

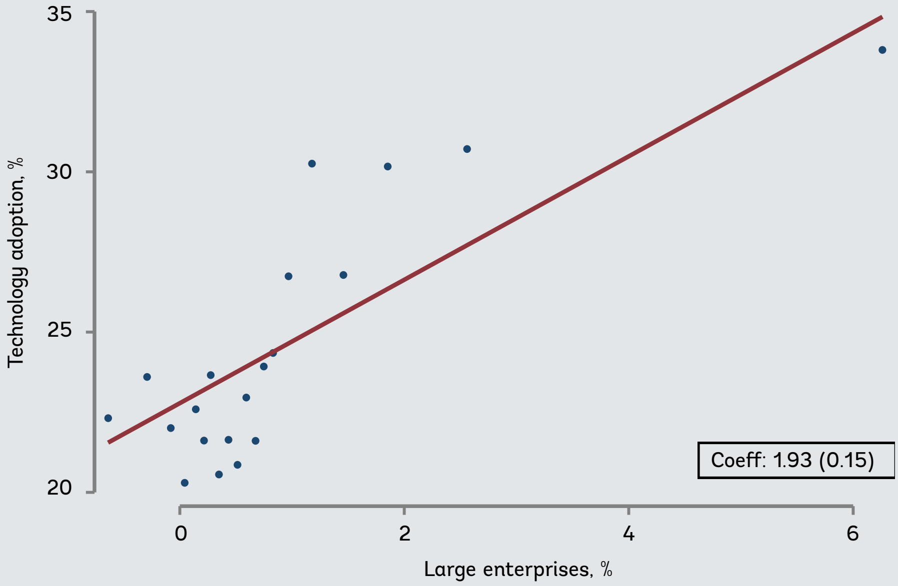
Note: erp/crm = enterprise resource planning and consumer relationship management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

Our results also show that firms that incorporate technology into their operations tend to increase the number of nonroutine cognitive tasks that workers perform while decreasing the number of routine manual tasks that workers perform. This is achieved by hiring more employees with university degrees.

We examine the relationship between sectoral market concentration and a sector's technological intensity, exploiting country-sector variation in the share of large enterprises and technology adoption. Figure O.4 presents the results for all technologies and points toward some evidence that those country-sectors that are characterized by higher market concentration, measured by a larger share of large enterprises, are also the ones that experience higher levels of technology adoption. The partial correlation coefficient (after controlling for time-invariant country and technology characteristics) is large at 1.93 and statistically significant. A positive relationship between technology adoption and market concentration is consistent with recent patterns observed globally by De Loecker, et al. (2020) and with the rise of "superstar" firms, which could eventually have ambiguous effects on future innovation and growth.[4]

[4] On the one side, larger firms and more concentrated sectors characterized by higher markups could lead to higher innovation because these *superstar* firms have greater capacity to invest in R&D and exploit economies of scale in generating new ideas (Autor et al, 2020b). On the other side, these dominant firms could also innovate less as lower competition reduces incentives to innovate, leading to lower productivity growth (Gutierrez & Philippon, 2020; Gutierrez et al. 2019), a scenario that could be defined as "inefficient concentration" (Covarrubias et. al., 2020).

**FIGURE O.4.** Sectoral concentration and technology adoption




**Note:** Residuals of technology adoption against residuals of large enterprises, after controlling for country and technology fixed effects. Slope coefficient and standard error (in parentheses) are presented in a text box. The figure is a binscatter plot of the residual of technology adoption rate after controlling for country and technology fixed effects and the residual of large enterprise share after controlling for country and technology fixed effects.

The microdata from Italy shows that firms that are bigger and more productive are more likely to adopt new technologies. As shown above, firms adopting new technology grow faster in terms of both size and productivity. These two effects combined lead to an automatic increase in market concentration, with bigger firms adopting more and becoming even larger relative to their competitors. The relationship between adoption and market concentration thus underscores the risks that a high concentration of technology adoption among a few firms could have for markets and consumers.

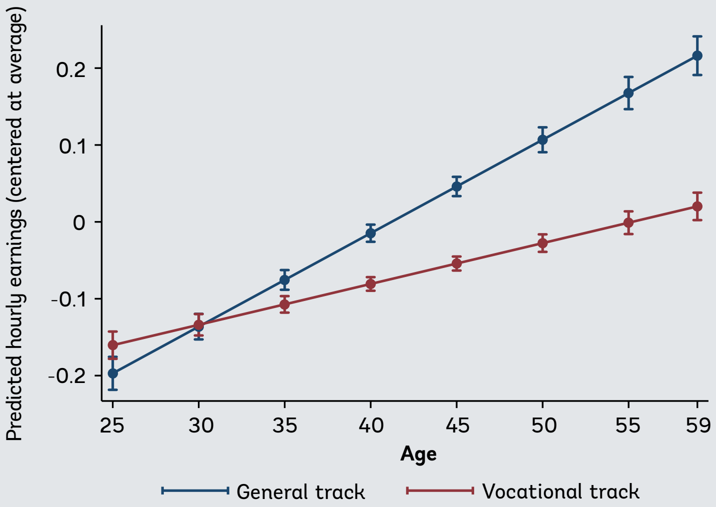
## O.4. European VET systems in an ever-changing labor market

Do European education systems provide their graduates with the skills needed to face the change in demand triggered by technological change? Building the right skills, especially among disadvantaged youth, is one of the most critical challenges to ensure that technological progress does not exacerbate income inequality in the EU. School-based VET systems in Europe provide formal schooling to almost half of the students enrolled in upper-secondary education, most of them from a disadvantaged socioeconomic background. Given its size and importance for equity, our analysis of the "skills provision system" concentrates on upper-secondary VET.[5]

Our research using the EU Labor Force Survey (EU-LFS) shows that upper-secondary VET graduates enjoy favorable employment outcomes compared to their peers with general secondary education degrees who did not attend university. But this advantage disappears five to seven years after entering the labor market. Moreover, our analysis using data from the Programme for the International Assessment of Adult Competencies (PIAAC) data shows that wage-income profiles for VET graduates are flatter than those for non-VET secondary graduates, with earnings for the latter overtaking those of the former around age 30 (see Figure O.5).

[5] Post-secondary vocational education is also an important component of the broader VET system in Europe, but we focus on the upper secondary component of the VET system because it is the largest one in terms of size and expenditure.

**FIGURE O.5.** Age profile of earnings of VET and general secondary graduates

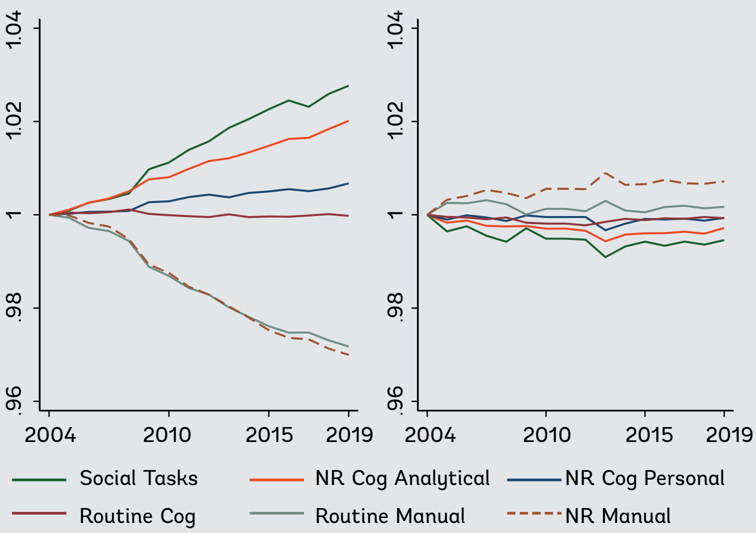



**Note:** this figure plots the predicted log hourly earnings (centered at the country mean) at different ages of general secondary graduates (blue line) and VET graduates (maroon line). The values are derived from a linear regression of log hourly earnings, which includes an interaction factor between age and educational track and country, gender, parental education, numeracy, and literacy as control variables. The sample is restricted to individuals from 25 to 59 years old whose highest educational attainment is upper secondary (ISCED 3) or postsecondary nontertiary education (ISCED 4). Countries in the sample are Belgium, Czech Republic, Denmark, Finland, Greece, Ireland, Italy, Netherlands, Norway, Poland, Slovak Republic, Slovenia, and Spain.

Source: authors' estimations using PIAAC data.

Unlike what has happened for most workers, the task content of jobs performed by upper-secondary VET graduates has changed little in recent years (Figure O.6). Our results show that VET graduates have skills that do not complement the new technologies because they are still engaged in routine and manual tasks at a high risk of being automatized, and they are less engaged in nonroutine cognitive tasks and the use of social skills in the job. Part of the explanation for the lack of complementarity between the tasks performed by VET graduates and those demanded by new technologies is the low foundational skills—numeracy, literacy, and socioemotional skills—among students with a technical diploma. Cognitive, foundational skills are highly associated with nonroutine cognitive tasks complementing technology.

**FIGURE O.6.** Change in task contents of jobs, all workers versus VET graduates




**Note:** this figure plots the evolution of the average task intensity of jobs, indexed to a value of 1 for 2004, for different employment and age groups across 20 countries in the EU-LFS microdata. The intensity of nonroutine cognitive analytical tasks, nonroutine cognitive personal tasks, routine cognitive tasks, routine manual tasks and nonroutine manual tasks is calculated using the procedures detailed in Hardy et al. (2018). The intensity in social tasks is calculated using the definition of Deming (2017) on the use of social skills in the job. Values are population weighted. Panel a corresponds to the average values for all employed individuals excluding VET graduates. Panel b corresponds to the average values for VET graduates only. NR = Nonroutine. Cog = Cognitive.

Source: authors' estimations using EU-LFS.

Our results cast doubt on the social and economic returns of the higher investment in producing upper-secondary VET graduates—a monetary cost roughly 15 percent higher per pupil compared to a general secondary education graduate. If vocational systems do not provide a labor market advantage over general education graduates, European education systems could be reproducing or even exacerbating existing inequalities, reducing social mobility, and weakening the social contract, particularly in technology-driven, dynamic labor markets. Modernizing education systems in Europe to guarantee that all graduates (regardless of whether they are on the VET or general track) have the necessary foundational skills could unleash productivity and promote economic inclusion.

### 0.5. Policy recommendations

It is unrealistic and naive to rely only on market forces and redistribution policies like taxes and transfers to address the challenges of technology adoption. To guarantee a fair and inclusive process of technological change, policies must be in place to ensure an equal distribution of its benefits. Merely relying on ex post redistribution will not be enough to overcome the obstacles posed by the latest technological innovations. Inclusive economic systems that provide equal opportunities for all individuals to participate in and benefit from markets create a virtuous cycle of technology, shared prosperity, and innovation. This report emphasizes the urgent need to develop and implement additional policies that ensure widespread and equitable advantages from technological advancements.

Our analysis has led to three policy recommendations for promoting inclusive institutions and maximizing the positive effects of technology on human wellbeing. First, we suggest promoting technology adoption, particularly among small businesses in Europe. Second, adapting technology to meet society's needs is both possible and desirable. Third, all young people should be equipped with the skills to adapt and reinvent themselves.

**Promoting technology adoption**: First, to prevent further market concentration and reduce the impact of technology on regional gaps, both the EU and governments of EU member states could introduce policies that ***promote the adoption of new technologies among small businesses***, with a special focus on those in lagging regions. Policies should not just promote "technology drops" but create incentives for making these complementary investments, such as improving managerial practices. A second challenge is the complexities and uncertainties arising from disparate market rules and standards across EU countries that deter small and medium enterprises (SMEs) from embracing new technologies. Europe has a critical agenda in enhancing integration to ensure a fully operational single market. Third, EU governments need to promote competition and market contestability. The new digital economy, particularly with the advent of advanced AI, requires a renewed focus on antitrust policy. Finally, there is a pressing need for improved measurement of technology adoption. Having granular, firm-level measurements can aid in identifying key enablers or obstacles and formulating policies that could enhance technology adoption among SMEs.

**Adapting technology to meet society's needs**: Through our research, we have found that technology implementation in European companies has led to a higher demand for university graduates, with the challenge of leaving behind those with less education, including workers with a vocational degree. To ensure fair job opportunities for all, it is important to eliminate policies that prioritize capital investment over investment in workers. Countries like the United States and EU member states have tax policies that unintentionally subsidize capital and investment, leading to increased use of machines and automation. By adjusting tax incentives to favor labor-intensive investment, we can create an environment that promotes quality employment and job growth. In addition, EU institutions have a great opportunity to invest in research and innovation to bring about technological advancements that can effectively integrate labor into the production process.

**Equipping all youth with the skills to adapt and reinvent themselves**: As technology continues to advance and global trade increases, job turnover increases and job tenure become shorter. It is becoming increasingly rare for individuals to stay in the same job for long. This poses a challenge for VET systems to prepare students with relevant professional skills that will remain useful in a fast-changing job market. Balancing the supply and demand of skills is difficult, and predicting which skills will be in demand is almost impossible. Therefore, European education systems must provide all graduates with foundational skills applicable to any career path they choose. By providing this core set of skills, current students and future workers can keep learning throughout their lives and adapt to new professions. Implementing a basic core curriculum shared among all upper-secondary education tracks, including VET programs, can ensure that students have these foundational skills. The practice of tracking students into either VET or general secondary school based on an examination should be reevaluated. Relaxing this restriction and allowing more students to pursue the academic track could improve their education and employment opportunities. Several policies have proven effective in improving cognitive foundational skills, such as high-dosage tutoring, extra instructional time, personalization of learning using new technologies, and teaching to the proper level. It is critical to put in place affective teachers' policies (pre- and in-service professional development, selection processes, in-service evaluation, and recognition, among others) to support any cost-effective intervention to improve learning.

The power of technology is undeniable because it opens new opportunities and creates job prospects. However, it also has the potential to displace existing jobs and industries. The impact of this transformative force is shaped by society's decisions, including how quickly it is embraced and its effect on income distribution and markets. It is important to remember that the future is not set in stone, and we have the power to shape it.

The tradeoff between efficiency and equity caused by technological progress since the Industrial Revolution can now be eliminated with the help of evidence, data, and knowledge on how public institutions affect this tradeoff. Technological progress is not an exogenous factor, but it is determined by social preferences that shape public policies. Social preferences should create incentives to shift from an equilibrium in which technological progress is characterized by ***creative destruction*** to one of ***inclusive innovation***. It is time to harness our social preferences and create a world where technological progress benefits everyone, especially those in need.

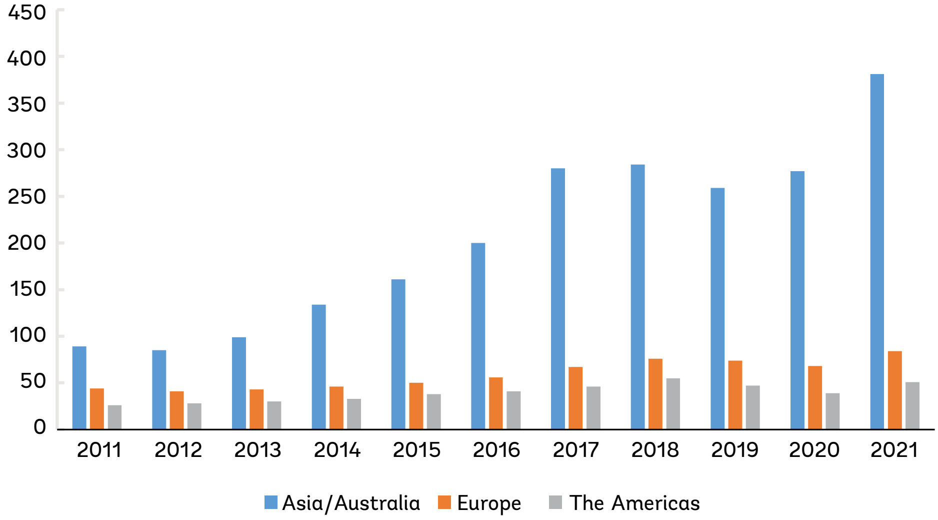
# CHAPTER 1 Linking Technology, Firms, and Labor Markets

*"Economic growth and technological change are accompanied by what the great economist Joseph Schumpeter called creative destruction. They replace the old with the new. New sectors attract resources away from old ones. New firms take business away from established ones. New technologies make existing skills and machines obsolete."*

Daron Acemoglu and James Robinson

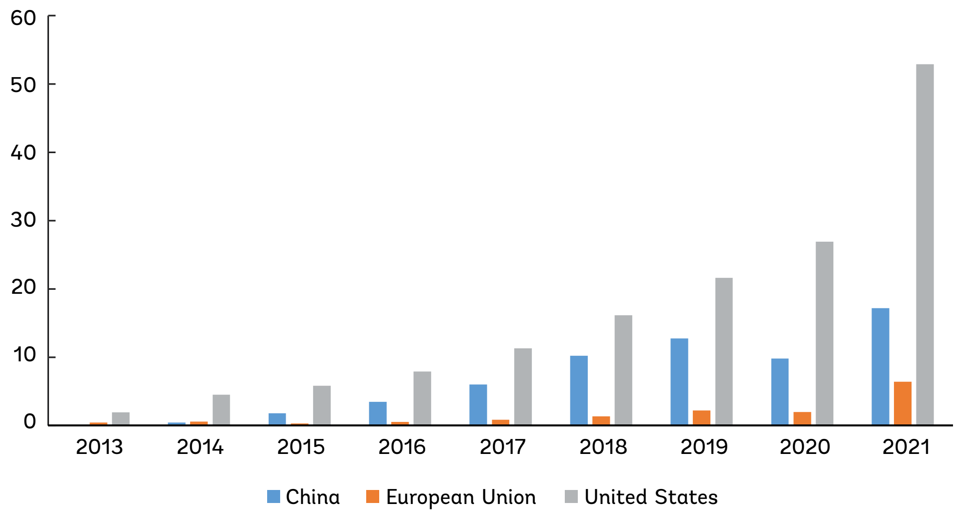
During the last 15 years, technological progress has advanced at an impressive rate. For example, the computational capacity of the fastest computers has multiplied by 100, and the number of parameters in the most advanced AI systems by 10,000.[6] Although advances in cutting-edge technology do not translate immediately into changes in the production process, the number of firms adopting technology has also experienced an increase in the last years. As shown in Figure 1.1, the number of industrial robots installed yearly in the manufacturing sector in Europe, Asia, and the Americas increased significantly between 2010 and 2019. A similar increasing trend can be found in private investment in AI companies. This increase is strongest for United States, leading with an investment amount equal to the eightfold and threefold of EU's and China's AI investments in 2021 (Figure 1.2).

**FIGURE 1.1.** **Annual Installation of Industrial Robots (thousand units)**




Source: Müller 2022

**FIGURE 1.2.** **Private Investment in AI by Geographic Area (in billions of US dollars)**

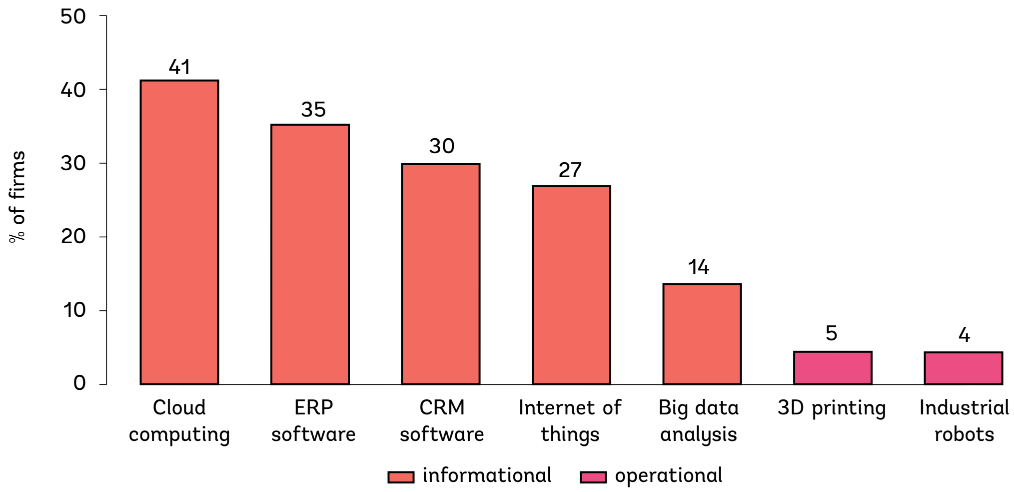



Source: NetBase Quid via 2022 AI Index Report

[6] https://ourworldindata.org/technological-change

Despite the growing importance of these new technologies in the workplace, only a fraction of European firms adopts them. According to data from the EUROSTAT Survey on ICT Usage among Enterprises, in 2022,[7] "informational technology"—including cloud computing, enterprise resource planning (ERP) software, and big data analysis—was the most adopted technology, with around one in four European firms using it (Figure 1.3). "Operational technologies," basically industrial robots and 3D printing, have been adopted by less than 5 percent of firms. EU averages mask important differences across member states. Scandinavian firms and those in Germany, the Netherlands, Belgium, and Austria generally have higher technology adoption rates. Romania, Bulgaria, Hungary, and Greece have the lowest technology adoption rates (EUROSTAT and authors' calculation).

**FIGURE 1.3. Technology adoption averages across EU27+ countries (% of firms in a country, average across EU27+, in 2022 or last year available)**

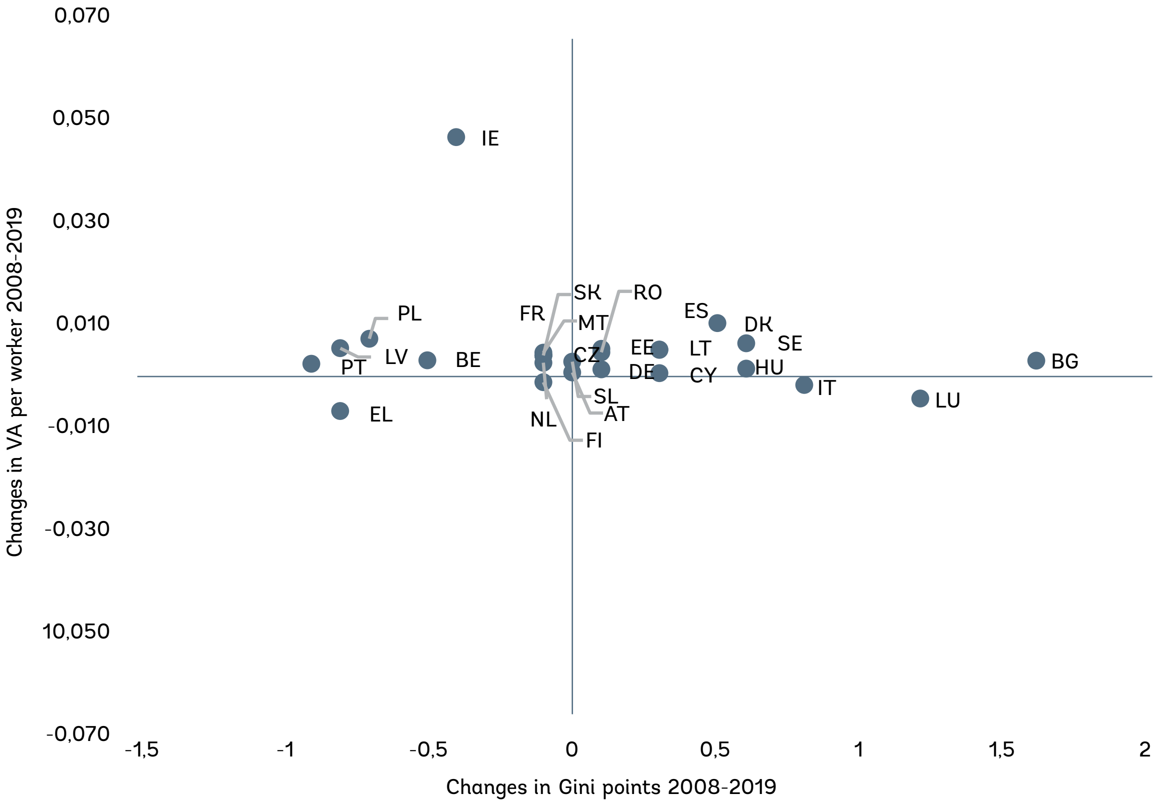



Source: EUROSTAT Survey on ICT Usage among Enterprises.

The era following the Great Recession saw a rise in technological advancements that led to a decline in middle-skill jobs, which had already been happening since the 1970s due, among other reasons, to offshoring. This resulted in a marginal increased income inequality in many EU countries. Figure 1.4 illustrates changes in productivity and income inequality across EU member states from 2008 to 2019. During this period, many EU countries experienced a slight increase in inequality, as measured by the Gini coefficient on household disposable income, with minimal changes in labor productivity. As a result, gross domestic product (GDP) growth rates in the EU remained low due to stagnant productivity. EUROSTAT reported an average yearly GDP growth rate of 1.3 percent in the EU-27 between 2008 and 2022, with GDP per capita growing below 1 percent per year during the same period.

[7] Eurostat is the statistical office of the EU. The figures correspond to 2022 or last year available: CRM and ERP: 2021, Cloud computing: 2021, IoT: 2021, Big data analysis: 2020, Industrial robots: 2022, 3D printing: 2020.

**FIGURE 1.4.** **Changes in productivity and inequality in EU member states, 2008–19**




Source: authors' computations using data from EUROSTAT. Inequality is measured by the Gini coefficient of per capita household income, and productivity is measured by gross value added (GVA) per worker at the country (NUTS0) level.

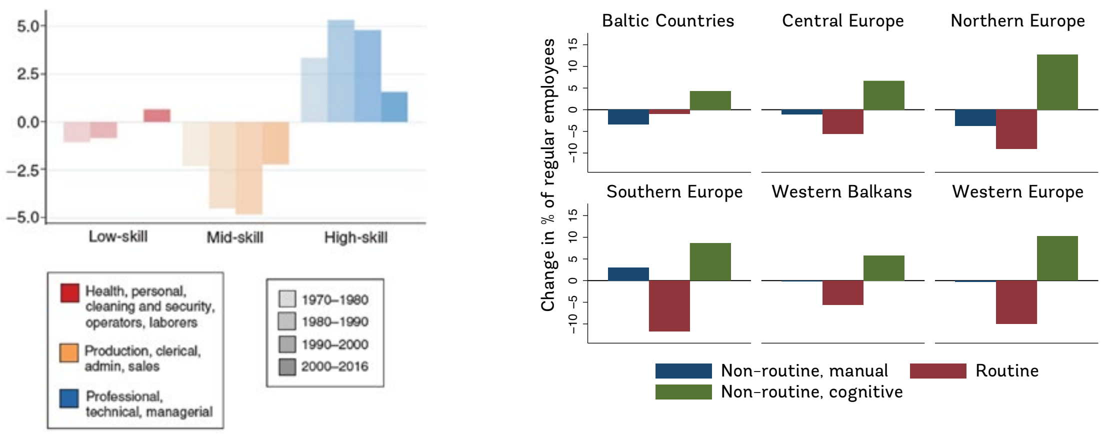
Perhaps more than the marginal deterioration in the distribution of household incomes in some EU countries (as shown in Figure 1.4), changes in the income of the richest 1 percent, which household surveys do not capture, may have driven social perceptions of inequality and its political implications. As documented by Bussolo et al. (2018), the number of billionaires in the EU and the value of their wealth as a share of GDP have increased constantly since the Great Recession. Similarly, vulnerability has increased in many countries, as households that previously were shielded from welfare shocks saw a higher risk of falling into poverty. This vulnerability and other social and economic aspects that matter for individuals' perceptions of inequality, such as unemployment and poverty risks (Bussolo et al., 2021), have fueled *distributional tensions* and anxiety among European citizens.

Technological progress partly explains the post-Great Recession period characterized by stagnant productivity, low economic growth, and rising distributional tensions. Technology can intensify preexisting disparities, with some regions, firms, and types of workers benefiting whereas others experience lower demand and lower wages. Economies with *contestable* and more flexible markets—including dynamic labor markets—can reap the benefits associated with technology adoption. However, increased income disparities or tensions around how to distribute the benefits of technology are more likely to be present in economies characterized by low skills, weak social protection systems, and rigid labor markets.

*"Technological change - in the context of globalization - has led to job shifts in both the US and Europe. Both saw a decline in routine jobs, but in Europe, unlike the US, nonroutine manual jobs did not increase".*

Recent evidence for the US and Europe documents the adverse distributional effects of technology in the context of international market integration or globalization. Between 1970 and 2016, the share of employment in mid-skill occupations in the US—such as office clerks, sales associates, and production workers—shrank while the number of high- and low-skilled occupations rose or remained unchanged (Figure 1.5, panel a). A similar pattern is seen in Europe between the 1990s and late 2010s, with the number of occupations involving routine tasks decreasing throughout the period (Figure 1.5, panel b), although the share of nonroutine manual jobs did not increase as in the US. According to the European Jobs Monitor 2019, "the more or less pervasive and resilient growth of high-paid jobs seems to be linked to technological change and general economic progress, the relatively anemic growth of mid-paid jobs tends to be associated with secular trends of deindustrialization and the computerization of routine cognitive tasks."[8] Data for the US shows that college graduates previously employed in mid-skill occupations shifted to high-skill jobs. However, most non-college graduates with previously mid-skill occupations transitioned to low-skill jobs, contributing to growing income disparities (Autor 2019). In Europe, many mid-skill workers performing routine occupations exited the labor force (Bussolo, Torre & Winkler, 2018), a fact that can explain the minimal increase in nonroutine manual jobs in this region. Differences in labor market institutions, particularly in social insurance, could explain the different fate of displaced routine workers in the US versus the EU (Albertini et al., 2017)

**FIGURE 1.5.** **Percentage change in occupational employment shares among working-age adults in the US (left) and Europe (right)**




Note: panel a taken from Autor 2019 and panel b updated from Bussolo et al. 2018.

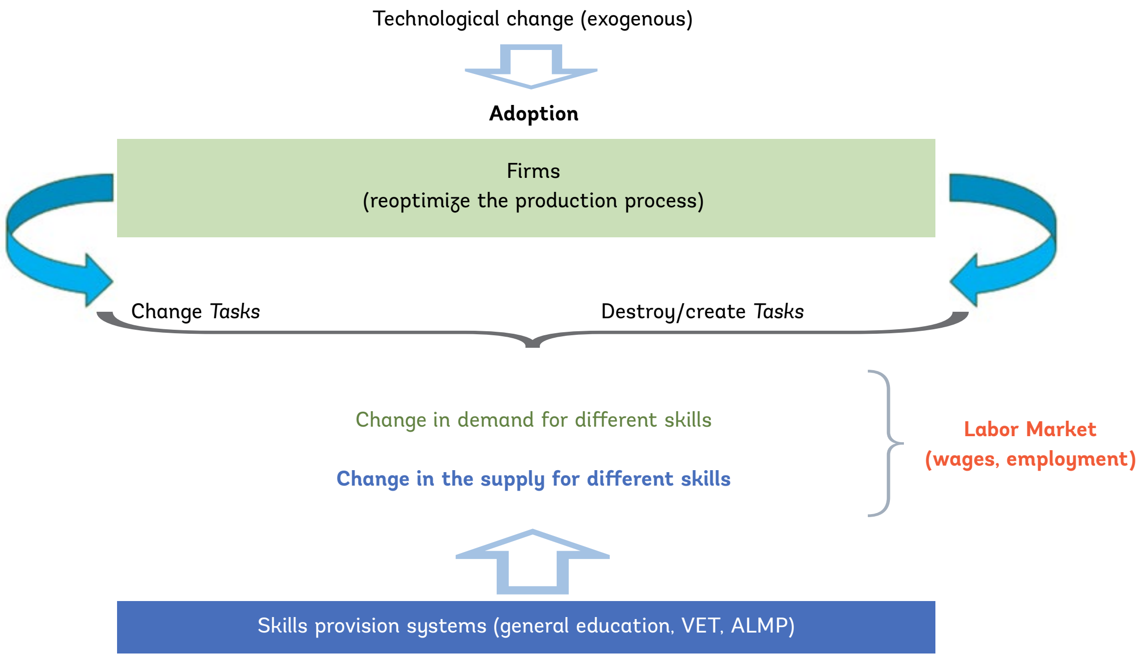
There has been a heated discussion surrounding the paradox of growing inequality and stagnant productivity amid rapid technological advancements. Cusolito and Maloney (2018) have reviewed this issue extensively. One theory is that the paradox may be attributed, in part, to a rise in market concentration. A few dominant firms, which seem less productive and innovative, have been acquiring smaller startups with high potential. Autor et al. (2020b) indicate that the decline of income's labor share in various advanced economies could be explained by the impact of technological progress and globalization on market concentration.

[8] https://www.eurofound.europa.eu/sites/default/files/ef_publication/field_ef_document/ef19036en.pdf

## 1.1 Conceptual framework linking technology, firms, and labor markets

Technological development is linked to growth and income distribution via firms and labor markets. Technology can increase productivity, profits and the size of firms. If technology is adopted only by a relatively small number of large firms, it can increase market concentration and reduce the share of national income going to labor, exacerbating distributional tensions. Technology can also change how total labor income is distributed among workers with different levels of education. This section develops a simple framework linking technology and labor markets through firms, their production processes, the tasks involved in such processes, and ultimately the demand for workers' skills. The framework underscores the importance of the ***skills provision system***, which includes the formal education system, vocational education, and short-term training courses or ALMPs, to determine the supply of skills. The labor market interaction between the demand and supply of skills determines the effects of technology on the wages and employment of different workers. Figure 1.6 shows the linkages between technological progress, firms, tasks, skills provision systems, and labor market outcomes analyzed in this report.

**FIGURE 1.6. Conceptual linkages between technology, firms, and labor markets**




### 1.1.1 *A taxonomy for different technologies*

This report classifies technologies on two dimensions according to their purpose, and maturity. (See Box 1.1 for more details.) In terms of purpose, building on the World Bank report "Europe 4.0" (Hallward-Driemeier et al. 2020), we distinguish between informational and operational technologies. Technologies are also different in terms of their maturity across technological waves. AI, 3D printing, and cloud computing are called "4th Industrial Revolution" technologies (Bowles 2014; Frey and Osborne 2017; UNIDO 2020). Some researchers argue that "4$^{th}$ Industrial Revolution" technologies could affect labor demand in a way that is unique and distinct from earlier waves of industrialization (Webb, 2020; Autor 2022).

**BOX 1.1. A taxonomy for distinguishing among different technologies analyzed in this report**

First, our taxonomy draws on Hallward-Driemeier et al. (2020), who recognize that different technologies solve different problems. The authors classify technologies according to their purposes and how they achieve efficiency gains:

- *Informational* technologies exploit the falling price of computing power and harness the exponential growth of data to provide improved and customized products and services at lower costs.
- *Operational* technologies lower costs by automating processes that workers previously executed.[9]

Second, we expand Hallward-Driemeier et al. (2020) by classifying technologies based on their 'maturity.' To provide a better conceptual underpinning to our empirical analysis, we classify technologies into 'waves' based on the concept of industrial revolutions.[10] Table B1.1.1 groups specific technologies based on these two dimensions (purpose and wave or maturity). The 3.0 technologies arose during the third industrial revolution and consist of digitized general business functions and automatization of specific processes in the firm. Examples include customer relationship management (CRM) and ERP software for informational technologies and industrial robots for operational technologies. The current technology level, 4.0, which is related to the fourth industrial revolution, comes with technologies that are self-controlled and integrate all firm processes. We consider informational technologies such as cloud computing, big data analysis, and the Internet of Things, and operational technologies such as 3D printing.

**TABLE B1.1.1. Technology classification**

| Technology wave | Informational technologies | Operational technologies |
|---|---|---|
| **Digitalization 3.0**<br>Third Industrial Revolution<br>Digital technologies allow for paperless control of processes in the firm | CRM<br>ERP | Industrial robots |
| **Digitalization 4.0**<br>Fourth Industrial Revolution<br>Connected, smart processes with real-time feedback | Cloud computing<br>Big data analysis<br>Internet of Things | 3D printing |

### 1.1.2 *Technology adoption and the demand for skills*

Innovations in technology can stem from a variety of factors, including advancements in scientific knowledge, production processes, and the introduction of new products or services. Additionally, government policies, market competition, and the availability of resources and skilled labor can also play a role. However, this study focuses on the factors that influence technology adoption by firms rather than technological progress itself. Such factors can be specific to the firm, industry-specific, or external to the firm, such as the availability of human capital and the quality of the regulatory environment. Firms are motivated to adopt new technologies because it typically improves their productivity, reduces costs, or enhances the quality of goods and services produced.

Once a new technology is adopted, it changes the *production function* of firms, which changes some tasks, destroys others, and creates new ones (middle part of Figure 1.6).

***"Firms adopt new technologies to boost productivity, lower costs, and improve product or service quality. When they do so, their production process changes, resulting in the creation, destruction, and modification of tasks, which in turn affects the demand for workers with different skills."***

[9] We slightly depart from Hallward-Driemeier et. al. (2020) by classifying Internet of Things (IoT) as an informational and not an operational technology. IoT refers to devices that collect and exchange data and can be remotely controlled over the Internet (Eurostat, 2021). Thus, its primary function is data exchange and management. More importantly, our analysis suggests that IoT has characteristics that are more similar to other informational technologies than operational technologies (such as low investment costs).

[10] The First Industrial Revolution (beginning of 19th century) epitomizes the transition from manual production to use of steam- and water power-driven machines. The Second Industrial Revolution (end of 19th century) introduces mass production and assembly lines enabled by electricity. The Third Industrial Revolution (in the 1970s) is characterized by automation through electronics and IT, whereas the Fourth Industrial Revolution connects the physical and digital spaces into a cyber-physical system (UNIDO, 2020).

We follow Acemoglu and Autor's (2011) framework and define jobs as collections of ***tasks***—specific activities or functions that workers perform. As in Acemoglu and Autor (2011), "skills" are the abilities, knowledge, and expertise that workers have and use in performing tasks. Technology's effect on the demand for skills operates via its impact on tasks.

Deming (2017) shows that the US market is increasingly rewarding social skills because teamwork has increasing relevance, and there is little scope for substituting social skills with an algorithm. Acemoglu and Autor (2011) find that unpacking the task contents of jobs is useful for analyzing the distributional impact of technologies. To analyze the potential impact of technology on tasks and skills we follow Deming (2017) and Acemoglu and Autor (2011) and define jobs in terms of their task content, distinguishing between six types of tasks: (1) nonroutine cognitive analytical, (2) nonroutine cognitive personal, (3) routine cognitive, (4) routine manual, (5) nonroutine manual (physical), and (6) social tasks. (See Box 1.2 for a detailed explanation of the relationship between jobs and tasks.)

**BOX 1.2. Classifying jobs in terms of their task content**

Jobs can be understood as collections of tasks that an individual performs. A task is a unit of work activity that produces output (Acemoglu and Autor, 2011). Autor et al. (2003) first distinguished tasks along two dimensions—routine/nonroutine and analytical/manual. Routine tasks correspond to procedural, rule-based activities that can be specified as instructions to be executed by a machine. Nonroutine tasks are those that are not codifiable in a similar way because they demand flexibility, creativity, generalized problem solving, and complex communications. Analytical or cognitive tasks involve information processing, whereas manual tasks require physical input from the worker. Acemoglu and Autor (2011) further distinguish tasks into five groups: nonroutine cognitive analytical, nonroutine cognitive personal, routine cognitive, routine manual, and nonroutine manual. Deming (2017) also identified the use of social skills in the job as an additional task dimension of occupations. The O*NET database on occupations includes detailed information on the tasks performed and abilities required for 968 occupations in the United States Standard Occupational Classification System (SOC). The five groups of tasks Acemoglu and Autor (2011) defined and the indicator of the use of social skills Deming (2017) defined can be identified in O*NET. Table B1.2.1 indicates the elements of the O*NET database used as summary measures of the six tasks.

Hardy et al. (2018) produced a crosswalk between SOC and ISCO 08 (International Standard Classification of Occupations '08), that allows for the estimation of the measures in Table B1.2.1 in the classification of occupations used by EUROSTAT in the EU Labor Force Survey.

**TABLE B1.2.1. O*NET summary measures of task content of jobs**

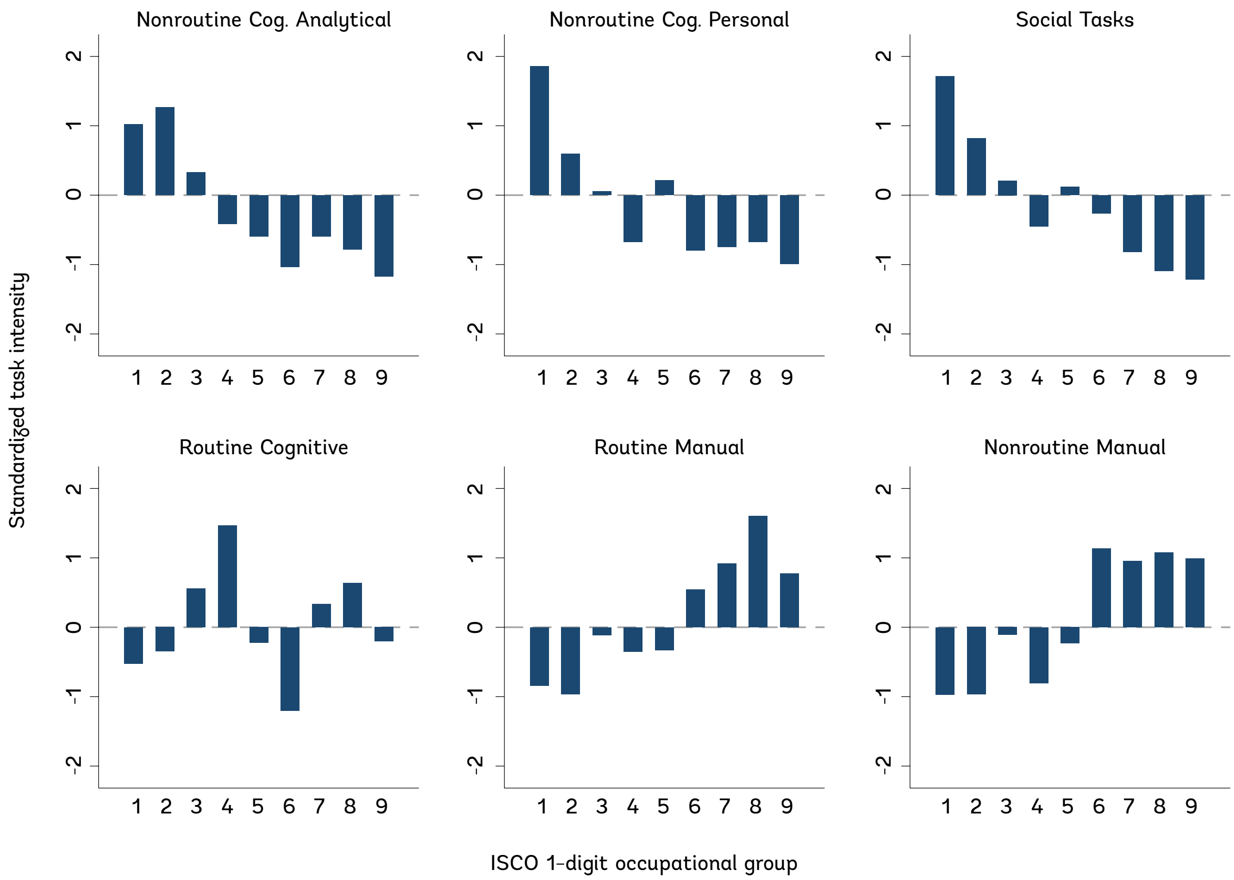
| Task type | O*NET element (code) |
|---|---|
| Nonroutine cognitive analytical | - Analyzing data/information (4.A.2.a.4)<br>- Thinking creatively (4.A.2.b.2)<br>- Interpreting information for others (4.A.4.a.1) |
| Nonroutine cognitive personal | - Establishing and maintaining personal relationships (4.A.4.a.4)<br>- Guiding, directing, and motivating subordinates (4.A.4.b.4)<br>- Coaching/developing others (4.A.4.b.5) |
| Routine cognitive | - Importance of repeating same tasks (4.C.3.b.7)<br>- Importance of being exact or accurate (4.C.3.b.4)<br>- Structured vs. unstructured work (4.C.3.b.8) |
| Routine manual | - Pace determined by speed of equipment (4.C.3.d.3)<br>- Controlling machines and processes (4.A.3.a.3)<br>- Spend time making repetitive motions (4.C.2.d.1.i) |
| Nonroutine manual (physical) | - Operating vehicles, mechanized devices, or equipment (4.A.3.a.4)<br>- Spend time using hands to handle, control, or feel objects, tools, or controls (4.C.2.d.1.g)<br>- Manual dexterity (1.A.2.a.2)<br>- Spatial orientation (1.A.1.f.1) |
| Social tasks (use of social skills) | - Coordination (2.B.1.b.x)<br>- Negotiation (2.B.1.d.x)<br>- Persuasion (2.B.1.c.x)<br>- Social perceptiveness (2.B.1.a.x) |

Source: Acemoglu and Autor 2011; Deming 2017.

Note: The code for each element corresponds to the O*NET 24.0 database. The summary measure for all the task types (except social tasks) is the sum of the score in each of the O*NET elements. In the case of the measure on social tasks (specifically, the use of social skills), the summary measure corresponds to the average score across the corresponding O*NET elements.

Figure 1.7 plots the value of the six task measures (also defined as task intensity) for the nine major groups of the ISCO 08 classification. The values are standardized to have a mean of zero and a cross-occupation standard deviation of one for the 126 3-digit occupations in ISCO 08. The measures of task intensity aim at summarizing the task content of jobs. The intensity in nonroutine cognitive tasks and the use of social skills is highest in the managerial and professional occupations, whereas it is lowest in the elementary occupations, plant and machine operators, craft-related trades workers, and agricultural workers. The intensity of routine cognitive tasks is highest for clerical support workers, whereas the intensity of routine manual tasks is highest for plant and machine trade operators. Nonroutine manual tasks are more common in agricultural workers and in plant and machine trade operators, elementary occupations, and for craft-related trades workers.[11]

**FIGURE 1.7.** **Task content of jobs by ISCO 08 major group**




Source: own elaboration based on Acemoglu and Autor 2011; Deming 2017; and Hardy et al. 2018. Note: this graph plots the standardized value of the six task types defined in Box 1.2 for the nine major groups (1-digit) of the ISCO 08 classification. These groups are: 1 = Managers; 2 = Professionals; 3 = Technicians and associate professionals; 4 = Clerical support workers; 5 = Service and sales workers; 6 = Skilled agricultural, forestry, and fishery workers; 7 = Craft-related trades workers; 8 = Plant and machine operators, and assemblers; 9 = Elementary occupations. The values are standardized to have a mean of zero and a cross-occupation standard deviation of one for the 126 3-digit occupations in ISCO 08.

[11] Just as any summary measure, they may not capture nuances in occupational classifications and may have certain biases. For instance, the measures are increasing in the number of tasks performed in the job—which implies that more complex jobs that involve multiple tasks may have a higher intensity across all types of tasks than more basic jobs, where only a few tasks are performed. In this sense, the measures are better used to compare different occupations along a same task dimension, rather than comparing several task dimensions for the same occupation.

### 1.1.3 *Education systems and the supply of skills*

Adapting education and training systems to put more emphasis on skills that will be in demand in the digital era have been highlighted as a core area for reform. (See, for example, Autor et al. 2022a). Concluding a systematic evidence review, Hötte et al. (2022) note that "effective up- and reskilling strategies should remain at the forefront of policy making along with targeted social support systems." Policies to enhance the supply of skills that reflect changing demand due to technological transition typically fall into two categories. First are educational policies that affect endowments people bring to markets (which Rodrik and Stantcheva (2021) call pre-production policies). Second are active and passive labor market policies aimed at workers already on the market but possibly unemployed (production stage policies). Our analysis of the skills provision system focuses on pre-production polices—notably the capacity of upper-secondary VET systems to provide the necessary skills in a technology-driven and globalized European labor market.

The interaction between a technology-driven rapid change in the demand for skills and a relatively rigid supply of skills determines the labor market equilibrium (wages and employment—the middle part of Figure 1.6). Private sector firms typically have incentives to adopt new technologies quickly, despite barriers (such as financing, regulations, and human capital). Education systems usually lack the incentives and the flexibility to change their curricular contents and supply of training courses to reflect changes in labor demand (see Box 1.3). In the short run, this makes the demand side of the labor market more elastic or responsive to technological changes vis-à-vis the supply side.

**BOX 1.3. Adapting the supply of VET courses in Greece**

**The evidence of VET schools' efforts to track their students' post-graduation success and employers' satisfaction with their performance is limited.** According to the results of the Training Assessment Project (TAP) survey[12] conducted in vocational (apprenticeship) schools managed by the Greek Public Employment Service (DYPA), preparing students for the world of work and developing a demand-driven approach to training are two areas for further improvement.[13] Forty-eight percent of VET schools do not track their students' employment paths after graduation, and 62 percent do not track their performance in the workplace. Most surveyed schools (64 percent) responded that they do not offer their students career guidance or counseling services, contradicting the idea that vocational schools need to adequately prepare students for the labor market. DYPA and the Ministry of Education and Religious Affairs (MoERA) are developing tracking systems for VET graduates.

**Even though new specializations have been introduced, interviews with school directors of VET schools in Greece reveal that many trade**s have not **changed over the last 20 years.** Most occupational profiles and curricula are not up to date. According to the TAP survey, 32 percent of the schools surveyed do not have an annual process for reviewing and closing low-performing programs. Curricula for most technical occupations taught in Greek vocational schools have not been updated since 2007. The Organization for the Certification of Qualifications and Vocational Guidance (EOPPEP) has started developing new accredited profiles for a few occupations in demand and is also planning to develop new-style job profiles over the next couple of years. The national mechanism for diagnosing labor market needs is used to an extent; however, it remains a significant challenge to better align the supply of skills in VET with labor market developments.

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[12] A survey developed by the World Bank Group and specifically under the Systems Approach for Better Education Results (SABER) Initiative. It aims to identify the conditions and common practices under which technical and vocational education and training institutions operate as well as those conditions and practices that are associated with quality instruction and positive employment outcomes. More information about the survey can be found here.

[13] The survey was carried out in August 2022, under the technical assistance project "Modernizing Vocational Education and Training Services of DYPA in Greece", Administrative Agreement of August 30, 2021 – EC Contract No REFORM/IM2021/029.

***"Differences in the speed of skill adaptation to technology create imbalances that affect worker wages and employment. Education systems - particularly upper-secondary VET systems - struggle to keep up with technological progress, making skills matching challenging."***

Differences in the pace at which demand and supply of skills adapt to new technologies create imbalances that shape technology's impact on workers' wages and employment levels. Skills provision systems, particularly education systems, are not designed for racing against technological progress, making the quest for skills matching challenging or even futile. Education systems are well suited for providing core or foundational skills needed in more dynamic labor markets. Foundational skills are the building blocks of learning for any individual to function effectively in the modern economy and society. Foundational skills typically include reading, writing, numeracy, critical thinking, problem solving, and social skills.

Our analysis of the skills provision system focuses on the capacity of upper-secondary VET systems to provide the necessary skills in a technology-driven and globalized European labor market. Two arguments justify our focus on pre-production policies, particularly upper-secondary VET systems. First, much of the discussion on the supply of skills related to the "future of work" has concentrated on "production policies" in the form of ALMPs (Autor et. al. (2022c); OECD (2019)). To our knowledge, our report is the first to assess the adequacy of secondary VET systems for a technology-driven, dynamic labor market. Second, the role of VET in skill development in the EU is crucial not only for the labor force as a whole but for those from a disadvantaged background. Nearly half of the EU's upper-secondary students are enrolled in VET, the highest share in the world. In all the EU member states, VET students tend to be from lower socioeconomic status and show lower cognitive foundational skills as measured by the OECD's Program for International Student Assessment (PISA) test. So, in the EU, making sure the VET systems provide graduates with the skills needed in a globalized and technologically driven labor market is critical. Despite our strong focus on upper-secondary VET, our policy section (Chapter 5) includes a discussion on alternatives to providing skills for the current workforce through ALMP.

## 1.2 Rage against the machine

William Lee, an English clergyman, invented the first stocking frame knitting machine in 1589. The machine revolutionized the process of knitting stockings, making it quicker and more efficient than traditional hand-knitting methods. Despite the machine's significant importance and Lee's innovative breakthrough, Queen Elizabeth I declined to grant him a patent to safeguard his invention, possibly delaying the Industrial Revolution and all its benefits by a few decades. The Queen's argument was simple yet common among politicians of her and our time: "Think about what this invention could do to my poor subjects. It would undoubtedly lead them to ruin by taking away their jobs and leaving them with no choice but to beg for their livelihood" (Acemoglu & Robinson, 2012).

Several years later, after the knitting machine was patented, the textile industry underwent a significant transformation, marking the beginning of the Industrial Revolution. Queen Elizabeth's concerns were not unfounded, and many textile workers lost their jobs as a result. A group of radical workers, calling themselves the Luddites, formed an organization in Nottingham with the aim of destroying the new textile machines and burning down emerging factories.

The impact of technology can be disruptive and displace certain workers, but so far, the existing evidence does not support the claim that technology will permanently reduce employment. Although technology can accomplish tasks once done by humans, displacing workers, it can also complement them. This shift can be challenging for those directly affected, but technology can also enhance the work of humans and create new jobs, leading to increased productivity and economic growth. Studies have shown that after an initial adjustment period, new jobs are created and overall employment levels usually remain stable (Autor, 2015).

***"Technology can replace tasks, but it can also create new ones."***

'According to Autor et al. (2022a), the US census index of occupations has added many new titles from 1940 to 2018, as shown in Table 1.1, reproduced from Autor et al. (2022a). Although some of these new titles, such as those listed in the right column of Table 1.1, are explained by changes in demand, preferences, and tastes, others result directly from technological advancements as shown in the left column of the same table. Autor and colleagues estimate that over 60 percent of all US employment in 2018 comprised titles that did not exist in 1940. This highlights the significant transformative impact of technology, not only in replacing workers, but also in creating new tasks, jobs, and occupations.

**TABLE 1.1. Examples of new titles added to the census alphabetical index of occupations, 1940 and 2018**

| Volume Year | Example Titles Added | |
|---|---|---|
| 1940 | Automatic welding machine operator | Acrobatic dancer |
| 1950 | Airplane designer | Tattooer |
| 1960 | Textile chemist | Pageants director |
| 1970 | Engineer computer application | Mental-health counselor |
| 1980 | Controller, remotely-piloted vehicle | Hypnotherapist |
| 1990 | Circuit layout designer | Conference planner |
| 2000 | Artificial intelligence specialist | Amusement park worker |
| 2010 | Technician, wind turbine | Sommelier |
| 2018 | Cybersecurity analyst | Drama therapist |

Source: Autor et al. 2022a.

Note: Table reports examples of new titles added to the Census Alphabetical Index of Occupations volume of year Y correspond to titles recognized by census coders between the start of the prior decade and the year preceding the volume's release. (For example, the 1950 CAI volume includes new titles incorporated between 1940 and 1949.)

### 1.2.1 *Taking uncertainties to a new level*

Although past predictions of a future without human work have yet to realize, some of the most recent technological innovations have raised these old concerns to a new level. New automation technologies' characteristics make them fundamentally different from earlier waves of technological progress. AI, in particular, is capable of carrying out tasks that do not follow a specific rule, considerably widening the set of tasks it can perform. Many tasks that were considered safe from automation, such as those focused on the creation of new original content, are now at risk of automation. The recent introduction of ChatGPT, a free online generative AI tool, has increased awareness among the general public of both the vast potential and the deep concerns associated with these technological breakthroughs. Newer, improved forms of AI—such as adaptive AI—will likely further polarize this dichotomy. As pointed out by Autor (2022) these new automation technologies raise questions that are virtually impossible to answer, generating a new level of uncertainty around what the future of work will look like. Predictions about the future are always speculative, but AI is making this exercise more uncertain than ever.

Some observers consider the capacities of AI to be so vast as to threaten the existence of human labor. Many worry that as AI—and its integration with robotics—increasingly substitutes for human labor in cognitive-intensive tasks and, in a possibly not so distant future, in socioemotional-intensive tasks, it will ultimately make human labor (mostly) redundant. Although potentially beneficial for humanity's welfare, this extreme scenario would also cause an unprecedented disruption in our societies. If not effectively governed the transition to this new equilibrium—"the End of the Age of Labor" (Korinek & Juelfs, 2022)—may result in a major deterioration of the social order. Although this scenario remains extreme and impossible to predict with any certainty, governments and societies should prepare for this eventuality. The debate on how to best accompany this transition and on how to best design this possible new equilibrium is growing. Although different approaches are being discussed, including implementing universal basic incomes (Yang 2021), guaranteeing a just society in the face of such epochal changes would require some radical rethinking of our current social contracts.

***"Exposure to new technology does not necessarily lead to its adoption. Actual adoption depends on multiple factors, making exposure alone an insufficient predictor."***

If the (quasi)complete substitution of human labor is ultimately only one extreme and uncertain scenario, it is easier to predict that AI will likely cause major disruptions in our economies. Many observers are skeptical about the likelihood of a future world without human labor (Autor, 2022). Few, however, disagree on the fact that the diffusion and further development of AI technologies will cause an important shift in the demand for skills demanded in the labor market. As already discussed in this chapter, this is not the first time that a new technology has changed the task content of human labor. As mentioned in Box 1.4, there exists a significant time gap between the introduction of technological advancements and their widespread adoption by companies. However, what will likely be different this time is the speed and magnitude of these changes. These rapid disruptions will require government and societies to take measures to make sure the costs and gains of these changes are equitably distributed among the members of society.

**BOX 1.4. Exposure to new technology does not translate automatically into adoption of new technology**

Findings by Frey and Osborne (2017), based on the susceptibility of jobs to computerization, suggested that nearly half of all jobs in the US might be at risk of being replaced in the next decades. Their finding received considerable attention in the media downplaying the fact that being exposed to a new technology does not translate into that technology being adopted. We analyze the relationship between first exposure to technology in 2000 and adoption among firms 20 years later for two technologies—AI and industrial robots.

To identify firms and workers potentially exposed to technology we rely on Webb's technology exposure measure (2020). Webb's (2020) index measures exposure for AI and industrial robots at the occupational level in 2000. We correlate this measure with information from the EUROSTAT ICT Survey on actual adoption of AI and industrial robots in 2020. We study the relationship between exposure and adoption using all sectors for AI and using manufacturing only for industrial robots. An important caveat in this exercise is that, whereas exposure is measured at the occupational (that is, worker) level, technology adoption is identified at the firm level. Given the substantial discrepancy in the share of firms and their respective share of employment in the economy, the estimate is bound to be relatively less precise.

Our main finding is that worker-level exposure to technology aggregated to the industry level is not related to the share of adopting firms in a country-sector 20 years later (Figures B1.4.1 and B1.4.2). The relationship between exposure and adoption for both AI and industrial robots is slightly negative but not statistically significant. Although Webb (2020) and other exposure measures can give predictions on the potential for technology adoption, they are an imprecise predictor of actual adoption. Actual adoption is a product of "exposure" and complementary drivers of adoption, such as those that we discuss further in Chapter 2. Exposure is a necessary but not a sufficient condition for adoption.

**FIGURE B1.4.1.** **Relationship between AI exposure and AI adoption**

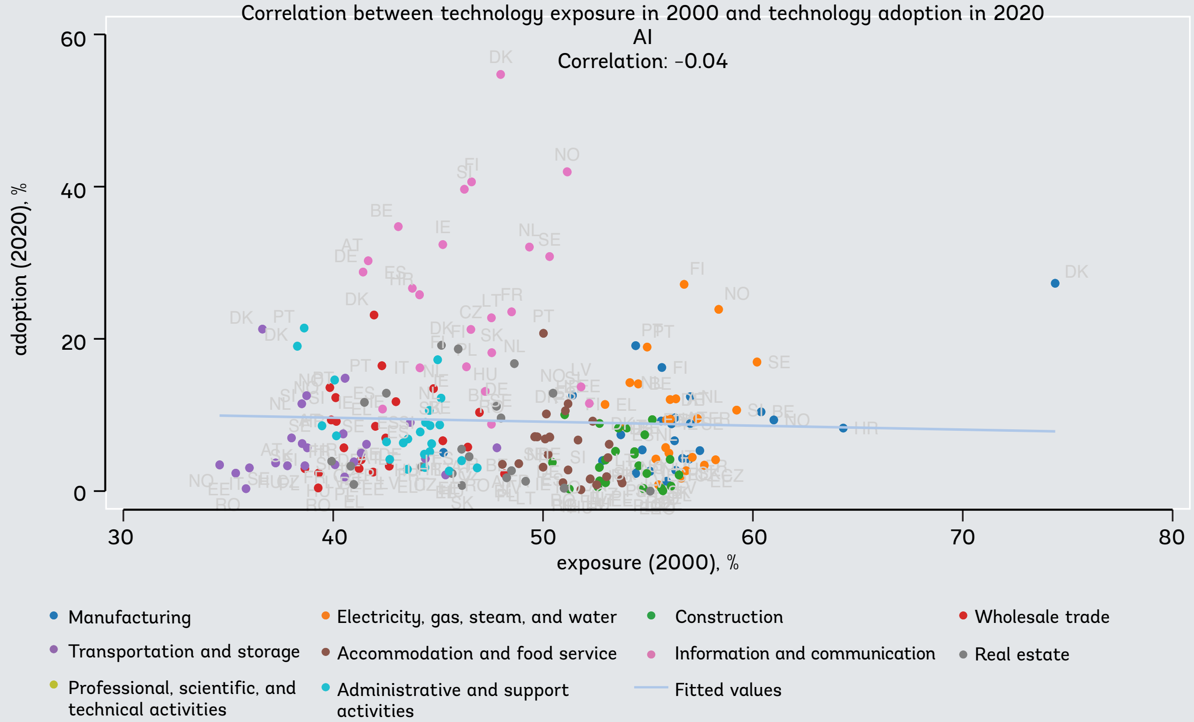
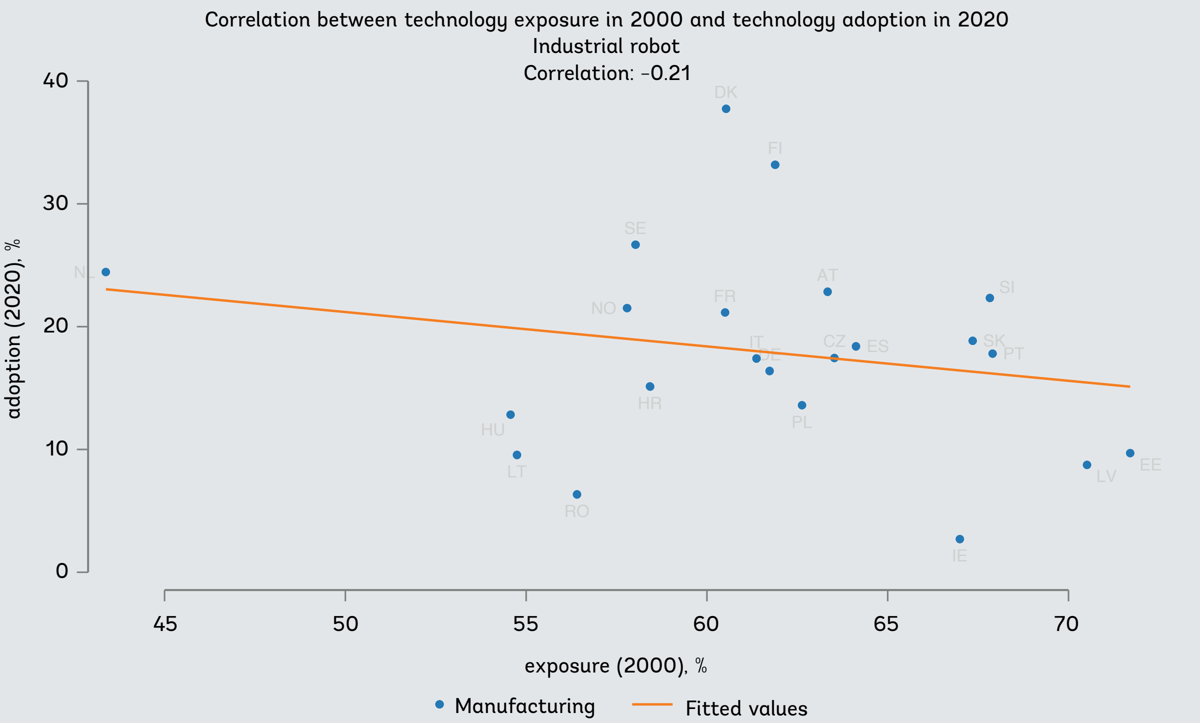



**FIGURE B1.4.2.** **Relationship between industrial robot exposure and industrial robot adoption**




Source: EUROSTAT Survey on ICT Usage among Enterprises, technology exposure measure from Webb (2020) calculated with EUROSTAT LFS data.

# CHAPTER 2 Patterns of Technology Adoption

*"The value of an idea lies in the using of it."*

Thomas A. Edison

## 2.1 Introduction

This section presents evidence on patterns of adoption of different technologies. To assess what impact technology can have on labor markets, it is important to discuss the pattern of adoption, and how different firms across regions and sectors adopt different technologies. Our analysis is based on Italian firm-level micro data and EUROSTAT data at the country-sector level.

We focus here on multiple technologies ranging from more novel ones, such as big data analysis or Internet of Things (IoT) or 3D printing, to more established ones, such as ERP and CRM. Technologies are different, and therefore we independently analyze their adoption patterns and drivers. To structure our analysis, we use a taxonomy that classifies technologies according to their purpose and maturity (see Box 1.1).

## 2.2 A large share of firms in the EU does not adopt modern technologies

A large share of firms in the EU adopts no digital technologies. Based on the Italian firm-level data we find that about one-third of firms with over 10 employees[14] adopt none of the six digital technologies analyzed, and another third adopt only one technology, whereas only 15.2 percent of firms adopt more than three technologies (Table 2.1). Basic information software—ERP and CRM—is the most widely adopted form of technology, followed by cybersecurity software and other forms of more advanced information technologies, such as cloud computing, Internet of Things, and big data analytics (Figure 2.1). Less than 5 percent of firms adopt robots and 3D printing technologies, two operational technologies that are used primarily in the manufacturing sector. Augmented reality, arguably the most advanced information technology among those included in the ICT 2017 survey is also the least adopted one, with only 1.4 percent of firms using it.

***"A full one third of all firms in the EU do not adopt any digital technologies"***

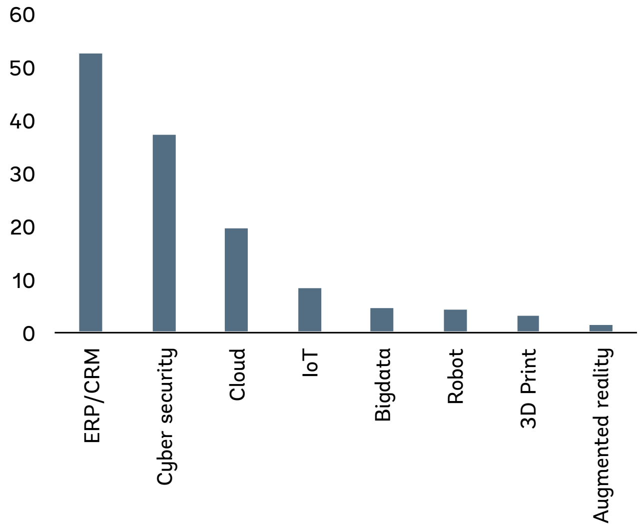
Different rates of adoption across technologies are due to various reasons. First, the sectoral scope of a technology matters because some technologies such as industrial robots have such a narrow scope that they can be used only in specific sectors such as vehicles and motor parts, whereas others such as ERP/CRM are broad technologies that used across most sectors. Second, the fixed costs of adoption differ significantly, and with recent advances of software as a service (SaaS) technologies such as ERP or CRM, have small fixed costs for adoption. Finally, maturity differs across technologies, augmented reality for example is a novel technology for which limited applications exist and businesses are less familiar with them compared to more established ones such as ERP or CRM.

[14] Those included in the ICT survey sample.

**TABLE 2.1.** Percent of firms adopting zero, one, or multiple technologies

| Number of technologies adopted | Percent of firms (10 employees or more) |
|---|---|
| 0 | 32.6 |
| 1 | 32.5 |
| 2 | 19.7 |
| 3 | 9.7 |
| 4 | 3.7 |
| 5 | 1.2 |
| 6 | 0.4 |
| 7 | 0.2 |
| 8 | 0.1 |

**FIGURE 2.1.** Share of firms adopting each technology (%)




Source: Survey of ICT Usage in Enterprises (ISTAT, Italy).

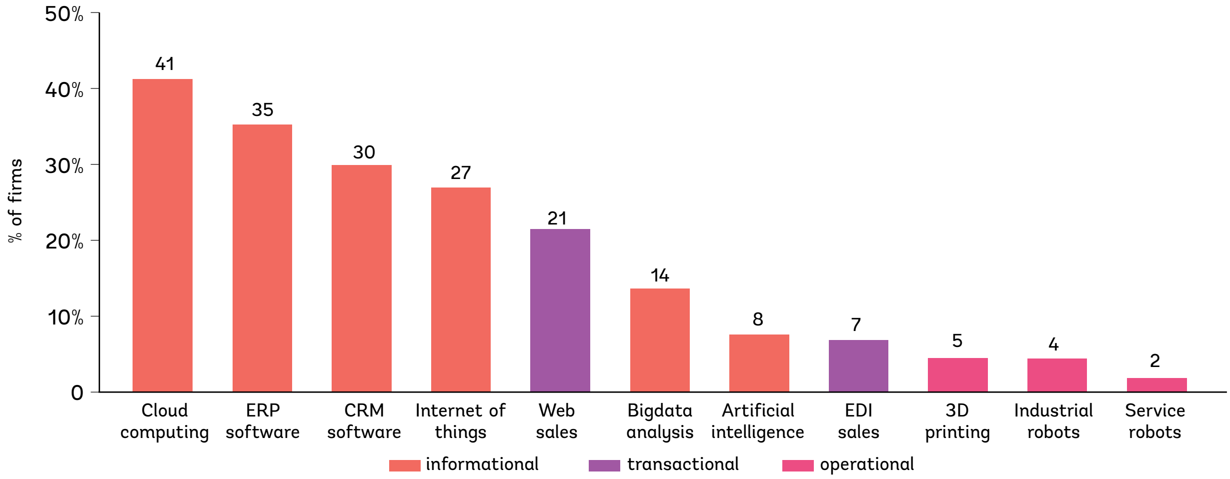
The large share of firms not using ERP and CRM software suggests that there is ample room to improve overall productivity at a relatively low cost by promoting a more widespread adoption of these basic information technologies among firms in the EU. Although ERP and CRM are the most adopted technologies, 47 percent of firms with more than 10 employees adopt neither of them. These technologies can improve the organizational efficiency of virtually any firm by improving strategic planning and promoting a more efficient management of the day-to-day business activities.

At the same time, these relatively basic and increasingly cheap technologies apply to virtually any sector. Similarly, although these types of software might still show economies of scale that make them more attractive for bigger businesses, their pricing is usually linked to the size of a company and its consumer base, making it affordable for smaller firms.[15] The large share of Italian firms not using even essential software for business planning and consumer management which can improve productivity at a small cost raises the question on the drivers of the relatively limited adoption of these technologies. This can help identify how policies can effectively ease any existing constraint to their adoption.

The results from Italy are confirmed by the country-level data from EU27+ with two main differences. First, the levels of technology adoption across EU27+ on average are even lower than in Italy, and the most adopted technology is cloud computing instead than ERP/CRM, which ranks second and third, respectively (see Figure 2.2).

[15] In particular, the possibility of purchasing CRM and ERP as software as a service (SaaS) through the cloud and paying a subscription fee that depends on the number of users and functions adopted allows the firms to implement these in a modular manner and drastically reduces their fixed costs.

**FIGURE 2.2.** Technology adoption in EU27+ (% of firms in a country, average across EU27+)

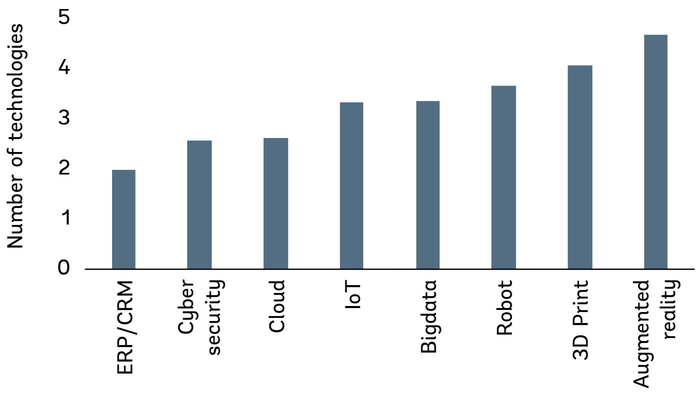



Source: EUROSTAT Survey on ICT Usage among Enterprises.

### 2.2.1 *Firms adopt different technologies following a hierarchical structure*

Data from Italy show that firms adopt different technologies following a hierarchical structure. Figure 2.3 shows the average level of technological sophistication—measured as the number of technologies adopted—of firms adopting each of the eight technologies considered in the analysis. The graph provides insights into the hierarchical structure of technology adoption decisions. ERP/CRM and cybersecurity are the first two "entry-level" technologies being adopted by firms with low technology sophistication. Firms with a medium level of technological sophistication start to adopt cloud, IoT, robots, and 3D printing at high rates relative to the average among all firms, whereas augmented reality is adopted primarily by firms with high technological sophistication. These patterns reinforce the idea that ERP and CRM are easy to adopt, requiring limited pre-adoption technological sophistication. Because they have a wide scope of applications across sectors, these technologies can benefit a wide range of firms. By contrast, robots and big data analysis are adopted primarily by firms with higher technological sophistication and often narrow sector-specific uses. Two factors are likely to explain these patterns. First, technologies such as big data and robots are likely to feature strong economies of scale, making them more likely to be adopted by larger firms, which are on average more technologically sophisticated. Second, advanced information technologies (such as big data analytics and cloud computing) are likely to have stronger technological complementariness and can thus require a more sophisticated technological infrastructure to be used effectively. Finally, augmented reality remains a niche technology, adopted only by highly sophisticated firms, operating primarily in the ICT sector.

**FIGURE 2.3.** "Ordering" of technology adoption




Source: Survey of ICT Usage in Enterprises (ISTAT, Italy).

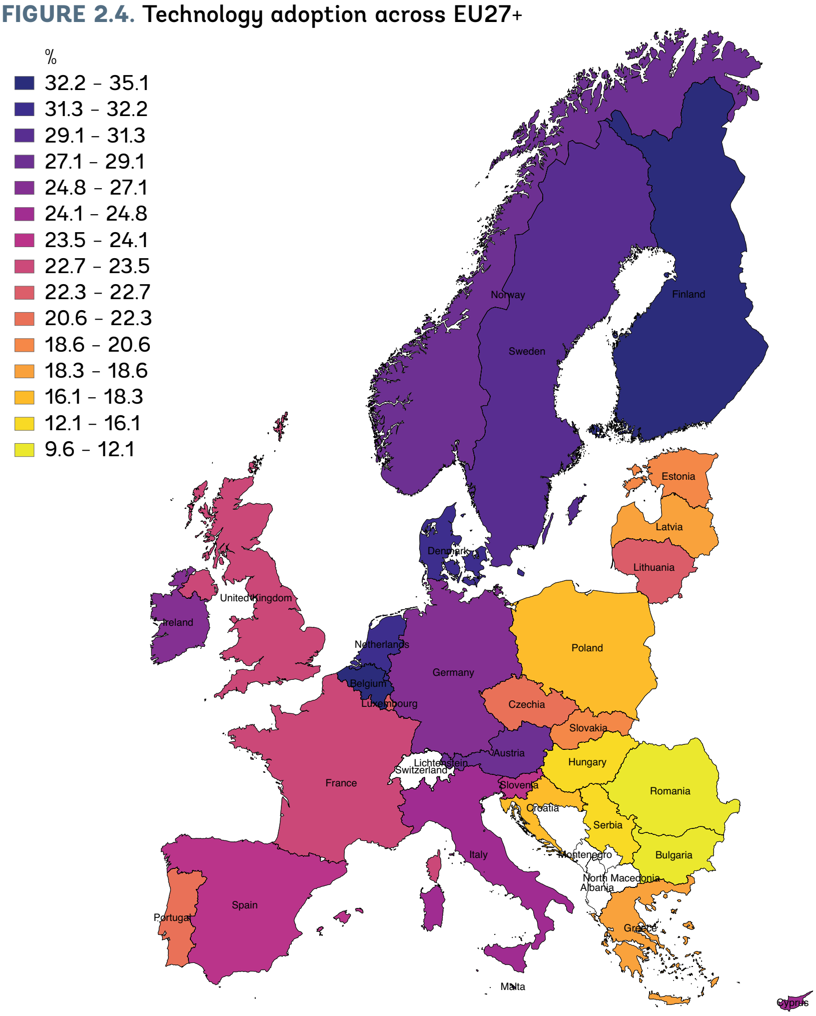
Note: The figure shows the average technological sophistication of firms adopting each technology.

## 2.3 Who adopts new technology?

### *2.3.1 Northern European countries lead in technology adoption*

Northern European countries lead in technology adoption, although countries in South-Eastern Europe are still far away from the European technological frontier. Northern European countries are leading across most technologies (Figure 2.4) and Western European countries follow closely, although Southern, Eastern, and South-Eastern European countries lag. However, the lagging countries have been catching up with the Northern European frontier, and for example Southern Europe has achieved full convergence to Northern Europe for industrial robots. Eastern Europe, at 78 percent adoption relative to Northern Europe, is close to convergence to the technology frontier, which is due to its high exposure to foreign direct investment (FDI) from Western Europe over the last three decades.

**FIGURE 2.4.** **Technology adoption across EU27+**



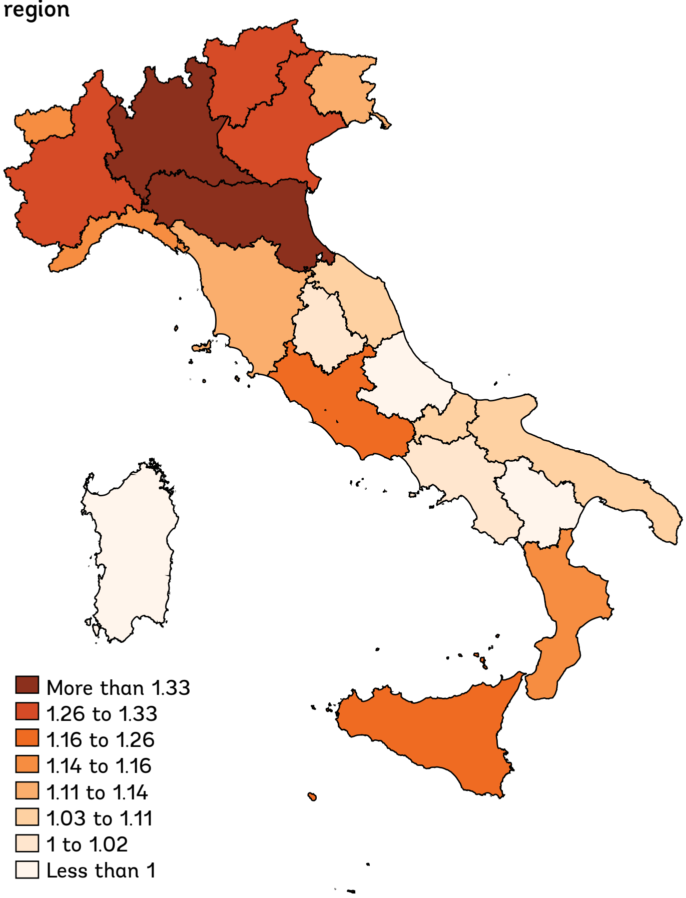

Source: Survey of ICT Usage in Enterprises (EUROSTAT).

Note: Technology adoption rate is defined as the average adoption rate within country across these seven technologies: CRM, ERP, cloud computing, industrial robots, big data analysis, Internet of Things, 3D printing. Last available survey year is used, which depending on the technology is 2020, 2021, or 2022.

***"Northern European countries lead in technology adoption, followed by Western and Southern European countries. Eastern European countries are lagging the most in adoption."***

Regional within-country differences in the level of technology adoption are also large. The stark within-country differences in technology adoption makes Italy an ideal case-study capturing much of the variation across EU member states (see Box 2.1). In Italy, firms in Lombardia and Emilia-Romagna—two regions with important advanced manufacturing sectors—lead in terms of overall technological complexity. Firms in these regions adopt on average 1.4 of the technologies covered in the ICT 2017 survey (Figure 2.5). By contrast, firms in the southern regions of Sardegna, Basilicata, and Abruzzo show the lowest level of technological sophistication, adopting on average less than one of the eight ICT 2017 technologies. Italian firms in the north of the country have a technological advantage in all but one of the eight surveyed technologies.[16] Regional adoption gaps tend to be larger for manufacturing technologies, a fact in part determined by the stark regional differences in the distribution of advanced manufacturing.

**FIGURE 2.5. Average technology sophistication by Italian region**




Source: Survey of ICT Usage in Enterprises (ISTAT, Italy).

Note: the figure shows the average number of technologies adopted by firms headquartered in each region.

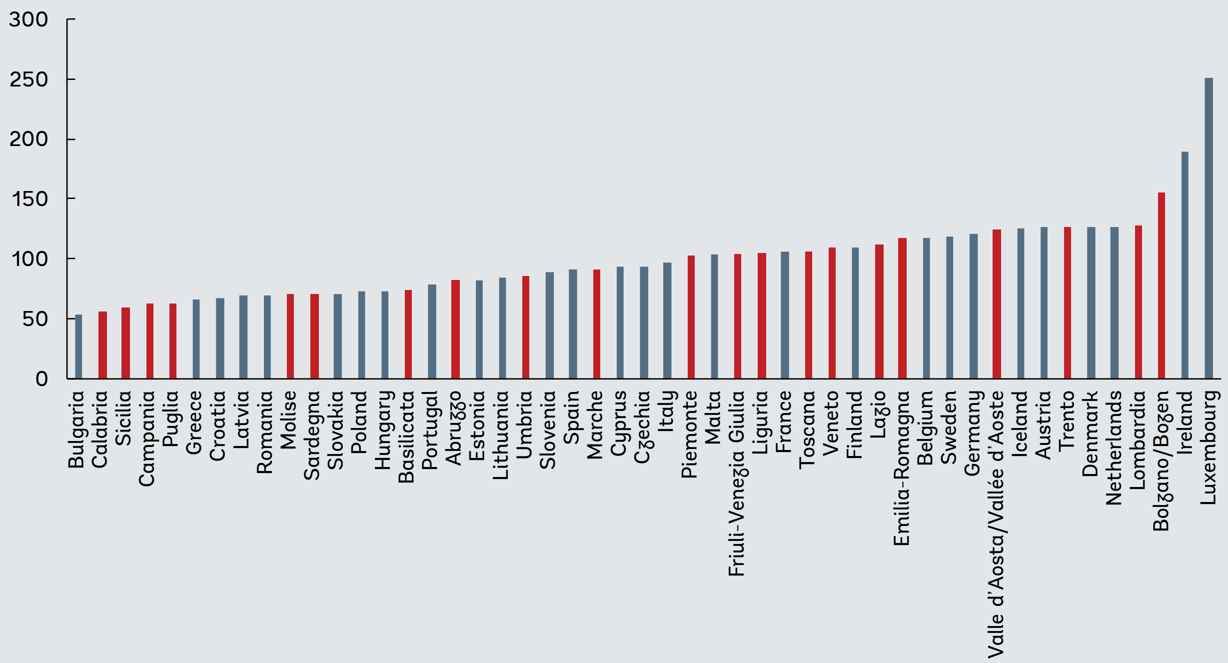
These regional differences suggest that closing regional technology adoption gaps could lead to large gains in overall productivity while promoting inclusion. Although regional technological gaps are, at least in part, the result of regional comparative advantages in advanced sectors, there seem to be untapped productivity gains that could be ripped by promoting technology adoption in lagging region. This is particularly the case for less advanced technologies—such as ERP and CRM—that can be applied to the production and organizational processes of firms in a wide variety of sectors. The regional gap in the adoption of these technologies thus does not seem justified by differences in the sectoral mix across regions. In countries where regional gaps in using these technologies are large, reducing these differences can help improve the operational efficiency of firms in lagging region and help close regional productivity gaps, with positive gains for the country as a whole. Policies should focus on identifying and targeting constraints on technology adoption specific to lagging regions (for example, lack of enabling factors such as infrastructure and skills). Targeting constraints on technology adoption in lagging regions is a cost-effective way of increasing the overall level of technological sophistication and the aggregate productivity of a country's private sector and reducing regional disparities.

[16] The average adoption rate of augmented reality is similar in the North and Center-South of the country. This is also the technology with the lowest overall adoption rate – 1.4 percent. Regional differences might become more pronounced when the technology use becomes more common beyond its use in niche markets/activities.

**BOX 2.1. Italy as a case study for EU-wide analysis**

Regional differences in economic development within Italy are large and are a good proxy for differences across EU countries. The Italian economy is far from homogeneous across the country's territory, with marked and persistent regional differences in economic development that mimic those observed across the EU. In 2019 GDP per capita—in purchasing power parity (PPP)—in the richest Italian regions was close to those of the richest country in the EU (with the exception of Ireland and Luxembourg), whereas GDP per capita in the poorest Italian region (Calabria) was only slightly higher than that of Bulgaria, the EU country with the lowest per capita income. Quantitatively, these regional differences are thus a good proxy for the differences between EU countries, making Italy an interesting representative case study for the EU economy.

**FIGURE B2.1.1. GDP per capita (PPP, 2019, relative to EU27)**

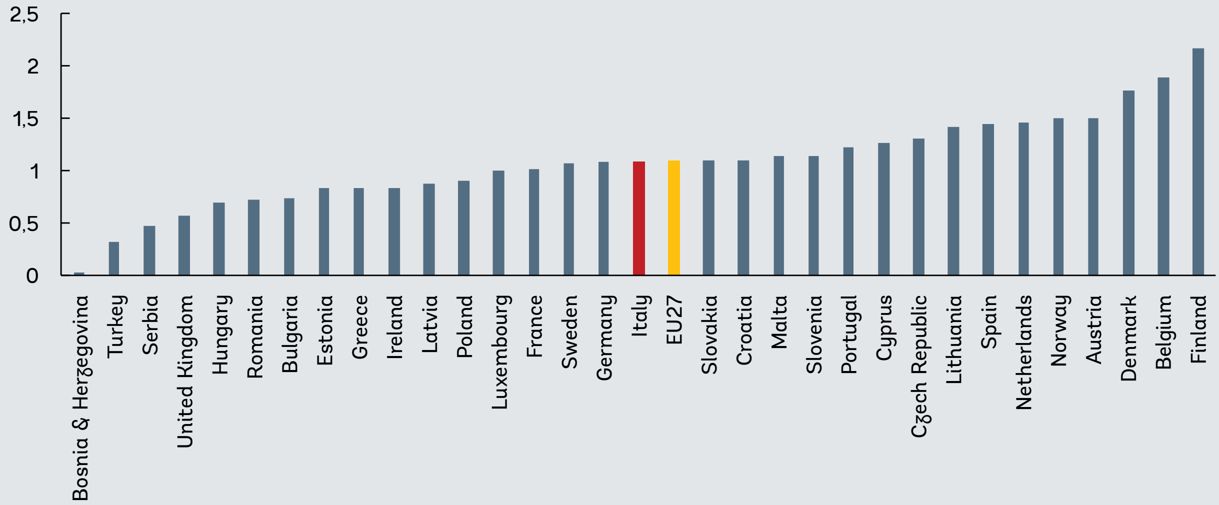



Source: EUROSTAT.

The levels of technology adoption by firms in Italy are in line with the EU average and heterogeneous across regions. The average level of technological sophistication among Italian firms is close to the EU average, with Italian firms adopting on average 1.08 of the seven technologies considered in this chapter compared to the 1.09 of the average EU firm.[17] The adoption rates by technology are also close to the EU-wide adoption rates, but Italy lags in the adoption of big data analytics. Relative to the dispersion in PPP GDP per capita, the regional dispersion in technology adoption tends to be lower compared to the EU cross-country dispersion in adoption rates but are in line with the cross-EU dispersion in the adoption of industrial technologies. Overall, although exceptions still apply, the patterns of technology adoption among Italian firms suggest that Italy is a good representative case study to analyze the adoption of technologies by firms in the EU.

[17] The seven technologies are ERP, CRM, Internet of Things, big data analytics, cloud computing, robots, and 3D printing. The main analysis in the chapter combines ERP and CRM because these two technologies were surveyed together in the Italian 2019 Enterprise Census.

**FIGURE B2.1.2.** Average number of technologies adopted by firms (2014–16)



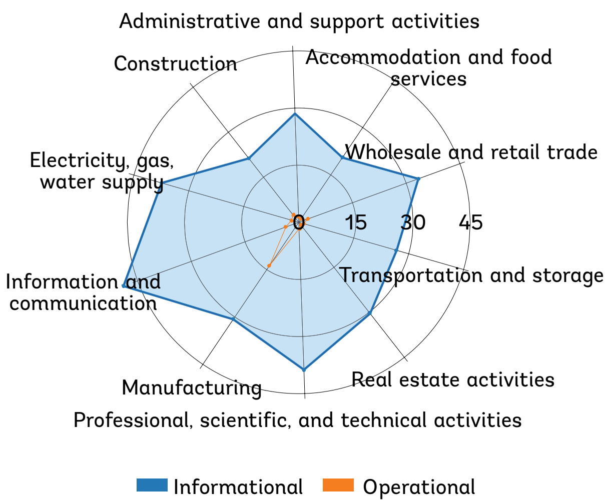

Source: Survey of ICT Usage in Enterprises (EUROSTAT, 2017).

### 2.3.2 *Country-level adoption rates mask substantial differences across sectors*

***"Not every technology is suitable for all sectors: while informational technologies such as cloud computing or ERP/CRM are broadly adopted across all sectors, operational technologies such as industrial robots are found almost exclusively in manufacturing."***

Country-level adoption rates mask substantial differences across sectors of the economy, in particular for sector-specific technologies (for example, industrial robots). Informational technologies are extensively adopted across most sectors, with ICT and professional services leading (Figure 2.6). (Operational technologies are almost exclusively adopted in manufacturing, with all other sectors' adoption rates close to zero.) The observed patterns of technology adoption show how the nature of tasks in a sector determines the applicability of specific technologies.

**FIGURE 2.6.** Technology adoption by sector, EU27+
(% of firms in a country, averaged across EU27+)




Source: Survey of ICT Usage in Enterprises (EUROSTAT).

Evidence based on micro-level firm data from Italy confirms that operational technologies are common in manufacturing, whereas services lead in the adoption of more advanced information technologies—ICT is the industry with the highest level of technological sophistication. Manufacturing leads in the adoption of 3D printing and robots, two operational technologies clearly linked to production activity of manufacturing firms. Sectoral gaps in adoption remain relatively small for ERP/CRM and cybersecurity, three technologies that can have a widespread application across sectors. ICT is the most technologically advanced sector, leading, in particular, in the adoption of advanced information technologies. Perhaps surprisingly, the financial sector lags in the adoption of standard information technologies. Only 16.5 percent of financial firms interviewed in the 2019 census declared that they used a CRM or ERP software and only 8.5 percent declared to use a cybersecurity software.[18]

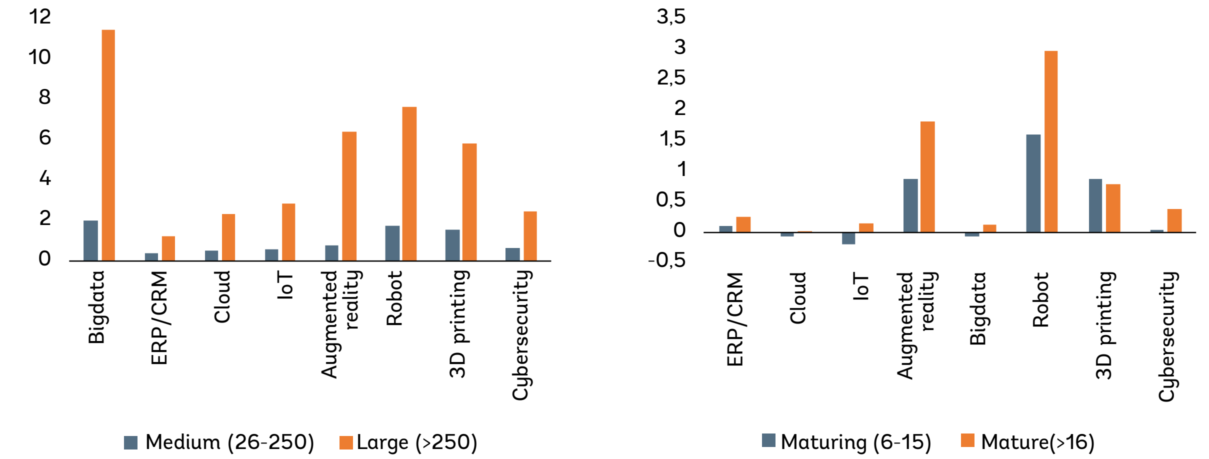
### 2.3.3 *Larger and younger firms adopt more technology*

Larger firms adopt more technology. The adoption gap between small and large firms is larger for more advanced technologies with a potentially higher scope for economies of scale. Operational technologies have a large adoption gap, with large firms adopting robots and 3D printing 7.5 and 5.7 times more often than small firms (see Figure 2.7). The adoption gap in these technologies is to be expected. Relative to information technologies, robots and 3D printing have higher fixed installation costs, which can be justified only when these technologies are used at scale, making them not cost-effective for small businesses. The gap between large- and medium-sized enterprises and small enterprises is particularly large for technologies that require large initial investments or skilled human capital. The adoption gaps between large- and medium-sized and small enterprises tend to persist over time.

> ***"There are large and persistent gaps in technology adoption in favor of larger firms"***

**FIGURE 2.7. Technology adoption by firms' size and age**

*a. Adoption by size—gap with small firms (10–25 employees)* *b. Adoption by age—gap with young firms (0–5 years old)*




Source: Survey of ICT Usage in Enterprises (ISTAT, Italy).

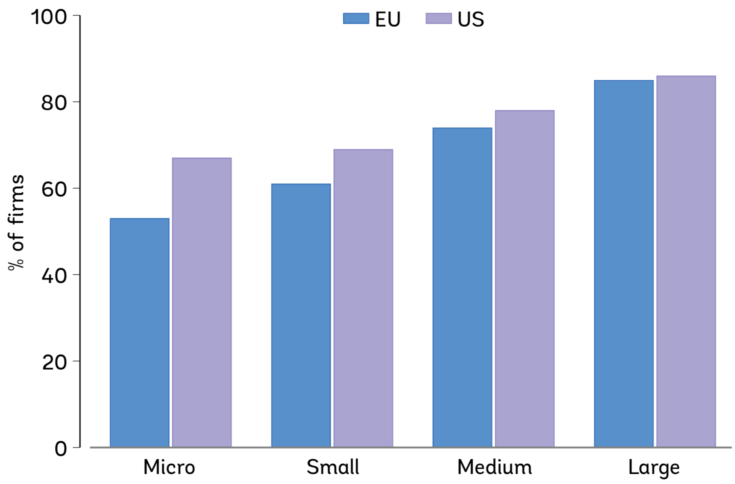
[18] The low percentage of firms using cybersecurity software is particularly surprising given the high cybersecurity risk faced by financial institutions. Part of this result could be explained by a widespread use of external services to ensure the cybersecurity of these firms, a practice that might not be well captured by the ICT and census questions.

Other things equal, younger firms have an advantage in the adoption of more advanced information technologies. Older firms tend to adopt more often operational technologies, a fact in part explained by the larger size of mature firms. Except for augmented reality—which is still a niche technology—the age gap in technological adoption disappears for advanced information technologies. The size adoption gap in Figure 2.7, panel a and the positive correlation between size and age show that, other things equal, younger firms have a comparative advantage in using advanced information technologies. This underscores the importance of promoting the entry of new startups in technologically sophisticated sectors to promote the overall technological upgrade of the private sector.

### 2.3.4 *There is ample space to increase technology adoption, especially among small firms in the EU*

An annual survey among 12,800 firms in the US and EU by the EIB found that 80 percent of firms in the EU in 2022 have adopted new technologies, compared to 88 percent in the US. However, these average gaps mask compositional differences that are important to highlight. Whereas large companies are everywhere more likely to embrace new technologies, there is no significant difference in adoption rates between large EU and US firms. The adoption rate difference between the EU and the US emerges more clearly among micro, small, and medium enterprises (MSMEs) and is larger for smaller firms. In the US, technology adoption rates are 67 percent for micro firms and 69 percent for small firms, whereas in the EU, these rates are 53 percent and 61 percent, respectively (Figure 2.8). To narrow the digital divide between the EU and the US, policymakers in the EU could promote the uptake of new technologies especially focusing on small and micro firms. Large firms may have benefitted disproportionately from new technologies adoption in the last decades, contributing towards increased market concentration (see Box 2.2 Technology adoption and market concentration in the EU).

**FIGURE 2.8. Differences in technology adoption between EU and US, by firm size**



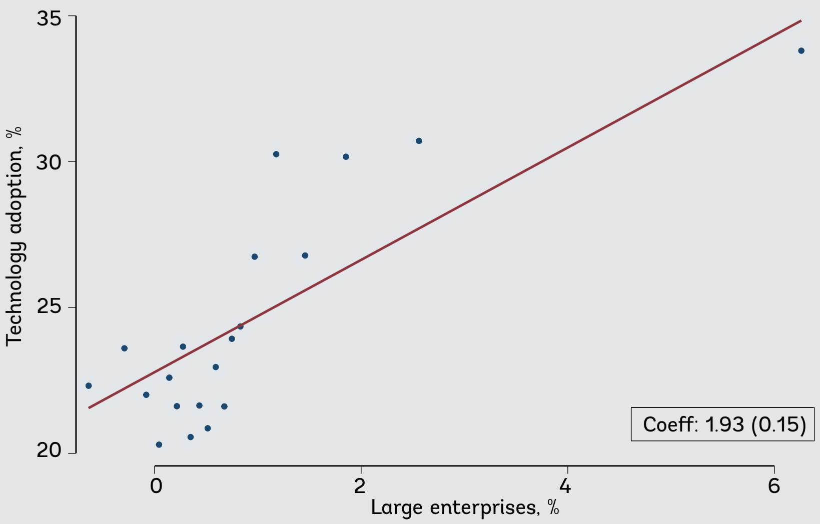

Note: Technologies include 3D printing, advanced robotics, Internet of Things, big data analytics, AI, drones, augmented or virtual reality, and digital platforms. Survey conducted in 2021.

***"The digital divide between the US and the EU is especially prominent for small and micro firms"***

**BOX 2.2.** **Technology adoption and market concentration in the EU**

A growing literature has suggested that during the last decades firm-level market power has increased significantly as measured by markups and profitability. This expansion of market power comes with a reallocation of market shares toward larger firms (De Loecker et al., 2020; De Loecker and Eeckhout, 2021). Although various factors could be driving this expansion, technology could play a key role. Increasing technology adoption by larger and more productive firms can have profound consequences for competition and the rise of superstar firms (Autor et al., 2020b), especially because technology adoption has productivity benefits (Tambe et al., 2020). Technology adoption also allows for higher scalability of production (Lashkari, Bauer & Boussard, 2022). Thus, if mostly large firms can adopt and disproportionately benefit from new technologies, over time, this is likely to increase divergence in economic outcomes between large and small firms. To test this hypothesis, we examine the relationship between sectoral market concentration and a sector's technological intensity. Using large enterprise shares across country-sectors, Figure B2.2.1 presents the results for all technologies and points toward some evidence that those country-sectors that are characterized by higher concentration, measured by a larger share of large enterprises, are also the ones that experience higher levels of technology adoption. The partial correlation coefficient (after controlling for time-invariant country and technology characteristics) is large at 1.93 and statistically significant.

**FIGURE B2.2.1.** **Sectoral concentration and technology adoption**




Source: EUROSTAT ICT Survey. Note: Residuals of technology adoption against residuals of large enterprises, after controlling for country and technology fixed effects. Slope coefficient and standard error (in parentheses) are presented in a text box. The figure is a binscatter plot of the residual of technology adoption rate after controlling for country and technology fixed effects and the residual of large enterprise share after controlling for country and technology fixed effects.

***"The fact that larger firms adopt new technologies at faster rates than smaller ones has important implications for market concentration."***

The results from the Italian firm-level analysis also point to the risk that technology adoption could increase market concentration. The data shows that firms that are bigger and more productive are more likely to adopt new technologies. They also show that after an adoption event, firms adopting new technology grow faster both in terms of size and productivity. These two effects combined lead to a mechanical increase in market concentration, with bigger firms adopting more and becoming even larger relative to their competitors. The relationship between adoption and market concentration thus underscores the risks that a high concentration of technology adoption among a few firms can have for markets and consumers. Policymakers must design efficient policies to address this risk. Making sure markets are contestable, antitrust laws are well enforced, promoting the entry of innovative startups that can challenge market leaders, and providing incentives for technology adoption among small firms in lagging regions are essential steps in this direction. We return to the discussion on technology adoption and market concentration in Section 3.3.

## 2.4 Determinants of technology adoption

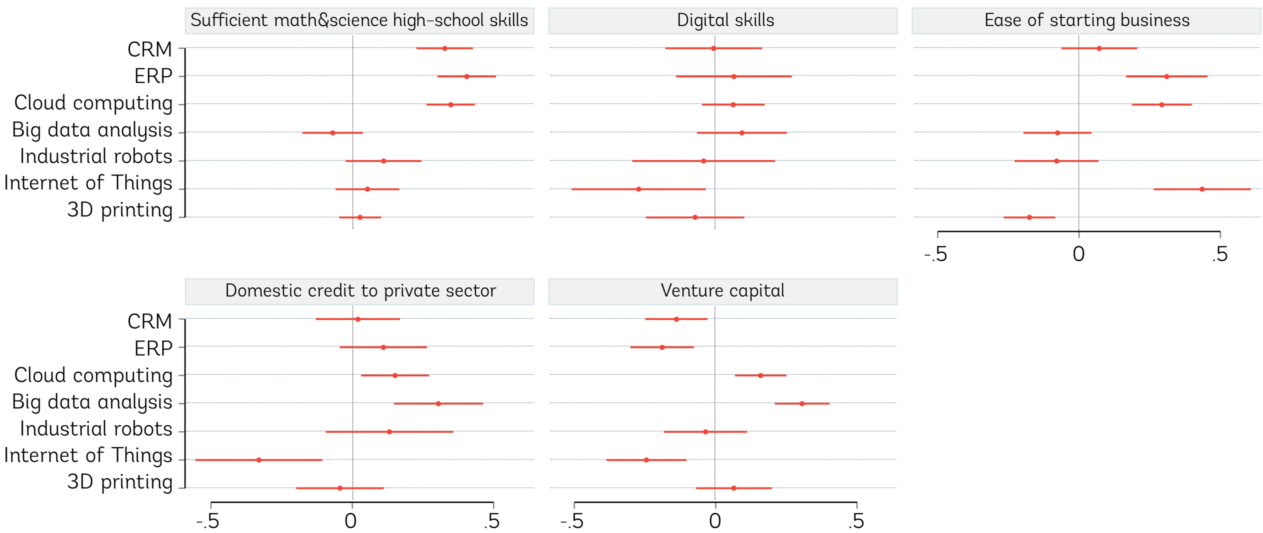
Understanding drivers of adoption is key for policy makers to prioritize investments and interventions that can expand adoption toward smaller firms and those that have been excluded from the benefits of technological progress. As pointed out in Box 1.4, the fact that the activity performed by a firm is exposed to a technology does not imply that that firm will adopt that technology. Adoption decisions are based on a cost-benefit analysis as firms evaluate net expected returns of adopting versus non-adopting. Several factors change the net returns of investments in new technologies and thus influence the extent to which exposure translates into actual adoption. This section discusses some of these factors. Some relate to the environment in which firms operate, whereas others relate to the firms' characteristics and their capabilities.

### 2.4.1 *Human capital, access to finance, and the regulatory framework enable technology adoption*

***The drivers of technology adoption -- math and science skills, digital literacy, availability of both traditional and novel sources of financing, and milder regulatory constraints -- point to actions policymakers can take to promote new technologies adoption."***

The environment in which firms operate can influence their adoption choices, changing the benefits and costs of adopting a new technology. This section discusses how technology adoption across country-sectors correlates with three of the key adoption factors identified in the literature (Comin & Hobjin, 2004; Cirera et al., 2022) as important for explaining differences in technology adoption across countries: human capital, access to finance, and the regulatory environment. The section provides a short review of these factors and presents a set of descriptive correlations between proxies for these enabling factors in 2014 at the country and country-sector levels with changes in technology adoption between the first (2014 or 2016 or 2018 or 2020, depending on the technology) and the last (2022) year available in our sample. The analysis is based on a sample of 32 European countries (EU27+) covering 18 sectors, and the results are summarized in Figure 2.9.[19]

**FIGURE 2.9. Determinants of technology adoption, external to the firm (EU27+)**




Source: Survey of ICT Usage in Enterprises (EUROSTAT). Note: Standardized slope coefficients of ordinary least squares (OLS) country-sector regressions of technology adoption on five adoption determinants external to the firm—sufficient math and science high school skills, digital skills, ease of starting business, domestic credit to private sector, and venture capital—controlling for sector fixed effects and real GDP per capita. Separate regression for each technology.

[19] See Appendix A Table A.1 and Table A.2 for a full list of countries and sectors included in the analysis.

The availability of human capital enabling the productive potential of new technologies is an important driver of adoption. Adopting a new technology when the skills needed to properly exploit it are not readily available is likely to be a poor investment. Although firms can in principle transfer these skills to their workers through on-the-job training, learning takes time and comes at a cost. The capacity of an educational system to prepare its workforce to efficiently use new technologies can thus reduce their adoption cost.[20] The existing economic literature has made this point clearly and provided evidence that basic cognitive or foundational skills such as numeracy, literacy, and problem solving determines the workers' capacity to use effectively new technologies and innovate (Hanushek & Woessmann, 2008). The capacity of an educational system to equip students with skills needed in the labor market, including foundational skills, are important drivers of technology adoption (Machin & Van Reenen, 1998; Autor et al., 2003). Our analysis across EU countries is consistent with this evidence. Measures of the availability of math and science skills and digital literacy among a country's population are positively correlated with technology adoption in the following years, and this correlation is stronger for information technology.

Adopting a new technology often requires paying large upfront setup costs, making the availability of reliable and affordable sources of financing a key enabling factor. A large body of empirical literature exists on the relationship between specific measures of financial constraints and technology adoption. For example, Midrigan and Xu (2014) find that lack of financing distorts firms' technology adoption decisions. The efficiency of the financial system determines which technologies will be adopted (Cole et al., 2016). Further, the existence of markets providing capital for high-risk endeavors can be crucial to help finance the adoption of novel technologies, especially for early adopters. This type of financing could be especially helpful for younger, smaller firms that lack internal funds and a financial track record to turn to more traditional forms of financing (Hall & Lerner, 2010). Cross-country correlations across EU countries provide a mixed picture. Although we find a positive correlation between the depth of credit markets and the share of firm adoption for all but two technologies, the correlation between the availability of venture capital and technology adoption is positive for the most recent 4.0 technologies—cloud computing, big data analysis, and 3D printing. These results suggest that risky finance is important for the adoption of more novel technologies which are not yet widely adopted.

New technologies can disrupt the market status quo and are often adopted by new firms, making certain regulatory constraints relevant to the adoption decisions. Regulatory barriers limiting the entry of new firms can reduce the adoption of new technologies, especially in highly dynamic sectors—such as IT-intensive sectors—where startups are the key drivers of the adoptions of advanced technologies. Similarly, regulations limiting competition or protecting certain firms can reduce the expected benefit of adoption by limiting the effective competitive advantage—market gains—that firms could derive from the adoption of new technologies. Cross-country evidence from the EU seems to partially support these arguments, showing that indicators on the ease of starting business are positively correlated with increases in adoption for CRM, ERP, cloud computing, and Internet of Things. More generally, because technology adoption requires the firms to invest, market distortions and misallocation reduce incentives to invest as they would reduce the expected returns (Iacovone et al., 2023).

[20] By making certain complementary skills more common, it can also reduce their price on the labor market.

### 2.4.2 *Technology adoption takes place among more productive firms, with skilled workers and good management*

The net returns of adopting a new technology can depend on certain enabling characteristics of potential adopters, making them an important factor in the adoption decision. This section uses firm-level data from Italy to describe some of these factors. The analysis focuses on firms that did not adopt a technology in 2014–16—as reported in the ICT 2017 survey—and looks at the factors that can predict their adoption of a new technology over the period 2017–18—as reported in the 2019 census. In doing this, the analysis focuses on the characteristics of firms before the adoption of the new technologies. It then correlates these characteristics with the probability of adopting a technology between 2017 and 2018.[21] This section focuses on the role of firms' productivity and on the pre-adoption skill composition of their workforce as enablers of technology adoption.

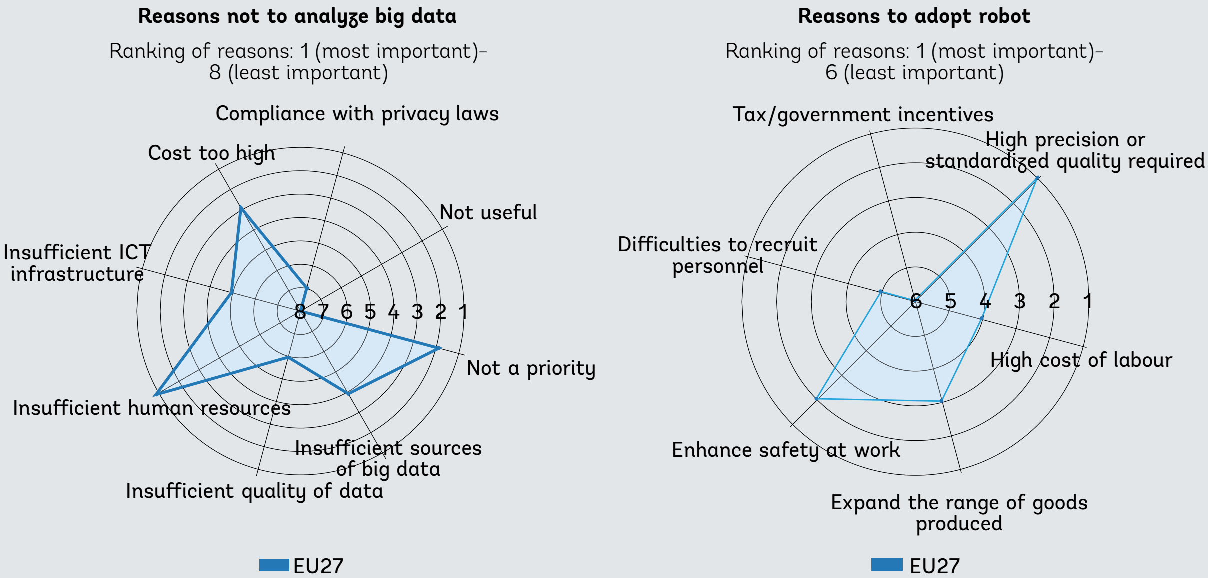
**BOX 2.3. Self-declared obstacles to technology adoption**

The EUROSTAT ICT Enterprise survey asks respondents to identify the most important obstacles in technology adoption and the reasons for adopting some others. A summary of the responses is presented in Figure B2.3.1.

The most often cited reason to not adopt AI is lack of human resources, followed by not seeing it as a priority and high costs (Figure B2.3.1, panel a). This underscores that the most recent informational technologies such as big data analysis have high adoption costs and may explain their low levels of adoption despite them potentially being a general-purpose technology (compare Acemoglu et al. 2022b).

Robots tend to be adopted to ensure high precision, standardized quality, and safety at work, whereas reasons such as high labor costs are only of secondary importance (rank 4 out of 6) (Figure B2.3.1, panel b).

**FIGURE B2.3.1. Self-declared reasons for (a) not analyzing big data and (b) adopting robots**




Source: Survey of ICT Usage in Enterprises (EUROSTAT).

[21] The results are from a regression of technology adoption on pre-adoption characteristics and control for a 3rd degree polynomial of the size of the firm (employment) and for 2-digit sector fixed effects.

The skill composition of a firm's workforce is an important determinant of its adoption of new technologies (see also Box 2.3 Self-declared obstacles to technology adoption). Firms that use higher levels of nonroutine cognitive tasks are on average more likely to adopt a new technology—see Table 2.2.[22] Similarly and related, having a higher share of workers holding a graduate diploma is a predictor of higher future adoption, but the evidence is noisier—see Table 2.2. These results reinforce the idea that the availability of complementary human capital to a technology is an important enabler of technology adoption.[23] Having the right set of skills already embedded in its current workforce reduces the expected adoption cost, reducing the time-consuming and costly process of hiring new workers with complementary skills—and potentially training them to perform firm-specific processes—and limiting the risk of delays in using the newly adopted technology. A more skilled workforce might also be more conscious of the potential benefits of new technologies and is more likely to push toward adopting these technologies.

**TABLE 2.2. Determinants of technology adoption, internal to the firm**

| | Intensity of nonroutine cognitive tasks | Share of graduates in firm workforce | Productivity |
|---|---|---|---|
| ERP/CRM | | | + |
| Cybersecurity | | | + |
| Cloud computing | | | + |
| Big data analysis | + | + | + |
| Augmented Reality | + | | |
| Internet of Things | + | | |
| Industrial robots | + | + | + |
| 3D printing | + | | |

Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: the full table of results is presented in Appendix A.

Among firms not using an advanced technology, those that are more productive have a higher probability of adopting it. The data shows that the relationship between a firms' productivity and its likelihood of adopting a new technology is positive and statistically significant for most technologies covered in the ICT survey (third column in Table 2.2). For example, a 1 percent increase in labor productivity increases the probability of adopting by about 0.23 percentage points. This result suggests that productivity is an enabler—or proxies for other enablers—of technological adoption. Other things equal, more productive firms are likely to be in a better position to reap the benefits of new technologies because they might already have several enabling factors that are complementary to new technologies or can maximize their benefits, such as better managerial practices, better access to larger markets, more widespread access to basic enabling technologies, and better links with productive suppliers. The effect is particularly strong for basic technologies, suggesting that highly productive firms are unlikely to forgo the low-hanging benefits of these technologies for a long period, indicating that more productive—and likely better-managed—firms are better at identifying opportunities to upgrade.

[22] The results in the table are based on the indexes of task content described in Box 1.2.
[23] Of course, firms can hire new workers with the right set of skills while or after adopting the new technology. However, when the labor market is frictional, and specific skills are scarce, having the right workforce already in place can reduce the expected costs of installing the new technology.

**BOX 2.4. Limitation of current data landscape on technology adoption among firms in the EU and how a recent World Bank initiative can help**

This report identified limitations in the current data landscape on technology adoption and use of technologies by firms in the EU. EUROSTAT ***Community Survey on ICT Usage and E-Commerce in Enterprises*** is the main source of data on the state of technology adoption by firms in the EU. This survey has the advantage of being an EU-wide standardized survey, allowing for a comparison of adoption levels across countries. It still has limitations that constrain the analyses. The survey 1) focuses on the extensive margin of technology adoption—adopting or not adopting a technology—but has limited information on the intensity of use of each technology; 2) the survey focuses on a limited set of technologies, with a list of covered technologies that changes over time; 3) the survey is homogeneous across sectors; 4) the survey has limited information on which tasks are carried out using any given technology.

The recently developed ***World Bank Technology Adoption Survey*** provides an example of how some gaps can be filled. The survey collects information on the use of 305 technologies to carry out 63 business functions. Some of these technologies and business functions are common across sectors—for example, ERP software used in HR processes—whereas others are sector-specific—such as thermal processing technologies in food processing anti-bacterial treatments. The survey collects information on both the most advanced and most used technology used by surveyed firms to carry out each business function, thus collecting information on both the extensive and intensive margin of technology use among firms. Overall, the information collected with the WB Technology Adoption Survey can support a more granular analysis of technology adoption among firms.

Good management practices such as performance monitoring, target setting, and people management foster technology adoption and allow reaping the benefits from new technologies. According to Bloom, Sadun, and Van Reenen's 2012 study, US multinationals operating in Europe experience greater productivity gains from adopting ICT than European firms. This is due to superior management practices. Various studies conducted across European countries have shown that low levels of technology adoption can be attributed to inadequate managerial capabilities (Calvino et al., 2022; Cirillo et al., 2023). Skilled managers can help with the adoption of complex digital technologies and reorganize business processes to leverage the complementarities between skilled workers and new technologies. Better-managed firms can realize higher returns from advanced digital technologies. An EU-wide survey of 12,800 firms in 2021 by the EIB revealed that management practices are closely linked to the adoption of digital technologies. Firms that adopt digital technologies are more likely to set traditional management goals such as strategic business monitoring and performance pay, as well as score higher on monitoring gender balance and climate targets, indicating a potential virtuous cycle of management practices aiding technology adoption and digital technologies aiding progress monitoring across various business goals.

***"Within the firm, factors such as the skills composition of the employees, the level of labor productivity, and management practices determine how fast a new technology would be adopted and to what extent the firm would reap the benefits from the adoption."***

The education of managers is an important driver of good management practices and is positively related to take-up of new technologies (Caselli & Coleman, 2001; Comin & Hobijn, 2004). A study of Brazilian firms found that managers with at least a bachelor's degree are four percentage points more likely to adopt advanced digital technologies in their companies (Cirera et al., 2021).

To promote technology adoption, policies should be aimed at imparting both good management practices and digital skills to managers, especially for small firms. According to Calvino et al. (2022), small businesses in the EU often have CEOs and middle managers who lack the necessary skills and capabilities. Therefore, policies aimed at increasing technology adoption should not only focus on providing financing or incentives, but also address management practices (Berlingieri et al., 2020). This means that policies promoting digital skills and managerial capabilities should be implemented alongside technology adoption policies. Although improving managerial capabilities can be challenging, managerial coaching, advising, and mentoring have been shown to enhance firm performance.[24]

## 2.5 Summary

This chapter analyzes technology adoption patterns based on firm-level data for Italy and sectoral data for the EU. The study focuses on various technologies, ranging from established ones like ERP and CRM to more novel ones like big data analysis and IoT. The findings reveal that a significant portion of firms adopt no digital technology, highlighting the potential for improving productivity through wider technology adoption. The adoption gap is larger among smaller enterprises, suggesting that policy makers should especially focus on this segment if they want to expand adoption in Europe. The chapter also finds that there are important differences in terms of adoption across different technologies. The firm-level adoption patterns follow a hierarchical structure. Easier-to-adopt technologies (that is, those requiring smaller initial investments) and more mature technologies like ERP and CRM being are more widespread. By comparison, more advanced technologies like robots and big data analysis are adopted primarily by larger and technologically sophisticated firms. There are also regional and sectoral differences in technology adoption, with Northern European countries and certain sectors leading such as ICT in adoption rates. The size and age of firms also play a role, with larger firms and younger ones having a greater propensity to adopt advanced technologies. In addition, the chapter discusses the obstacles and drivers of technology adoption, emphasizing the role of drivers internal to firms (emphasizing the role of complementary factors, such as firm managerial capabilities, workers' skills and their share of nonroutine cognitive tasks) and external to the firms (such as access to finance and a suitable business environment). Finally, the chapter also suggests a potential risk of increased market concentration resulting from technology adoption by larger and more productive firms. Overall, the findings emphasize the need to address barriers to technology adoption and promote inclusive and widespread adoption of technology for enhanced productivity and competitiveness. They call for special attention to the barriers to adoption in lagging regions and among smaller businesses.

[24] Teaching randomly chosen Indian firms modern management practices leads to 17 percent increase in productivity (Bloom et. al., 2013), whereas small group-based management consulting led to persistent improvement in management practices at Colombian auto parts manufacturers (Iacovone et al., 2022).

# CHAPTER 3 Technology Adoption, Change in Tasks and Labor Demand

*"The ethos in Silicon Valley and the innovation community similarly favors labor-replacing technologies. Governments do have tools at their disposal that could be used to reverse these biases and to steer technology in a more labor- and development-friendly direction."*

Dani Rodrik

## 3.1 Introduction

How incumbent firms and startups adopt and deploy the new technologies is key to determining how these technologies impact labor markets. As technologies become available, existing firms and startups must face the decision to adopt them, which depends on their expected returns and the costs of adoption, given their current know-how and absorptive capabilities (Verhoogen, 2023). Relying on detailed data[25] across EU27+ we assess the patterns of technology adoption across countries and sectors, and different firms.[26]

In this chapter, we present evidence on the impact of technology adoption and the patterns of adoption, relying both on EU-wide data and a case study on Italy. It is important to distinguish across different technologies because their characteristics, drivers of adoptions, and implications for labor markets can differ. In this chapter, we do not focus on technologies in a generic and homogeneous manner but distinguish among different technologies depending on their purpose and level of maturity.

## 3.2 The impact of technology adoption in firms

This section presents the results of an event study analysis on technology adoption in Italian firms. Adoption events are defined as the adoption of a technology by a firm not using it in earlier years. These events are identified by comparing data from the 2017 ICT survey (covering the 2014–16 period) and the 2019 Firm Census (for the 2016–18 period) separately for six technologies.[27] To limit concerns about the endogeneity of the technology adoption decision (for example, adopters being on a different growth path compared to non-adopters), the analysis relies on a synthetic difference-in-difference approach that follows the method presented in Arkhangelsky et al. (2021)—see Box 3.1.

**BOX 3.1. Synthetic difference-in-difference à la Arkhangelsky et al. (2021)**

The standard difference-in-difference approach would compare changes over time among firms that are treated with those among untreated firms. It then identifies the effect of a treatment—here technology adoption—as the change in the difference between treated and untreated firms, before and after the treatment. This approach relies on a key assumption: without the treatment, the outcome of interest among treated and untreated firms grows at the same rate. When this is not the case the estimated treatment effect would pick up differences in trends and would thus be uninformative about the actual effect of the treatment.

The synthetic difference-in-difference approach used in this section mitigates some of the endogeneity concerns that can undermine standard difference-in-difference approaches. For each treated firm, the approach used in this section generates a synthetic control firm—generated as a combination of real untreated firms—for which the trend of the outcome variable in the pre-treatment period matches that of the treated firm. Under the assumption that this similarity in trends would have persisted absent the treatment, this method ensures that the difference-in-difference estimate captures the actual effect of the treatment. Although this method addresses some of the limitations of standard difference-in-difference approaches, some caveats still apply. In particular, any factor, independent of the treatment, affecting the treatment group (but not the control) in the post-treatment period violates the identification assumption underlying this method.[28]

[25] The Eurostat Survey on ICT Usage and E-commerce in Enterprises provides information on actual adoption among firms across a broad range of technologies in a standardized, representative, and comparable manner for all EU27+ countries.

[26] It should be noted that albeit these data are collected at firm-level we will rely on aggregated statistics at country, country-sector and country-firm size level as made available through Eurostat and not on the underlying micro-level firm data which are not publicly available.

[27] Although the original dataset includes information on eight different technologies, the analysis in this chapter focuses on six technologies because we exclude two technologies: augmented reality and cybersecurity. Augmented reality is excluded because the very low rate of adoption for this technology does not provide enough variation to precisely identify its effect on adopters. Cybersecurity is excluded primarily because, as explained in Appendix A, after controlling for the simultaneous adoption of other technologies, its effect on adopters vanishes.

[28] This would, for example, be the case if firms that adopt a technology do so in anticipation of a future event (such as an increase in future demand) that would have happened even without the adoption of the new technology and that differentially affects adopters relative to non-adopters.

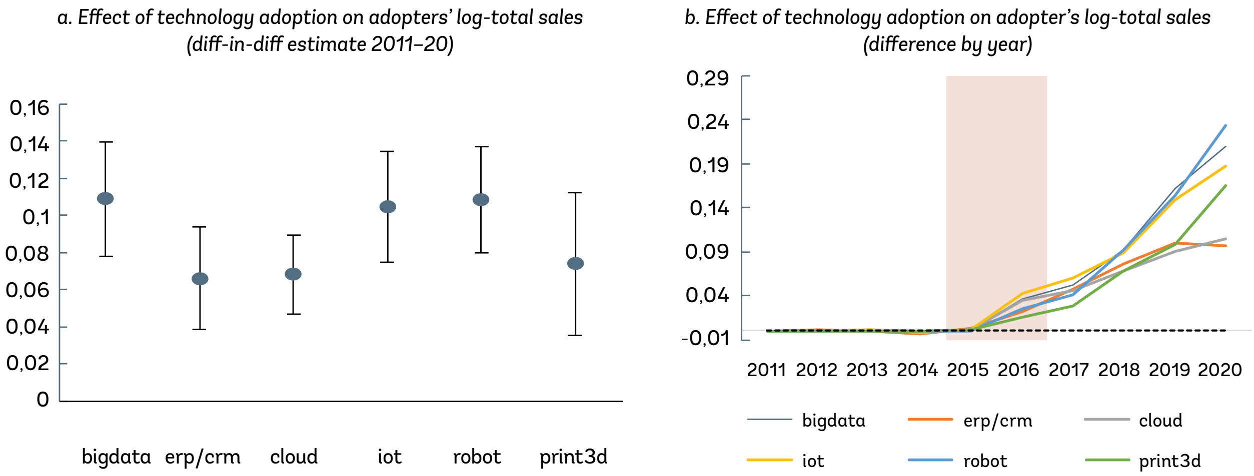
### 3.2.1 *New technologies promote growth and job creation among adopting firms*

## *"Firms that adopt new technology grow faster than non-adopting firms"*

Firms that adopt new technologies grow faster than firms on a similar growth path before the adoption event, and this effect is not homogeneous across technologies. The results suggest that the adoption of a new technology helps firms expand their activities by providing them with a competitive edge over their competitors.[29] These results are in line with others found in the literature.[30] How the adoption of a new technology can provide a competitive advantage to the adopter varies across technologies. Operational technologies that increase production efficiency—such as robots and 3D printing—allow adopters to reduce production costs, which can then be translated into lower prices, and an increase in the demand for products.[31] Information technologies such as big data analytics can help the adopter improve its targeting of consumers, by more efficiently directing its marketing and adopting more targeted pricing strategies. Information technologies, such ERP and CRM, can increase the organizational efficiency of the adopter, reducing disruptions in its day-to-day business activities and improving the quality of its interactions with consumers.

Although the adoption of all six ICT 2017 technologies is associated with an increase in the growth rate of adopters, the effect is larger for the adoption of robots, big data analytics, and IoT (Figure 3.1, panel a). Not only these effects are statistically significant, but their magnitude is economically meaningful and large. For example, by 2019—4 years after adoption—firms adopting robots had a turnover close to 15 percent higher than non-adopters, whereas firms adopting big data analytics had a total turnover 16 percent higher (Figure 3.1, panel b). Sometimes multiple technologies are adopted at the same time, so when assessing the impact of each individual technology separately, we may be attributing to it effects that arise because this technology is adopted together with another one. Controlling for simultaneous adoption of multiple technologies does not change the overall picture but marginally reduces the effect of the adoption of each individual technology (see Appendix A).

**FIGURE 3.1. Effect of technology adoption on adopters' sales**




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relationship management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

[29] This interpretation is valid under the parallel trend assumption of the difference-in-difference approach.

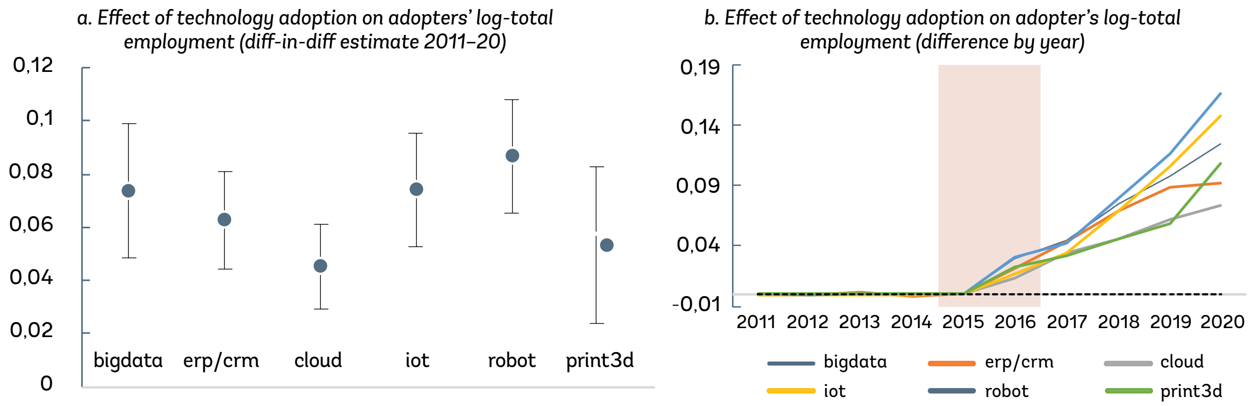
[30] See Acemoglu et al. (2023) for evidence on the effect of robot adoption on the value added of adopters and Aghion et al. (2021) for evidence on sales, profits, and prices.

[31] This channel could not be directly tested because information on product prices is not available in the data used for the analysis.

*"The evidence does not support the argument that new technologies have direct negative effect on adopters' labor demand"*

The growth of firms adopting a new technology comes with an expansion of their workforce (Figure 3.2, panel a), thus showing no signs of a direct negative effect on labor demand. The data show that, after the adoption of a new technology, firms experience faster employment growth than comparable firms (Figure 3.2, panel a).[32] By 2019—4 years after adoption—firms adopting robots and big data are about 11 (9) percent bigger than non-adopting firms (Figure 3.2, panel b). Thus, the argument that the adoption of new technologies causes a direct decrease in the overall labor demand in adopting firms does not seem supported by Italian data. This evidence refers to the direct effect of technology adoption on adopting firms, not on the overall effect on aggregate labor demand—Section 3.3 discusses this point in more in detail. This finding is in line with evidence from existing literature, showing that technology adoption on average does not decrease the labor demand of adopting firms.[33] Once again, the effect of the adoption of different technologies on labor demand is not homogeneous, with the adoption of robots, big data analytics, and Internet of Things having the strongest effect on employment growth whereas cloud computing is the technology with the lowest impact. The effect of technology adoption on firms' sales persistent during the Covid-19 pandemics, with the crisis widening the gap between adopters and non-adopters of operational technologies (Box 3.2).

**FIGURE 3.2. Effect of technology adoption on adopters' employment**




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relation management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

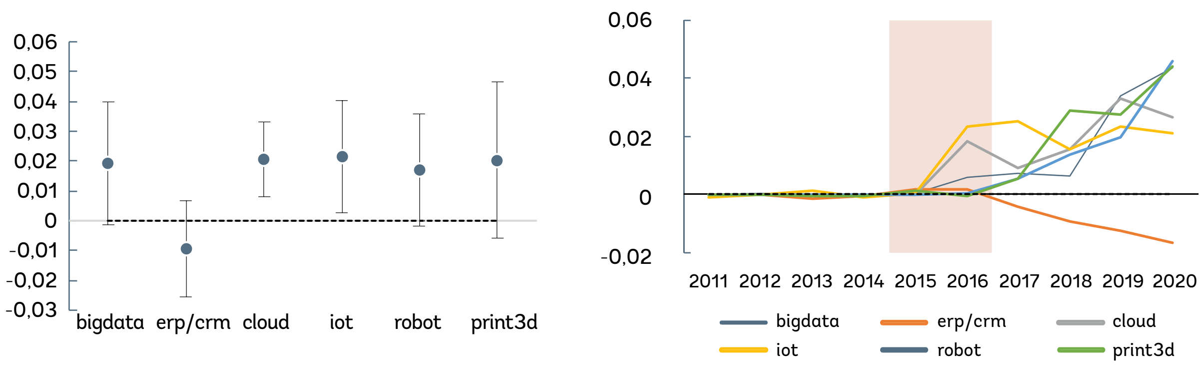
The positive effect of technology adoption on the labor demand of adopting firms is a direct consequence of expanding their activities. The data show that, except for ERP/CRM, the total value of sales in adopting firms increased more than proportional compared to the increase in employment (Figure 3.3, panel a). By 2019 and relative to non-adopting firms, in firms adopting big data analytics and robots, sales grew about 3.3 and 1.9 percentage points faster than employment, respectively (Figure 3.3, panel b). If adopters' productivity—as measured by their sales per worker ratio—increased, it also suggests that, if their activity would not have grown, they would have reduced their labor demand, with a negative direct effect on employment (Figure 3.3). Section 3.3 discusses how this can play a role in the determination the effect of technology adoption on aggregate labor demand.

[32] Comparable firms are matched firms that were previously on a similar employment trend.
[33] See, for example, Acemoglu et al. (2023) for evidence from the Netherlands on the effect of robot adoption on the total hours worked in adopting firms, Acemoglu et al. (2020), and Aghion et al. (2021) for evidence from France on the effect on total employment and adopters' labor share, Benmelech and Zator (2022) for evidence from Germany on the effect on employment, and Koch et al. (2021) for evidence on the effect on employment in Spanish firms.

**FIGURE 3.3.** **Effect of technology adoption on adopters' sales per worker**

*a. Effect of technology adoption on adopters' sales per worker (diff-in-diff estimate 2011–20)*

*b. Effect of technology adoption on adopter's log sales per worker (difference by year)*




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relation management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

***"For workers' wages at adopting firms, the positive impact of new technology adoption is more modest"***

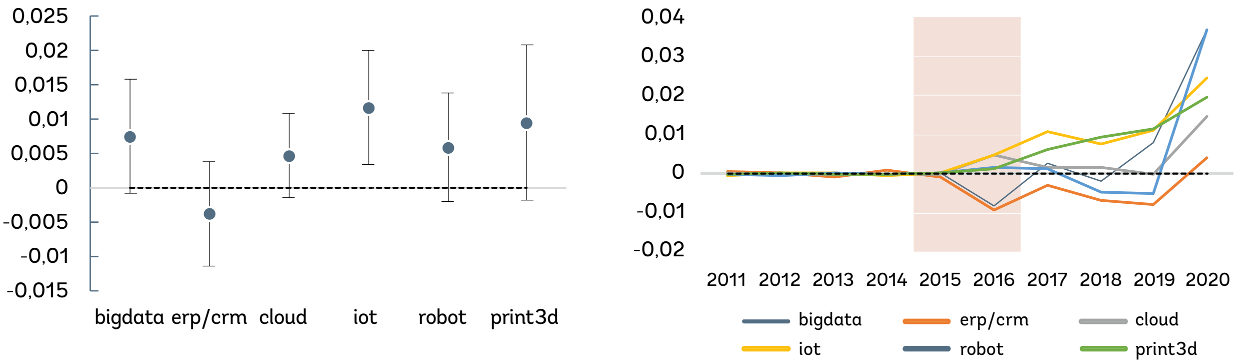
For some technologies, there is evidence of a positive effect on the average wages in adopting firms, but the magnitude of the effect is small (Figure 3.4, panel a). The estimated impact on the average wages of adopting firms is positive for most technologies, but significant—at standard confidence levels—only for the adoption of Internet of Things related technologies. However, much of the estimated effect is driven by a jump in average wages among adopters during 2020.[34] Part of the changes in the average wage paid by adopters might reflect either some rent sharing or a change in the bargaining of workers in adopting firms. However, at least part of this effect is likely a compositional change in the workforce employed by adopting firms. On the one hand, Section 3.2.2 shows evidence of an increase in the level of skills demanded by adopting firms, a fact that could explain part of the increase in wages. On the other, Appendix A shows that, in relative terms, the workforce's average age in adopting firms dropped—a direct consequence of an increase in hirings—a fact that, other things equal, would reduce the average wage paid by adopters. No matter the cause, the change is relatively small. Between 2015 and 2019, the cumulative change in the average wage paid by adopters ranged between an increase of about 1.1 percent—for adopters of 3D printing technologies—and a decrease of about 0.8 percent—for adopters of ERP/CRM technologies (Figure 3.4, panel b).

[34] See Box 3.2 for an interpretation of this pattern.

**FIGURE 3.4.** **Effect of technology adoption on the average wage paid by adopting firms**

*a. Effect of technology adoption on adopters' log average wage (diff-in-diff estimate 2011–20)*

*b. Effect of technology adoption on adopter's log average wage (difference by year)*




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relation management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

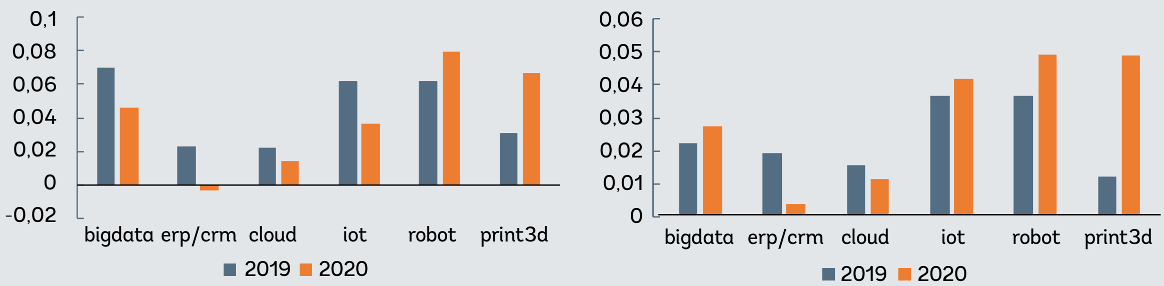
**BOX 3.2.** **Technology and firms' performance during the COVID crisis**

The effect of technology adoption on firms' turnover and employment persisted during the pandemic, but the crisis magnified previous trends only for operational technologies. The data show that adopters continued to grow faster than non-adopters during the crisis, suggesting that the pandemic did not change the pre-trend (Figure B3.2.1, panels a and b). At the same time—under the assumption that pre-crisis growth differentials would have persisted in 2020 at a pace like the one seen in 2019—there is no evidence of a differential impact of the pandemic on adopters of advanced information technologies, whereas there is evidence that adopters of operational technologies—and adopters of 3D printing in particular—coped better with the pandemic (Figure B3.2.1).[35] This could be a direct consequence of the specific nature of the 2020 pandemic shock. Firms adopting automation technologies in their production process could perform a larger share of their production process without human presence, limiting the negative effect of social distancing measures on their activities.

**FIGURE B3.2.1.** **Differences between adopters and non-adopters in 2020 and 2019**

*a. Growth rate in adopters vs. non-adopters differentials in log-sales*

*b. Growth rate in adopters vs. non-adopters differentials in log-employment*




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relation management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis.

35 The data show that in 2020 firms adopting big data and IoT saw a slowdown in their growth premia relative to non-adopters, suggesting that the pandemic might have impacted them more than non-adopters - relative to a counterfactual where they continued the growth differential remained equal to that observed in 2019. The opposite is true when considering employment growth.

Differences in the average wage paid by adopters relative to non-adopters soared during the pandemic, but this is likely the result of lower use of part-time work among these firms. For all technologies, the growth rate of the adopters vs. non-adopters wage differential soared in 2020. In other words, the total wage bill paid by adopters relative to their total employment dropped less than among non-adopters. This is likely due to the widespread use of short-time work schemes to preserve employment among firms affected by the pandemic. As part of the wage bill in firms using these schemes is covered by the government, they reduce the total wage bill paid by the beneficiary firm. As non-adopters were more likely to see larger drop in sales in 2020, they were also likely to rely more intensively on short-time schemes, a fact that would explain the jump seen in 2020 in Figure 3.4, panel b.

### 3.2.2 *Firms adopting new technology demand workers with more education*

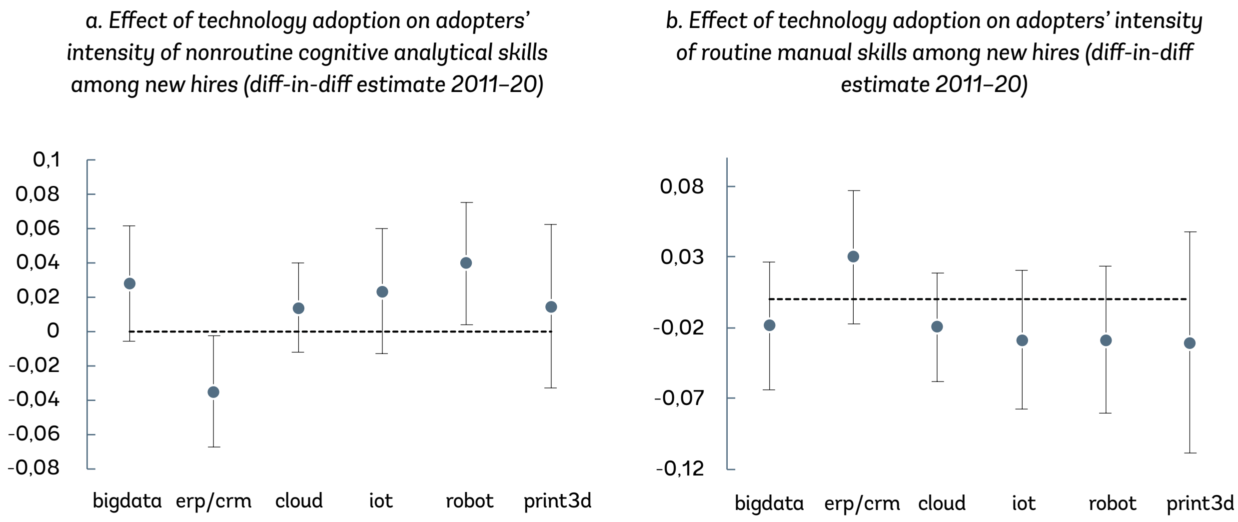
Among firms adopting advanced technologies, there is a shift away from routine manual tasks and toward nonroutine cognitive analytical ones with an associated increase in the average education of new hires, but the evidence remains noisy. As discussed in the previous chapter, extensive literature suggests that advanced technologies might complement some tasks while substituting others, thus changing the mix of tasks required to be completed to efficiently carry out a production process.[36] Because carrying out different tasks requires different skills, this technology-induced change in the task content of production processes can change the skill-specific labor demanded. In some cases, if enough new tasks are created, a new occupation might emerge.

Figure 3.5 shows the effect of technology adoption on the intensity of two types of tasks—nonroutine cognitive analytical (panel a) and routine manual (panel b)—in the jobs performed by newly hired workers. For the analysis in this chapter, nonroutine cognitive analytical and routine manual arguably represent the two extreme cases of task exposure to advanced technologies. (See Section 1.2.2 for a discussion of the definition of task content of jobs.) Routine manual tasks are highly automatable and are thus at higher risk of being substituted by new technologies. Nonroutine cognitive analytical tasks are most likely to be complementary to the adoption of new technologies, as many of the highly analytical tasks needed to use advanced technologies fall into this category. The effect of adoption on the demand for nonroutine cognitive analytical tasks is positive for operational technologies and advanced information technologies but only statistically significant for robots. The opposite effect is seen for routine manual tasks, with negative—but once again noisy—estimates of the impact of adoption on the demand for these tasks for all technologies, except ERP. The data thus support the idea that technology adoption changes the task composition of jobs in adopting firms, shifting it toward cognitive analytical tasks and away from manual tasks. Nonetheless, these effects are too noisy to draw a firm conclusion and should thus be interpreted with caution.

***"Technology adoption changes the task composition of jobs in adopting firms, shifting it toward cognitive analytical tasks and away from manual tasks."***

[36] See for example Acemoglu and Autor (2011) and Goos et al. (2014) for a discussion on the task-specific effect of technologies. Recent examples of work on the task- or worker-specific effect of the adoption of new technologies include Acemoglu, Autor, et al. (2022), which provides empirical evidence specific to AI, and Acemoglu et al. (2023), which provides evidence of the specific effect of the adoption of robots on different types of workers.

**FIGURE 3.5. Effect of technology adoption on the demand for routine intensive and nonroutine intensive tasks**




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relation management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis.

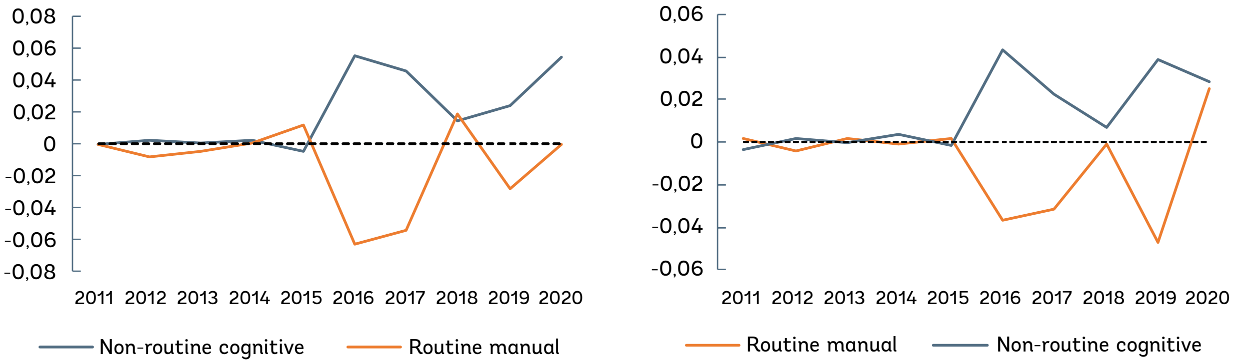
The shift in the mix of tasks was stronger in the first few years after the technology adoption, indicating that firms adjusted their workforce early on and quickly settled on a new equilibrium. Figure 3.6 shows the evolution of nonroutine cognitive and routine manual tasks performed by newly hired in Italian firms adopting new technology—compared to the evolution among non-adopting firms. Figure 3.6 captures the changes in task intensity following the technology adoption, as it concentrates in new hired workers. The results show that the largest change in nonroutine cognitive task intensity took place two years after the technology was adopted.[37] Similarly, the index capturing the intensity of routine manual tasks decreases by 22 percent two years after the event of technology adoption. These results show that the adoption of robots had a sizable initial effect on the composition of tasks performed in adopting firms. Most of this effect is concentrated in the first two or three years after the adoption period, suggesting that firms adjusted their workforce early on and while they were still adopting the new technologies by creating more jobs intensive in cognitive analytical tasks and less intensive in routine manual tasks. As this initial change in the composition of hirings was meant to adjust the equilibrium task mix of the jobs performed in the firm, estimates on the task mix performed by new hires increase rapidly early in the adoption period. After this initial adjustment, the composition of new hires among adopters reflected—through the normal process of worker turnover—the new equilibrium task composition performed by their workforce. The new equilibrium task mix among new hires among adopters was thus more cognitive-intensive than before the adoption event but less so than during the initial adjustment period.

[37] As calculated from EU-LFS data. See Chapter 4.

**FIGURE 3.6.** **Effect of the adoption of robots and big data analytics on the demand for routine intensive and nonroutine intensive tasks**

*a. Effect of robot adoption on tasks performed by new hires (adopters vs. non-adopters)*

*b. Effect of big data analytics adoption on tasks performed by new hires (adopters vs. non-adopters)*




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

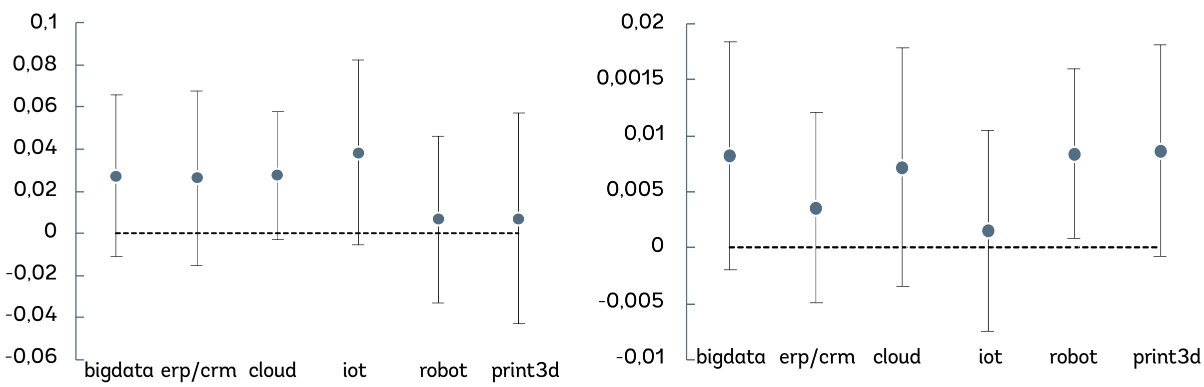
> ***"Technology adoption increases the demand of adopting firms for workers with higher education level."***

There is some evidence that changes in the task composition of jobs among adopters came with changes in the skill composition of their labor demand—leading to an increase in the average education level of their employees. Because higher education graduates have the skills to perform nonroutine cognitive tasks, the change in the task composition of jobs in firms adopting new technologies led to an increase in the demand for workers with higher educational levels. The data show evidence supporting this argument, even though estimates of these effects remain noisy. The share of workers with a graduate degree increased after the adoption of new technology, even though the effect is statistically significant—at standard confidence levels—only for the adoption of robots (Figure 3.7, panel a). A similar pattern is seen when considering changes in the average years of education among workers employed in adopting firms. The data show a positive effect for most technologies, but estimates are only marginally significant for big data and 3D printing, and significant for robots (Figure 3.7, panel b).

**FIGURE 3.7.** **Effect of technology adoption on the characteristics of the adopters' workforce**

*a. Effect of technology adoption on adopters' average years of education (diff-in-diff estimate 2011–20)*

*b. Effect of technology adoption on adopters' share of graduate workers (diff-in-diff estimate 2011–20)*




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relation management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis.

## 3.3 Technology adoption, market concentration, and aggregate labor demand

The aggregate effect of technology adoption on labor demand depends on both its ***direct*** effect on adopters and its ***indirect*** (general equilibrium) effects on other firms.[38] The results based in Italian firms only capture the effect of technology adoption on the labor demand of adopting firms. However, the adoption of technologies by a group of firms also affects the other firms in the market (also known as the general equilibrium effect). The effects of technology on non-adopting firms determine its impact on aggregate labor demand through these channels:

> ***"Technology adoption affects labor demand also indirectly, through its effect on the market equilibrium"***

1 ***Market-stealing effect***: as adopters gain a competitive advantage over other firms, they grow faster than their competitors. The adoption of new technologies thus generates a market-stealing effect where adopters gain market shares at the expense of non-adopters. These market-stealing dynamics can hurt the labor demand of firms competing with adopters.

2 ***Market size effect***: adopting new technologies in a subgroup of firms changes the equilibrium prices in the product market. Technologies help adopting firms reduce production costs and eventually offer final goods at a lower price. Technology adoption can expand the aggregate quantity demanded by reducing average prices in the economy. Other things equal, this ***market size effect*** increases the aggregate demand for labor.

3 ***Linked sectors effect***: adopting new technologies in a particular sector also has consequences for industries that either provide or buy inputs from adopting firms. Downstream sectors can benefit from the lower inputs prices made possible by increased productivity among their suppliers. Reducing production costs can then be passed through their products' prices, boosting labor demand. Technology adoption also generates new demand for upstream industries producing capital goods and inputs complementary to the latest technologies, potentially changing the mix of inputs demanded by adopters. These changes can trickle down to the ***demand for labor in linked sectors***, contributing to the overall change in labor demand.[39]

> ***"The competitive environment, the nature of the adopted technology, and the characteristics of the labor market all mediate the overall effect of technology adoption on aggregate labor demand"***

Several mediating factors determine how the combination of these three channels translates into a change in the overall demand for labor and in the demand for specific skills. Focusing on the effects of technology within the sector of adoption, three factors are likely to play an important role in mediating the effect of technology adoption on aggregate labor demand.

1 ***Competition***: the level of competition and firms' market power play a key role in mediating how a reduction in the production costs of a product is passed through its prices, thus governing the intensity of the effect of a cost-saving technology on the product's demand. In highly competitive markets, cost-saving technologies substantially reduce prices, because firms find it optimal to expand production and reduce prices to beat the

[38] See Aghion et al. (2022) for a survey of the literature on the role of the direct and indirect effect of technology adoption on labor demand.
[39] The literature has found evidence of this cross-sector spillover effect. Mann and Püttmann (2021) and Dauth et al. (2021) find positive employment effects of automation technologies—and robots in particular—adopted in manufacturing on the employment in linked services industries.

competition. But when firms face lower competitive pressure, they tend to absorb the decrease in production costs without decreasing prices. In these environments cost-saving technologies thus generate higher markups in adopting firms, with a muted effect on product prices. ***The larger the market power of adopting firms, the lower the market size effect induced by their adoption of cost-saving technologies***.

2 ***Labor-saving technology***: the second factor relates to the nature of the newly adopted technology and how the technology changes the production process in an adopting firm. ***The higher the labor-saving intensity of the technology, the lower the transmission of changes in output to labor demand***—with a correlation between changes in output and changes in employment that can turn negative for high labor-saving technologies.

3 ***Elasticity of labor supply***: labor market conditions, specifically how responsive the labor supply is to changes in firms' demand, determine technology effects on aggregate employment. Other things equal, ***the tighter the labor market, the stronger the transmission from aggregate product demand to wages and the weaker its transmission to employment***.[40] Thus, in a tighter labor market—a situation where many firms compete for few workers—a technology-induced increase in labor demand will generate a higher increase in wages and a lower increase in employment.

Estimates of the direct effect of technology adoption among Italian firms show that adopters grow faster than their competitors (Figure 3.1), thus gaining market share. The evidence also shows that adopters tend to have higher initial levels of sales per workers (Figure 3.3, panel a) than non-adopters and that this difference increases after an adoption event (Figure 3.3, panel b). These two pieces of evidence show that holding the size of the market fixed, the combination of the direct effect of technology adoption on adopters and of the indirect market-stealing effect it induces have a clear negative impact on labor demand. The sign of the overall effect of technology adoption on aggregate labor demand thus depends on the magnitude of the market size effect that the adoption of new technology can induce through its effect on prices. Aggregate labor demand increases only when the efficiency gains from technology adoption generate an increase in output that is large enough to more than compensate for its labor-saving and market-stealing effects.

Using data on the US and several European countries, existing literature shows that although the direct effect of technology on employment in adopting firms is usually positive, the overall effect on aggregate employment is mixed.[41] Box 3.3, for example, provides sector-level evidence based on EU-wide data, showing a weak, mostly negative correlation between adoption rates and sectoral employment growth. Ensuring that higher technology adoption does not translate into an excessive market power among adopting firms and that it instead translates into lower prices for consumers is thus crucial to ensure a more equitable technology adoption process.

40 A tight labor market is a situation where the demand for labor is large, but the supply is limited—firms post many vacancies but relatively few workers are looking for a job.

41 Acemoglu et al. (2020) and Acemoglu and Restrepo (2020) find a strong overall negative effect of robot adoption on employment in the US and France. Using data from the US and several European countries, Graetz and Micheals (2018) and Benmelech and Zator (2022) find negative direct effects of robot adoption on employment in adopting firms, but only a weak overall negative effect on employment. Mann and Püttmann (2021) and Dauth et al. (2021) show that while the adoption of robot led to a decline in manufacturing employment, this was compensated by an increase in services employment, leading to only minor aggregate employment changes. Aghion et al. (2021) show evidence that the adoption of robots in French manufacturing firms led to an overall increase in industry employment.

*"Indirect effects, beyond those on adopting firms, can be large and should be taken into account when assessing the effects of technologies on the labor market"*

Similarly, existing evidence suggests that the initial relative skill composition of jobs in adopting and non-adopting firms is a key driver of the overall effect of technology adoption on skill-specific labor demand. As discussed in Section 3.2.1, the Italian firm-level data shows that the evidence on the effect of technology adoption on the demand for skilled workers—measured by years of schooling or share of workers with a university degree among new hires—is positive but statistically noisy. What seems clearer from the data is that the initial skill composition among adopters and non-adopters is different (Table 2.2)—before adoption, workers in adopting firms perform cognitive tasks more intensively than workers in non-adopting firms. The market-stealing effect estimated in Figure 3.1—and its transmission to labor demand—thus implies that market shares are reallocated toward firms with a stronger demand for nonroutine cognitive tasks. Therefore, even without a direct effect of technology adoption on the skill-specific labor demand among adopters, this reallocation effect changes the aggregate skill mix demanded in the labor market, increasing the relative importance of skills better suited to perform nonroutine cognitive tasks. Overall, these results suggest it is important to consider both the direct effect of technology adoption on adopting firms and the indirect, general equilibrium effects on the rest of firms. Indirect effects can be large and should be considered when assessing the overall effects of technology on the labor market.

### BOX 3.3. Sectoral cross-country patterns in the EU

We use sectoral data from several EU countries to complement the firm-level evidence from Italy presented so far. We rely on aggregate data from the EUROSTAT Survey on ICT Usage and E-commerce in Enterprises and additional EUROSTAT data. Although this analysis has the advantage of being based on a broader set of countries, compared to the firm-level analysis based on Italian data, it provides mostly descriptive evidence because it presents correlations absent a robust identification strategy. Appendix A explains the specification used for the analysis.

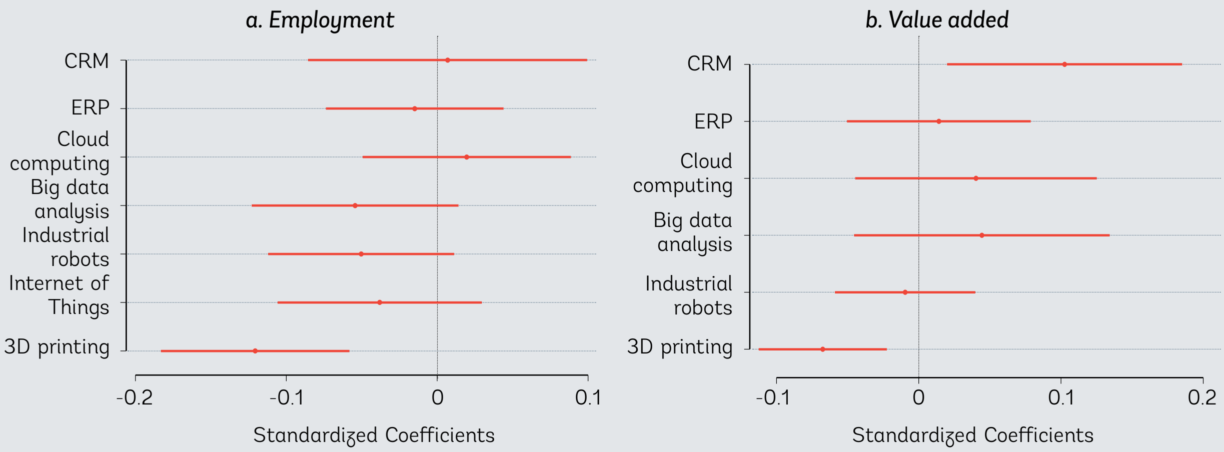
There is evidence of an increase in sectoral labor productivity after adopting most new technologies. As discussed in Section 3.3.1, the results based on Italian firm-level data show that a higher share of adopters in a certain sector should increase sector-level labor productivity by increasing the productivity of adopters and the reallocation labor toward more productive firms. EU-wide sectoral data seem to confirm this conclusion (Figure B3.3.1), showing that an increase in the share of adopters in a sector is correlated with an increase in labor productivity in that sector. Even though most estimates are not statistically significant at conventional levels, they are positive—except for 3D printing. Due to the large standard errors, this evidence should be interpreted with some caution. Nevertheless, the consistently positive correlation across different technologies reinforces the idea that the adoption of new technologies is on average associated with an increase in sectoral labor productivity.

**FIGURE B3.3.1. Correlation between changes in technology adoption and changes in labor productivity (cross-country, within-sector)**


Source: EUROSTAT ICT Survey, EUROSTAT SBS, and authors' calculations.

Increases in sectoral productivity translate into a reduction in sectoral employment due to a weak relationship between technology adoption and market expansion. As pointed out in Section 3.3.1, because of the effects of technology adoption on labor productivity, technology's impact on labor demand depends on its market size effect. EU-wide data show that, for most technologies, a higher adoption rate in a sector is associated with either no change or a limited increase in sectoral value added (Figure B3.3.2, panel b). Due to this limited market size effect, the higher labor productivity associated with a higher adoption rate translates into a reduction in sectoral employment (Figure B3.3.2, panel a)—albeit, except for 3D printing, the coefficients are not statistically significant at the conventional significance level. Overall, EU cross-country data suggest that on average technology adoption is not associated with a market size effect that is strong enough to offset its negative effect on labor demand.

**FIGURE B3.3.2. Correlation between changes in technology adoption and changes in employment and value added (cross-country, within-sector)**




Source: EUROSTAT ICT Survey, EUROSTAT SBS, and authors' calculations.

Note: CRM = customer relationship management; ERP = enterprise resource planning.

## 3.4 Summary

The evidence in this chapter indicates that implementing advanced technologies has a significant impact on the performance of adopting firms. Following the adoption, these firms experience faster growth in sales, employment, and productivity compared to non-adopters. This suggests that technology plays a crucial role in determining a firm's success and provides adopters with a competitive edge. However, there are also some concerns to consider. The adoption of technology is more common among large firms, which can lead to an increase in market concentration and the concentration of market power among a few adopters. Additionally, there is evidence of technology-induced skill substitution, with workers holding a university degree experiencing a rise in labor demand. This could widen the wage gap between university graduates and other workers.

The effects of technology on aggregate labor demand largely depend on how productivity gains among adopting firms are transmitted into aggregate output. Although the evidence in this section focuses primarily on the direct effects of adoption on adopting firms, the aggregate implications of technology adoption on the economy depend on how its direct effects transmit to the market equilibrium. The evidence suggests that the aggregate effect of technology adoption on the aggregate labor demand will largely depend on how firms and markets pass the gains of technological adoption to consumers. Minimizing the potentially harmful effect of technological adoption on workers—and maximizing its gains for the economy—requires making sure technological productivity gains are passed through to prices and wages. A strategy to mitigate the risks that technology increases market concentration and constraints the benefit for workers is to promote technology adoption among small and micro firms.

# CHAPTER 4 Vocational Education and Training in Changing Labor Markets

*"In order to keep up with the world of 2050, you will need not merely to invent new ideas and products—you will above all need to reinvent yourself again and again."*

Yuval Noah Harari

## 4.1 Introduction

This chapter analyzes the adequacy of skills provision systems in Europe to face the challenges introduced by technological progress. Our analysis focuses on the role played by formal education systems, particularly upper-secondary VET, in shaping the effects of technology on the labor market and income distribution. Half of the students in upper secondary in the EU are enrolled in VET, and these students tend to come from disadvantaged backgrounds. Hence, we emphasize this critical component of the skills provision system for promoting productivity and inclusion in the EU.

As the results in earlier chapters show, when firms adopt new technologies, the tasks perform within those firms become more cognitive, analytical, and social and less routine and manual. Workers with specific skills—proxied by their education level or degree—are more able to perform these tasks. For example, according to the results from the Italian firm-level analysis, university graduates have the right skills to perform cognitive, analytical, and social tasks, all of which complement technological progress. Are VET graduates getting the skills that let them perform cognitive, analytical, and social tasks to benefit, in the form of higher wages or employment, from technological progress?

The focus of this chapter is on upper-secondary VET. Postsecondary VET is an important component of the skill provision system of EU countries. However, its reach is more limited in terms of the population covered, and the resources spent on it are small compared to the investment that countries do in upper-secondary VET. As such, we focus our attention on the part of the VET system that has the largest coverage and accounts for most of the budget. Thus, in this chapter, when we refer to "VET students" and "VET graduates," we refer to upper-secondary VET students and graduates, respectively. "VET graduates" should be understood as upper-secondary graduates from VET institutions that did not pursue further studies, either in postsecondary or tertiary institutions. "Foundational skills" refers to cognitive skills, such as literacy and numeracy, and non-cognitive skills, such as socioemotional skills, which include social skills.

This chapter uses data from all editions of PISA, PIAAC, and the EU Labor Force Survey covering 2004-19 to measure cognitive skills, tasks performed at work, and labor market outcomes of VET and non-VET graduates, respectively.[42] We complement the EU-wide analysis of skills, tasks, and labor market outcomes of VET and non-VET graduates with the firm-level analysis for Italy, letting us identify the role of VET graduates in firms adopting new technologies.

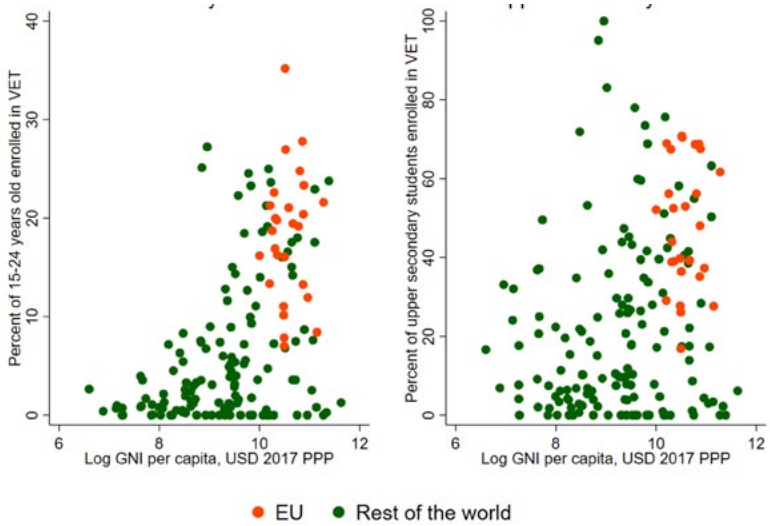
The empirical analysis of labor market outcomes in this chapter is correlational because the cross-country set up does not allow for a causal analysis that identifies the effects of vocational training separately from those of other confounding factors. However, to the degree that is possible, the analysis will allow controlling for some of these factors—such as the different nature of VET systems across countries, socioeconomic conditions, the gap in literacy and numeracy, and age, time period, and birth cohort effects. The analysis sheds light on the difference in labor market outcomes between VET and non-VET graduates when these factors are accounted for.

[42] See Appendix B for more details on data sources and definitions.

## 4.2 VET systems in the EU

The educational system of the countries in the EU is characterized by a strong presence of VET institutions. The participation of people 15–24 years old in VET in EU countries is relatively high compared to the rest of the world (Figure 4.1, panel a). In the average EU country, about 18 percent of the young aged 15 to 24 are enrolled in some technical vocational education or training, compared to 8 percent in high-income non-EU countries and 5 percent in the remaining countries.

**FIGURE 4.1. Participation of 15–24-year-old and upper-secondary students in VET in EU and the rest of the world**




Source: World Bank, ILO, and UNESCO 2023 and UNESCO Institute of Statistics.

Note: This graph plots the enrollment in VET among 15–24 years old (panel a) and among upper-secondary students (panel b). The sample is restricted to countries with latest data point from 2011 onwards. The horizontal axis plots the log of GNI per capita, PPP (constant 2017 international $).

***"The share of upper-secondary students enrolled in VET tracks is 48 percent in the average EU country, while in high-income non-EU countries this share is 19 percent"***

A similar pattern is seen when focusing on students enrolled in upper-secondary education (Figure 4.1, panel b). Within this group of students, the share enrolled in VET tracks is 48 percent in the average EU country, representing over 8.7 million students of the 17.9 million students enrolled in upper secondary in EU countries during 2020. In high-income non-EU countries, the share of upper-secondary students enrolled in VET tracks was 19 percent, whereas in the remaining countries, the share was 21 percent. Within the EU, the highest percentages of enrollment in VET among upper-secondary students are in Slovenia (70.8 percent), the Czech Republic (70.5 percent), Croatia (69.3 percent), and Austria (68.7 percent), whereas the lowest shares are found in Cyprus (16.8 percent), Ireland (24.1 percent), Lithuania (24.7 percent), and Malta (27.6 percent).

The centrality of vocational education in the European educational landscape is not an effect (nor a cause) of its relatively high income levels. High-income countries in other regions of the world have lower enrollment rates in VET compared to EU countries. The importance of VET in Europe stems from the region's history: formal VET institutions emerged with the development of manufacturing industries, and its characteristics—whether more intensive in classroom learning or in apprenticeship schemes—were shaped by each country's industrialization process.[43]

[43] See Cedefop (2004) for a rich historical review of the development of VET systems in Europe.

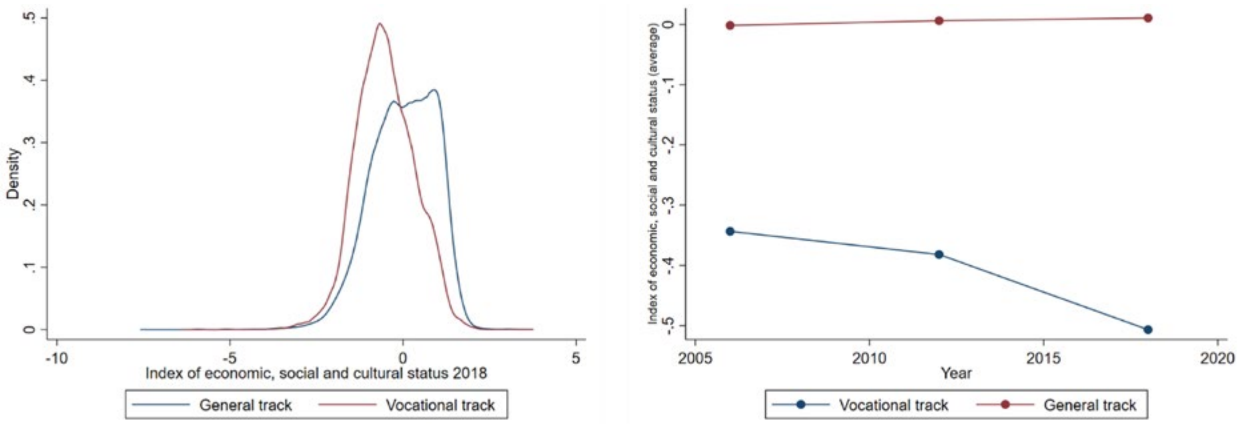
### 4.2.1 *VET students come from a relatively disadvantaged socioeconomic background*

The role of VET in skills development is important for the entire labor force in the EU but particularly for those with a vulnerable background. Data from the 2018 PISA round indicates that the average value of the index of economic, social and cultural status—a measure capturing differences in students' social backgrounds—for upper-secondary students enrolled in the vocational track is significantly lower than among general track students across the EU (Figure 4.2, panel a). This difference exceeds half a standard deviation in nine of the 12 EU countries with information, and it is over 80 percent of the standard deviation in Hungary and Slovenia. Educational background of students' parents is significantly different among VET and non-VET students: 34 percent of vocational students have a mother with tertiary education, and 30 percent have a father with tertiary education, whereas among general track students, these values are 50 percent and 49 percent respectively.

**FIGURE 4.2. Socioeconomic background of VET and general track students in EU countries**

*a. Distribution of the index of economic, social, and cultural status by track, EU countries, 2018*

*b. Evolution of the index of economic, social and cultural status by track, EU, 2006–18*




Source: Authors' estimates based on PISA 2018.

Note: Panel a of this graph plots the distribution of the index of economic, social and cultural status among upper-secondary students in EU countries sampled in the 2018 round of the PISA survey. The blue line plots the distribution of the index for upper-secondary students in the general track. The maroon line plots the distribution of the index for upper-secondary students in the vocational track. Panel b plots the evolution of the index of economic, social and cultural status among upper-secondary students in EU countries sampled in the 2006, 2012 and 2018 round of the PISA survey. Only countries with a meaningful sample of vocational track students are included (Belgium, Bulgaria, Czech Republic, France, Greece, Croatia, Hungary, Italy, Luxembourg, Portugal, Romania, and Slovenia). The index has a value of zero, which corresponds to the average of each survey respondent's country.

This difference between the sociocultural profile of vocational track students and general track students has been increasing. Figure 4.2, panel b presents the evolution of the average index of economic, social, and cultural status for the students of the two tracks in the 2006, 2012, and 2018 rounds of PISA. The index's difference increased by 54 percent when comparing the values of the 2006 round to those of the 2018 rounds. In this, the social background of the average VET student is increasingly more disadvantaged than that of the average student in the general track.

There are different reasons why upper-secondary VET students tend to come from a more disadvantaged socioeconomic background. On the one hand, this is a family choice. Parra-Cely (2023) uses data from the Netherlands and estimates the value parents attach to their children's secondary school tracks by measuring their willingness to travel to school. His estimates show that, for equally proficient children, highly educated parents will let their offspring commute longer distances to attend tracks that grant direct admission to a university, whereas parents from lower socioeconomic status prefer their children to have shorter commutes to school even if this limits their possibilities to go to university by enrolling into vocational tracks. The author estimates that about half of the enrollment gap between pupils with low and highly educated parents can be attributed to the heterogeneity of family preferences alone.

Educational practices also influence the selection of students into each track. Carlana et al. (2023) find that, in Italy, teachers at the end of lower secondary recommend students from lower socioeconomic status to follow vocational tracks even if they are as proficient as students from higher socioeconomic status, who are recommended to follow general tracks leading to tertiary education. For example, 54 percent of students in the top decile of math scores are recommended to the top academic tracks if their mother has less than high school education, and 81 percent are given the same recommendation if their mother has college education. This bias in track recommendations may result from implicit stereotypes held by teachers, which also affects immigrant children in school (Carlana et al., 2022).

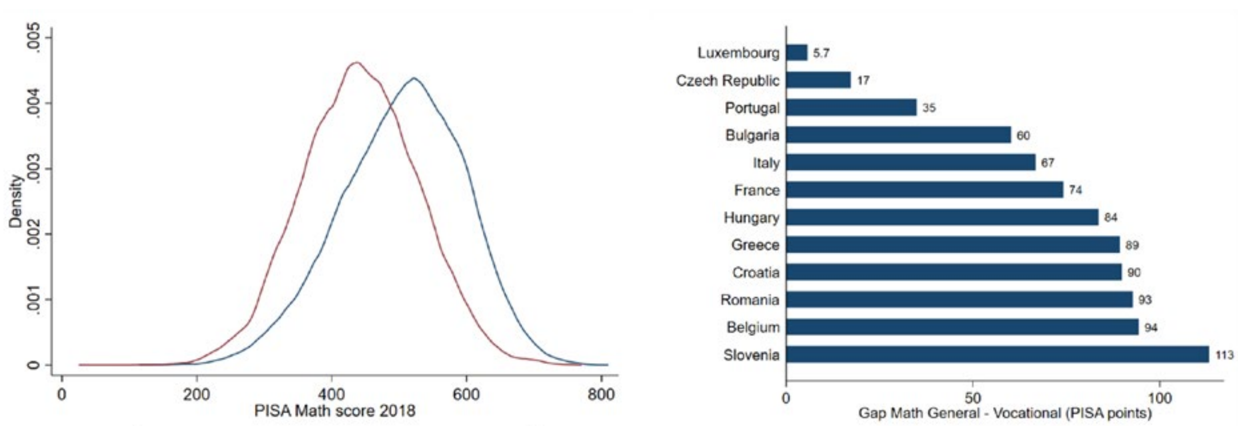
### 4.2.2 VET students have lower cognitive skills

***"In PISA 2018, the average share of vocational track students below the minimum level of skill proficiency in math in EU countries was 39 percent, whereas for general track students it was 17 percent."***

Despite the large heterogeneity of VET systems across EU member states, the academic outcomes of their students tend to follow a similar pattern. The PISA 2018 scores in math, reading, and science are significantly lower for upper-secondary students in the vocational track than for students in the general track (see Figure 4.3, panel a for the case of math scores; a similar pattern is present for reading and science scores). The average share of vocational track students below level 2 of proficiency (usually understood as the minimum level of skill proficiency) in math was 39 percent in EU countries in PISA 2018, whereas for general track students it was 17 percent in the same set of countries. In reading, these shares were 45 percent and 18 percent respectively, and in science they were 48 percent and 21 percent respectively.

**FIGURE 4.3. Math scores in PISA 2018 by VET and non-VET students, EU countries**

*a. Distribution of scores* *b. Vocational-general gap by country*




Source: Authors' estimates based on PISA 2018.

Note: This graph plots the distribution of the scores in math among upper-secondary students (panel a), and the difference between the average score for vocational track students and general track students in EU countries sampled in the 2018 round of the PISA survey. Only countries with a meaningful sample of vocational track students are included (Belgium, Bulgaria, Czech Republic, France, Greece, Croatia, Hungary, Italy, Luxembourg, Portugal, Romania, and Slovenia). In panel a, the blue line plots the distribution of the scores for upper-secondary students in the general track. The maroon line plots the distribution of the scores for upper-secondary students in the vocational track.

Although in all countries vocational track students underperform with respect to general track students, the magnitude of this difference is heterogeneous. Figure 4.3, panel b presents the difference in average scores in math between vocational and general track students in EU countries in the 2018 round of PISA (similar values are found for the case of reading and science). Luxembourg and the Czech Republic are the countries where this difference has the lowest magnitude. The largest differential in math is seen in Slovenia, where vocational track students have an average score 113 points lower than that of general track students—a difference equivalent to around a whopping four years of schooling.[44] Large differences, exceeding the equivalent of three years of schooling, are seen in Belgium, Croatia, Greece, and Romania.

There is a significant underperformance of VET students, and the gap between VET and non-VET students has been increasing. In 2006, the underperformance of vocational track students compared to general track students was 43 points in math, 52 points in reading, and 43 points in science. By 2018, these values had increased to almost 61 points in math, almost 75 points in reading, and 67 points in science.

Although underperformance of VET students is common across countries, general track students also have a relatively low performance in cognitive skills in some EU countries. In Bulgaria, Greece, and Romania, more than a quarter of general track students are below level 2 of proficiency in math, reading, and science according to the results of PISA 2018. In the Czech Republic and Luxembourg over 20 percent of general track students are also below that level.

### 4.2.3 *VET systems across the EU are heterogeneous*

VET systems in upper secondary can be characterized along different dimensions, showing great heterogeneity and high diversity between EU countries.[45] The first dimension is the nature of entry into the system. Students can enter a vocational program by means of a voluntary and unrestricted choice, after passing a voluntary but selective exam or by "tracking" (that is, by being recommended or selected into the vocation track following strict criteria). The age of entry can also be different, with some systems (for example, the Netherlands and Lithuania) having an early entry at the lower secondary level and others (for example, Norway, Poland, and Romania) in the later years of upper secondary. Integration with parallel, non-vocational tracks is another relevant dimension: in some systems (for example, Croatia, Greece, and France), students can easily switch between the general and the vocational track of upper secondary, whereas in others (for example, Germany, the Netherlands, and Sweden), they cannot, or if they can, they need to fulfill some curricular requirement (for example, Slovenia).

The nature of learning within the VET system can also be very different. In some systems (for example, Croatia, Slovenia, and the Czech Republic), learning is primarily academic and classroom-based. In others (for example, Austria, Germany, and Switzerland), it mostly happens in a workplace setting, with apprenticeships being the most straightforward example. The duration of vocation programs is also different, with some lasting for several years (for example, five years in Hungary and four years in Malta, Slovenia, Netherlands, and Sweden) whereas others (for example, Cyprus and the Czech Republic) are only one or two years.

[44] Following Woessmann (2016) "[a]s a rule of thumb, learning gains on most national and international tests during one year are equal to between one-quarter and one-third of a standard deviation, which is 25–30 points on the PISA scale." In the case of Slovenia, 113 points of difference would be equivalent to between 4.52 and 3.77 years of schooling.

[45] Routes with various entry characteristics, minimum age, duration, and possibility of access to higher education, among others, coexist within different countries of the EU. The examples provided here are incomplete and are meant to show some heterogeneity across countries.

The diploma obtained when finishing a vocational program may differ across systems. In some (for example, Croatia, Finland, and Greece), these diplomas allow for a continuation into tertiary education, whereas in others (for example, Germany, Norway, and Poland), they do not. In some systems (for example, Croatia, Estonia, Germany, and Greece), vocational diplomas serve as professional certificates that let individuals work in certain occupations, whereas in others (for example, Hungary and France), they are simply certificates of completion.

From an institutional perspective, the degree of involvement of social partners—namely, business chambers, trade unions, and nongovernment organizations—may also differ across systems. In some (for example, Croatia and Denmark), social partners actively participate in the design of curricula. In others, (for example, Greece), they actively participate in the design of learning activities and the recognition of certificates. In still other systems (for example, Spain), this participation is more limited.

VET systems across Europe differ across all these dimensions. Table 4.1 presents the classification of EU countries' systems in just two: the age of entry into the system and the share of work-based learning. As the table shows, there is no clustering of countries in a specific combination of these two dimensions. Rather, countries differ simultaneously along them. In this sense, VET systems are heterogeneous across the EU and far from following a similar, homogeneous model.

**TABLE 4.1. Age of entry and work-based learning in EU countries' upper-secondary VET systems**

| | | Age of entry | | |
|---|---|---|---|---|
| | | 12–14 | 15 | 16–17 |
| Share of work-based learning | Below 33% | Italy, Hungary | Croatia, Portugal, Slovenia | France, Greece, Poland, Sweden |
| | Between 33% and 50% | Netherlands, Lithuania | Romania, Slovak Rep. | Czechia, Estonia |
| | Higher than 50% | Austria, Bulgaria, Germany | Belgium, Denmark, Latvia, Spain | Finland, Ireland, Norway |

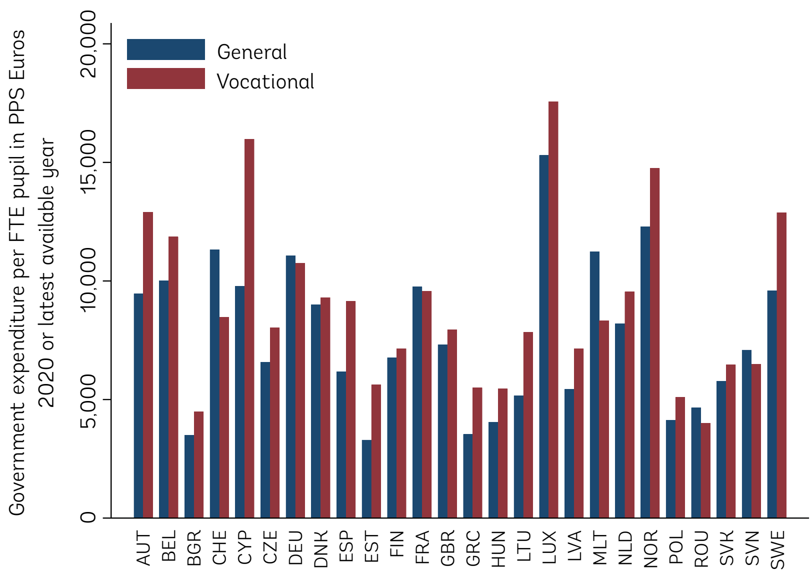
Source: own elaboration based on Cedefop and EUROSTAT.

***"In the average country in the EU, government spending per pupil in the vocational track of upper secondary is over 15 percent higher than the spending per pupil in the general track."***

Another aspect of upper-secondary VET systems that is worth pointing out is the level of spending allocated to them. In the average country in the EU, government spending per pupil in the vocational track of upper secondary is over 15 percent higher than government spending per pupil in the general track of upper secondary (Figure 4.4). Only in Germany, Malta, Romania, Slovenia, and Switzerland is the government spending per pupil in vocational track lower than in the general track. The average spending per pupil in the vocational track hides, however, considerable heterogeneity. In some vocational tracks, the average spending per pupil can be up to double that of a general track pupil because of higher capital expenditure.[46]

[46] Source: Eurostat, Educational expenditure statistics, Expenditure of the educational institutions by education level, program orientation, type of institution and expenditure category.

**FIGURE 4.4.** **Government spending per pupil by track in 2020**




Source: EUROSTAT, Educational expenditure statistics (table educ_uoe_fine09).

Note: This graph plots the average government spending per full-time equivalent (FTE) pupil in the upper-secondary general track (blue bars) and the upper-secondary vocational track (maroon bar) by country. The sample is restricted to those countries where data on spending by track is available. The values are expressed in Euros at purchasing power standard (PPS) and correspond to 2020 or the latest available year.

## 4.3 Labor market outcomes among VET graduates

In many EU countries, the cost of producing a VET graduate is much higher than that of a graduate from the general secondary track. This higher cost is justified by the labor market advantage VET systems should generate for its graduates. By emphasizing professional competencies, VET systems should provide students with low academic achievements and relatively disadvantaged backgrounds with better employment and earning prospects. In this section, we exploit data from PIAAC and the EU Labor Force Survey to compare the earnings and employment profile of VET graduates with graduates from the secondary education track without tertiary education. In this sense, our most important counterfactual comparator for upper-secondary VET graduates that did not obtain tertiary education are upper-secondary graduates that followed a general track but did not pursue further education. An alternative comparator, usually discussed in the policy arena, could be lower secondary graduates or upper-secondary dropouts. This comparator assumes that the most valid counterfactual situation for an upper-secondary VET student is dropping out of education. Evidence from the academic literature disputes the validity of this counterfactual[47] and we will compare the outcomes of VET graduates primarily with those of general secondary graduates.

[47] Matthewes and Ventura (2022) look at 16-years-old students in England who, based on the distance to the nearest school, are on the margin between attending upper secondary VET and attending general track upper secondary, and between attending upper secondary VET and dropping out. They find that 85 percent of the marginal students are on the margin between attending upper secondary VET and attending general track upper secondary, and only 15 percent of the marginal students are on the margin between upper secondary VET and dropping out of education. Birkelund and van de Werfhorst (2022) perform a similar analysis in Denmark and, while they do not estimate the share of marginal students in each margin, they point out that, in the younger cohorts which finished lower secondary in 2003-14, the share of drop-outs was below 8 percent and was mostly explained by individuals with physical and mental health disabilities as well as individuals in secure institutions and prisons.

The results in this section should be interpreted cautiously since we do not have a valid ***identification strategy*** to isolate VET's impact on labor market outcomes. The differences in hourly earnings or employment levels between VET and students that went to the general secondary education track (and did not go to university) presented below could be the outcome of a selection process rather than the result of the difference between the two tracks. So far, based on the PISA test, we have documented that VET students tend to be poorer and have lower cognitive skills than those who went to the general secondary track. However, students in the general secondary track at age 15—when the PISA test is applied—include those who will go to university and those who will not. The group to which we compare VET graduates' labor market outcomes is the general secondary school graduates who did not attend university. This comparison group has, in almost every country, the same years of formal schooling as VET graduates.[48] In our analysis of employment levels we rely on an age-period-cohort decomposition that allows controlling for factors that differ by age, period of analysis, and birth cohort. Factors that vary within these dimensions are not controlled for, so the results should be interpreted accordingly.

### 4.3.1 VET graduates have lower earnings along the life cycle

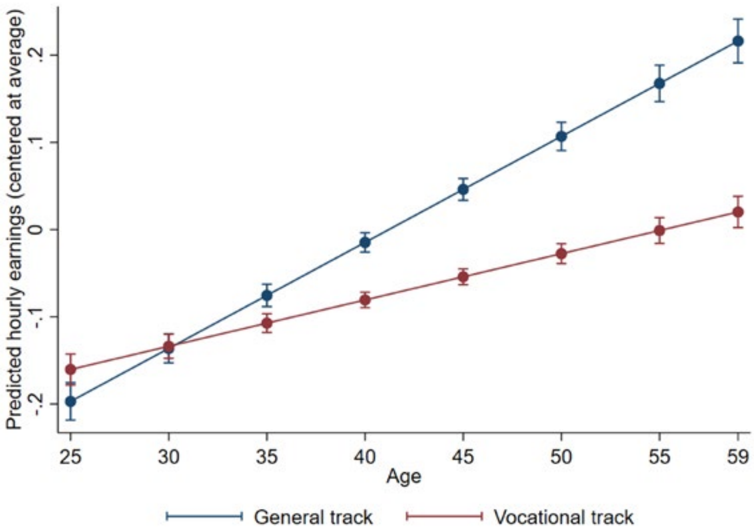
***"A vocational track graduate earns per hour worked about 3.5 percent less than a general graduate of the same age, gender, location, parental education, numeracy, and literacy."***

The earnings of different education groups are best studied with PIAAC, an adult skills assessment that, apart from including labor earnings information, allows controlling for individual characteristics such as literacy and numeracy of respondents. An analysis using PIAAC data for a sample of 14 EU countries[49] shows that the hourly earnings of VET graduates are, on average, 3.5 percent lower than that of general secondary education graduates that did not pursue higher education (labeled as "general track graduate" onwards) when conditioning on a set of individual characteristics like age, gender, location, parental education, numeracy, and literacy. That is, a vocational track graduate earns per hour about 3.5 percent less than a general track graduate of the same age, gender, location, parental education, numeracy, and literacy. The negative association of vocational studies to labor market earnings is large in some countries (over 9 percent in Belgium and exceeding 12 percent in Spain and the Slovak Republic) but also not significant in others (such as Finland, Italy, and Norway).

Another relevant aspect of the earnings profile of VET graduates is their relatively low returns to experience. On average, VET graduates see their labor earnings increase about 0.5 percent for every year of experience, whereas general track graduates see an increase twice as large—about 1.2 percent for every year of experience. There is an initial advantage of VET graduates in labor market earnings but—given their ***flatter*** age-earning profile—this quickly reverts over time (Figure 4.5).

[48] Depending on each country's educational system, VET graduates may have at most a difference of one year of schooling (either one more year or one less year) with respect to general secondary graduates who did not attend university.
[49] Belgium, Czech Republic, Denmark, Finland, Greece, Ireland, Italy, Netherlands, Norway, Poland, Slovak Republic, Slovenia, and Spain.

**FIGURE 4.5.** Age profile of earnings of VET and general secondary graduates




Source: authors' estimates using PIAAC.

Note: this figure plots the predicted log hourly earnings (centered at the country mean) at different ages of general secondary graduates (blue line) and VET graduates (maroon line). The values are derived from a linear regression of log hourly earnings, which includes an interaction factor between age and educational track and country, gender, parental education, numeracy, and literacy as control variables. The sample is restricted to individuals from 25 to 59 years old whose highest educational attainment is upper secondary (ISCED 3) or postsecondary nontertiary education (ISCED 4).

An interesting complement to this analysis is the findings of Cnossen et al. (2022), who look at the implications for labor market earnings of the skill content of VET degrees in the Netherlands. The authors find that graduates from VET degrees with a higher content of technical, specialized skills see lower earnings than graduates with a higher content of resource-management skills (like financial administration, project management, product storing) and basic, cognitive skills. On the one hand, a 10 percent increase in the degree's curriculum allocated to technical, specialized skills (vis-à-vis the share allocated to basic skills) is associated with a 0.7 percent decrease in earnings. On the other hand, a 10 percent increase in the share of the degree's curriculum allocated to resource-management skills (vis-à-vis the share allocated to basic skills) is associated with a 3.2 percent increase in earnings. Graduates from VET degrees with a high content of social skills tend to sort into sectors of the economy that reward these skills, so their earnings are higher than those of VET graduates from degrees with a low content of social skills. However, conditional on the sector of employment, the earnings associated to a degree with a higher content of social skills are slightly lower than those associated to a degree with higher content of basic, cognitive skills. A similar analysis by Langer and Wiederhold (2023) on the skills taught in dual apprenticeships in Germany shows there are almost no significant returns to manual and administrative skills, whereas cognitive, digital, and social skills taught in vocational training show significant returns.

### 4.3.2 *VET graduates enjoy employment advantages, but these disappear a few years after entering the labor market*

According to EUROSTAT data, young VET graduates tend to have significantly higher employment rates than young graduates of general education in most EU countries. On average, the employment rate of VET graduates aged 20–34 was 76.1 percent in 2020, compared to just 58.3 percent for general education graduates of the same age. However, this snapshot may not represent the actual patterns of employment seen along the life cycle by vocational and general track graduates.

***"VET graduates have a higher employment rate than all other educational groups for the age group 20 to 24 years old, but this advantage quickly disappears"***

A decomposition of the employment rate into age, period, and cohort (see Box 4.1 for methodological details) using the sixteen years of data from the EU Labor Force Survey (EU-LFS) covering the period 2004 to 2019 and 17 EU/EEA countries[50] shows that VET graduates have a higher employment rate than all other educational groups for the age group 20 to 24 years old (Figure 4.6). VET graduates transition more quickly into work after graduation than general education graduates (Vandeweyer and Verhagen, 2020). This advantage quickly disappears, and the rates of VET graduates remain almost at the same level as general secondary graduates for the rest of their professional lives, whereas they remain consistently below those of tertiary graduates. This evidence is consistent with the findings of Hanushek et al. (2017), although in their analysis—derived from a single cross-sectional sample for Germany—the employment rates of vocational graduates remain above those of general education graduates until around age 35.

**BOX 4.1. The age-period-cohort decomposition**

One of the main challenges in analyzing trends in economic choices and characteristics over the life cycle is to separately identify the variation caused by age, the variation associated with the time periods that affect all age groups, and cohort-level variation. A common approach to this challenge is the age-period-cohort (APC) decomposition, which estimates the life cycle profile of a variable (for example, job tenure in our case), the effects of shocks common to all individuals and specific to a period, and the effects specific to each cohort. A cohort is defined as a group of individuals entering a system simultaneously (for example, the year they were born or the year they enter the labor market); a period is defined as when the outcome is measured (for example, survey year); and age is the time since the system entry (for example, the time since a person was a born or entered the labor market).

We model the employment outcome $E_{iapc}$ of individual $i$ as a linear function of the individual's age ($a_i$), period ($p_i$), and cohort ($c_i$) effects. We define $E_{apc}$(the average employment outcome who were age $a$ in survey year $p$ and cohort $c$) such that $E_{apc} = \frac{\sum_{i=1}^{n_{apc}} E_{iapc}}{n_{apc}}$, where $n_{apc}$ is the number of individuals in the corresponding APC cell. We also define vectors of age, period, and cohort dummies: $\boldsymbol{A}_k = \mathbb{1}[k = a], k = 1, \dots, K, \boldsymbol{P}_l = \mathbb{1}[l = p], l = 1, \dots, L,$ and $\boldsymbol{C}_m = \mathbb{1}[m = c], m = 1, \dots, M,$ where $K$ is the number of age categories, $L$ is the number of survey rounds, $M$ is the number of generational cohorts, and $\mathbb{1}$ is an indicator function.

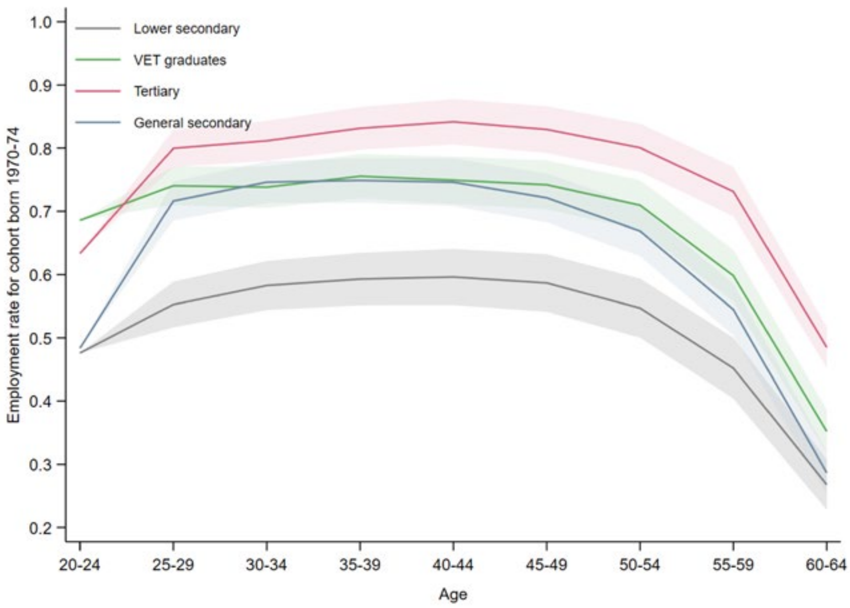
[50] Belgium, Czech Republic, Denmark, Estonia, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Romania, Slovak Republic, and Switzerland. See Appendix B for a detail of the country sample. Appendix C includes the age and cohort profiles of employment rates by educational group for each country.

Then, $E_{apc} = \sum_{k=1}^{K} \alpha_k \boldsymbol{A}_k + \sum_{l=1}^{L} \pi_l \boldsymbol{P}_l + \sum_{m=1}^{M} \gamma_m \boldsymbol{C}_m + \varepsilon_{apc}$, (1) where denotes the error term. To estimate model (1) using the APC method, we construct a panel of individuals by their APC identifiers. The EU-LFS collects age information in five-year intervals, and we combine survey years and cohorts to correspond to these five-year intervals to preserve the APC relationship. Thus, we have nine age intervals (from 20–24 years old to 60–64 years old), three survey-year intervals (2004–09, 2009–14, 2014–19), and 12 birth cohorts (from 1940–45 to 1995–99).

The linear relation between age, period, and cohort requires us to impose two constraints on the model parameters to achieve identification. A popular approach introduced by Deaton and Paxson (1994) requires that the period effects be orthogonal to the age and cohort effects, implicitly assuming that structural trends in the period effects are absorbed by the age and cohort effects. This approach has been criticized for its arbitrariness. The maximum entropy (ME) estimator generates a distribution of estimates that satisfies the linear constraints of the standard APC models and produces estimates of the expected values of parameters corresponding to the ME probability distribution (Browning et al., 2012). We thus use the ME method for our estimation.

Source: Adapted from Bussolo et al. (2023)

**FIGURE 4.6. Age profile of employment rate by educational group**

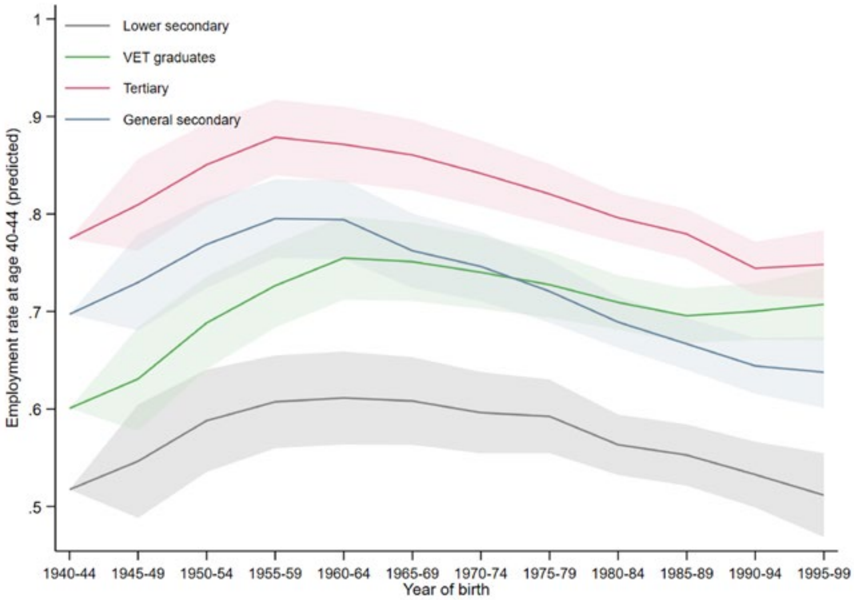



Source: authors' estimates using EU-LFS.

Note: this figure plots the age profile of the employment rate for various educational groups. The profile is derived from an age-period-cohort decomposition of the employment rate of individuals in each educational group over the period 2004–19 in 17 EU/EEA countries. To ease the interpretation of the graph, the values presented correspond to the predicted age profile of the employment rate for the cohort of individuals born in 1970–74.

The analysis of the cohort profile of the employment rate (Figure 4.7) shows that the youngest cohort of VET graduates seem to have closed (and even reversed) the gap with general secondary graduates that is present for older cohorts, and have also narrowed significantly the gap with tertiary graduates—although in the latter case the narrowing of the difference seems to be also due to a decrease in the employment rate of younger cohorts of tertiary graduates vis-à-vis older cohorts.

**FIGURE 4.7.** **Cohort profile of employment rate by educational group**



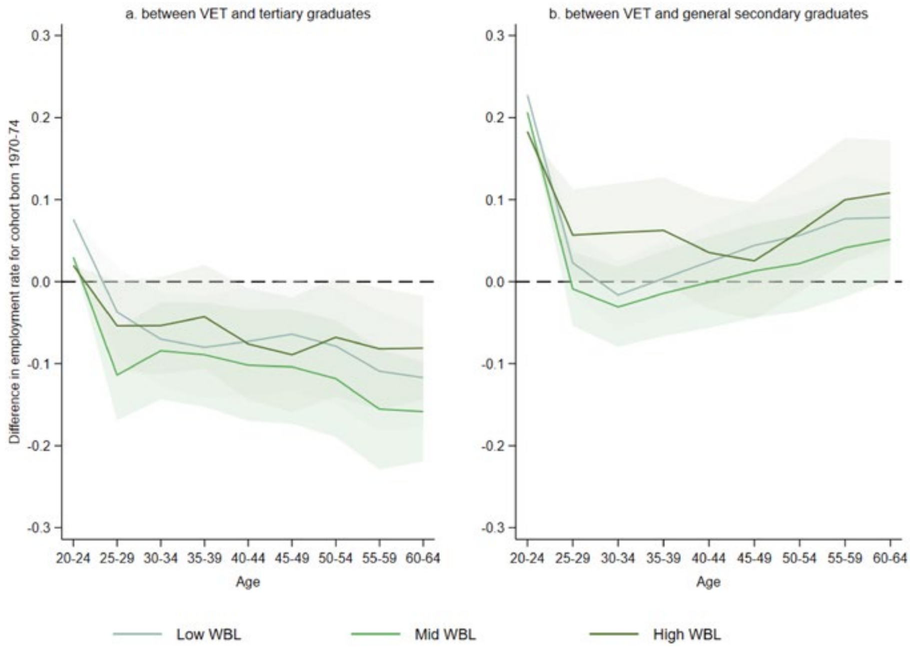

Source: authors' estimates using EU-LFS.

Note: this figure plots the cohort profile of the employment rate for various educational groups. The profile is derived from an age-period-cohort decomposition of the employment rate of individuals in each educational group over the period 2004–19 in 17 EU/EEA countries. To ease the interpretation of the graph, the values presented correspond to the predicted cohort profile of the employment rate at age 40–44.

The characteristics of VET systems across countries are not associated with different patterns of employment across educational groups. VET graduates' initial advantage in the employment rate at the beginning of professional life disappears similarly across VET systems. Figure 4.8 plots the difference in the employment rate between VET and tertiary graduates (panel a) and between VET and general secondary graduates (panel b) for countries grouped by the share of work-based learning in their VET systems—Figure 4.8 is basically the same graph as Figure 4.6 for VET graduates but expressing the employment rate as a difference with respect to that of tertiary graduates and that of general secondary graduates, respectively. Although point estimates may suggest that differences are smaller for countries where VET systems have a high share of Work-Based Learning (WBL), the confidence intervals overlap with those of the other country groups.[51] A similar pattern is seen when we group countries based on the age of entry to the VET system. The differences in employment profiles for VET and other graduates are not statistically different across countries with different ages of entry into the VET system.

[51] Cahuc and Hervelin (2022) study the effect of workplace versus school-based vocational education on youth employment in France. They find a positive impact of increased workplace education on youth employment, although they caution that this impact is almost entirely explained from retention in the training firm without having a significant impact on employment in later stages of the professional life. A similar pattern is found in the study by Neyt et al. (2020) on the dual apprenticeship programs in Flanders (Belgium), which identifies a short term labor market advantage (that fades out quickly) for the program with the most days of on-the-job training. These findings could explain why in Figure 4.8, despite the point estimates suggesting a larger employment advantage of VET graduates in high WBL countries, the difference is not statistically significant, particularly in late stages of the professional life.

**FIGURE 4.8.** **Difference in employment rate over age between VET and general secondary/tertiary graduates, by share of WBL in VET system**




Source: authors' estimates using EU-LFS.

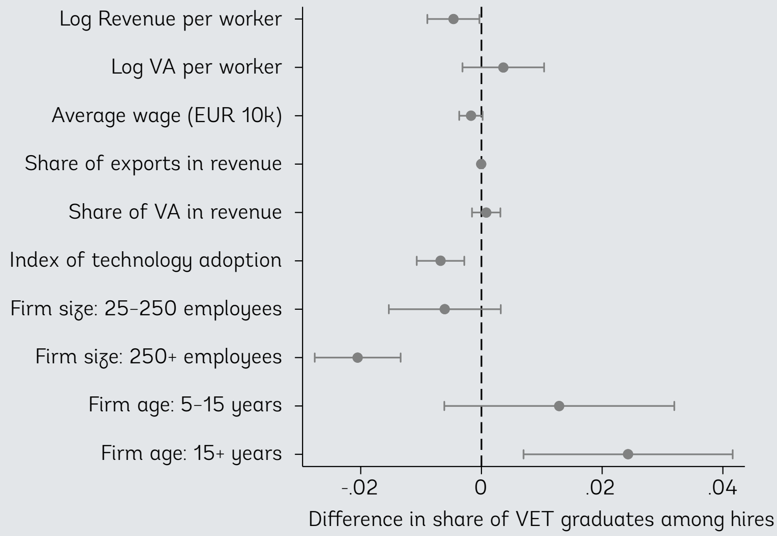
Note: this figure plots the age profile of the difference in employment rate between VET and tertiary graduates (panel a) and VET and general secondary graduates (panel b). Three profiles are plotted in each panel, one for each country group based on the share of WBL in VET (low, mid, and high—see Table 4.1). Each profile is derived from an APC decomposition of the employment rate of individuals in each educational group over the period 2004–19 in the corresponding country group. To ease the interpretation of the graph, the values presented correspond to the predicted difference in the age profile of the employment rate for the cohort of individuals born in 1970–74.

As we will discuss in the next section, the lack of labor market advantage among VET graduates—compared to labor market outcomes of general secondary education graduates—could be related to the tasks they are performing, the relationship between these tasks and technological progress, and the type of firms hiring them (see Box 4.2 for more details).

**BOX 4.2.** **Which firms hire VET graduates? Insights from Italy**

Although labor force surveys usually provide detailed information on the characteristics of the workforce, they are less informative about the characteristics of employers. The matched employer-employee database provided by ISTAT, the Italian statistical institute, provides a better picture of the characteristics of firms that hire VET graduates. A snapshot from 2018, the last pre-COVID year with full data on hires, shows that, on average, VET graduates represented 6.8 percent of total hires. This share, which can be interpreted as a "VET hiring intensity" varies across firms. A summary of the simple correlations between firm characteristics and VET hiring intensity are graphically presented in Figure B4.2.1.

**FIGURE B4.2.1. Correlation between firm characteristics and VET hiring intensity**




Source: own elaboration based on ISTAT.

Note: this graph plots the simple correlation coefficients between firm characteristics and the share of VET graduates among hires in 2018. For the case of firm size and firm age, the coefficients correspond to the result of a simple regression with the different size and age categories as dummy independent variables. The reference category for firm size is between 0 and 25 employees, and the reference category for firm age is between 0 and 5 years. The index of technology adoption corresponds to the number of technologies adopted by the firm out of the following eight: ERP, cloud computing, internet of things, augmented reality, big data, robots, 3D printing, and cybersecurity.

Firms that are older, smaller, and less productive than the average tend to hire more VET graduates. For example, a firm that is older than 15 years hires 2.4 percentage points more VET graduates than a firm that is less than five years old, a difference that represents about 35 percent of the average VET hiring intensity. Similarly, a firm that is larger than 250 employees hires 2 percentage points fewer VET graduates than a firm that is smaller than 25 employees, a difference that represents about 30 of the average VET hiring intensity. In terms of productivity, one indicator (revenue per worker) is associated negatively with VET hiring intensity, whereas another indicator (value added per worker) has a correlation that is not statistically different from zero. Last, a simple index of technology adoption shows that the more new technologies a firm adopts, the lower is VET hiring intensity.

These results show that firm characteristics associated with better performance—size, productivity, and technological dynamism—are correlated negatively with VET hiring intensity. The less dynamic firms of Italy include more VET graduates in their hiring drives. This may be a factor contributing to the poor earnings and employment profile that VET graduates have along the later stages of their professional life.

## 4.4 VET graduates and the changing task contents of jobs

This section uses the EU Labor Force Survey to identify the six types of tasks defined in Chapter 1 for each worker in the data set. This lets us distinguish the tasks performed by VET graduates and compare them with the tasks perform by workers with other education levels—general secondary graduates. We then show how the task content of different jobs has changed over the last 20 years, partly driven by technology. Finally, we show if and how the tasks performed by VET graduates change when firms adopt new technologies.

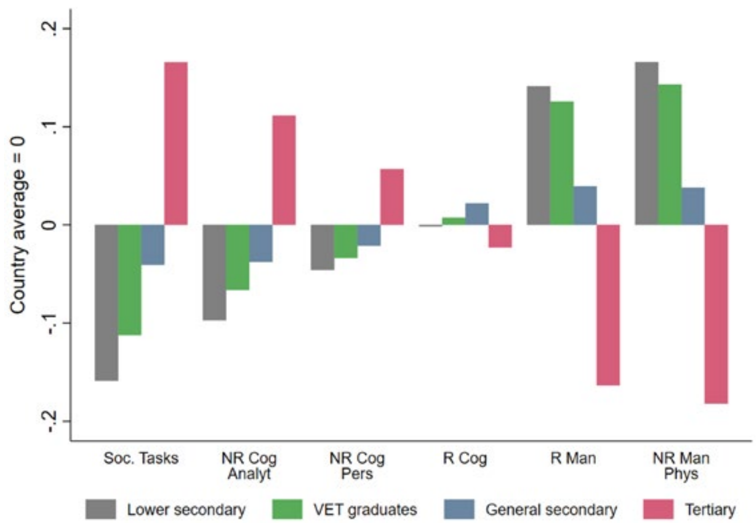
### 4.4.1 VET graduates perform manual tasks

***"The jobs of VET graduates are more intensive in manual tasks than the average job in the economy, and less intensive in nonroutine cognitive and social tasks."***

Figure 4.9 shows the task intensity of jobs performed by workers with different education levels (graduates expressed as a ratio of the country average). VET graduates' jobs are, in terms of their task content, like that of lower secondary graduates and significantly different from that of tertiary graduates. The values correspond to a pool of 19 EU countries in 2019. Tertiary graduates' jobs are more intensive than the average in social and nonroutine cognitive tasks (both analytical and personal), whereas they are less intensive in routine cognitive tasks and particularly so in manual tasks, either routine or nonroutine. The jobs of lower secondary and VET graduates follow the opposite pattern: they are more intensive in manual tasks than the average and less intensive in nonroutine cognitive and social tasks than the average. As for task contents, general secondary graduates' jobs are between the tertiary graduates' and those of VET graduates.

The tasks performed by workers with a VET degree are farther away from the tasks demanded by new technologies: social and nonroutine cognitive. Workers with a general secondary education diploma (who did not go to university) perform tasks closer to the ones complementing new technologies. In terms of labor market advantage in a technology-driven economy, workers with a VET diploma do not have an advantage vis-à-vis workers with a general secondary degree; to the contrary, they perform tasks similar to those performed by workers that only finished lower secondary.

**FIGURE 4.9. Task intensity of jobs performed by different educational groups, 19 EU countries, 2019**

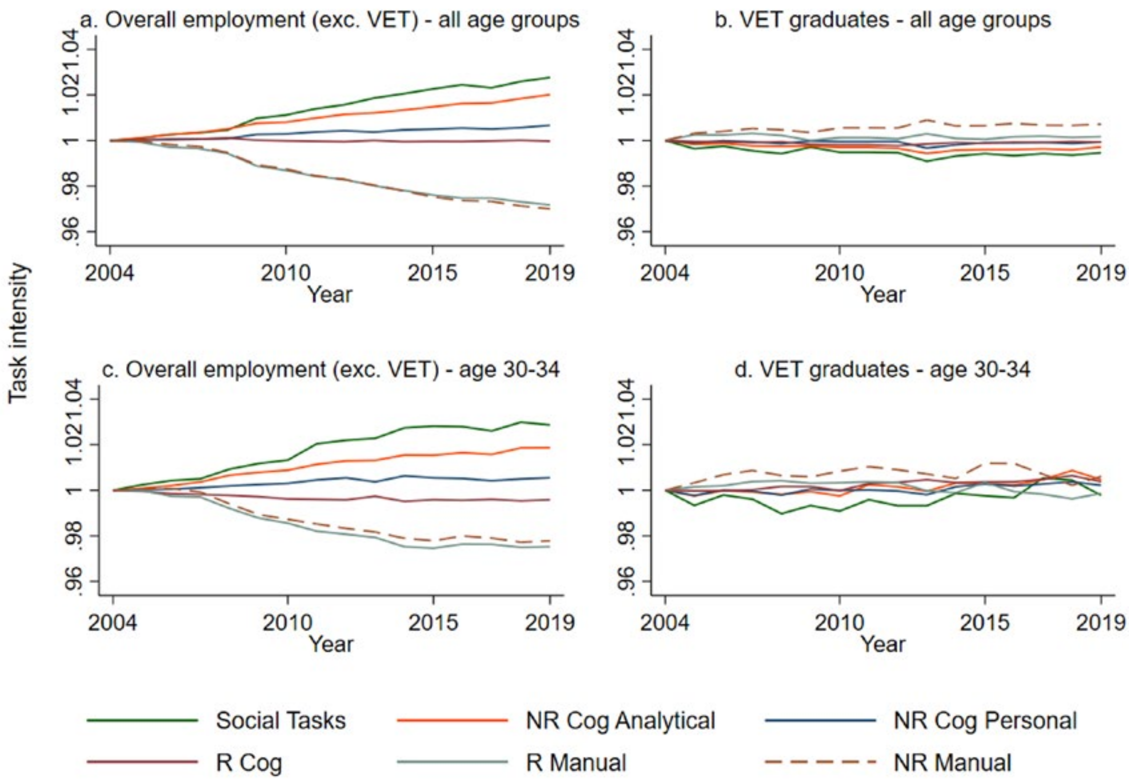



Source: authors' estimates using EU-LFS.

Note: this figure plots the task intensity of different educational groups' jobs across six types of tasks. The intensity of nonroutine cognitive analytical tasks, nonroutine cognitive personal tasks, routine cognitive tasks, routine manual tasks and nonroutine manual tasks is calculated using the procedures detailed in Hardy et al. (2018). The intensity in social tasks is calculated using the definition of Deming (2017) on the use of social skills in the job. The task intensity is expressed as a difference with the average task intensity of the individual's country. Values are population weighted and pooled for the whole sample. The sample consists of all employed individuals in 2019 in 19 countries in the EU-LFS. NR Cog An. = Nonroutine Cognitive Analytical; NR Cog. Pers. = Nonroutine Cognitive Personal; R Cognitive = Routine Cognitive; R Manual = Routine Manual; NR Manual = Nonroutine Manual

Figure 4.10 shows the evolution of the task content of jobs over the last two decades, distinguishing between jobs performed by workers with a VET degree versus those performed by all other workers. If we concentrate on panel a of Figure 4.10, the nature of jobs has changed significantly over the last two decades across the EU. Partly driven by technological progress, jobs have become more intensive in nonroutine cognitive tasks and social tasks (Acemoglu & Autor, 2011; Deming, 2017). At the same time, they have become less manual. The change in the task content jobs is even larger when we reproduce the patterns in panels a and b of Figure 4.10 but among workers aged 30 to 34 (Figure 4.10, panels c and d). This pattern has been common to all countries in the region, except for the trend in routine cognitive tasks, whose intensity in overall employment has remained stable in Central and Eastern European countries but has declined in the rest of the EU (Keister & Lewandowski, 2017).

**FIGURE 4.10. Evolution of task content of jobs**




Source: authors' estimates using EU-LFS.

Note: this figure plots the evolution of the average task intensity of jobs, indexed to a value of 1 for 2004, for different employment and age groups across 17 countries in the EU-LFS microdata. The intensity of nonroutine cognitive analytical tasks, nonroutine cognitive personal tasks, routine cognitive tasks, routine manual tasks and nonroutine manual tasks is calculated using the procedures detailed in Hardy et al. (2018). The intensity in social tasks is calculated using the definition of Deming (2017) on the use of social skills in the job. Values are population weighted. Panels a and c correspond to the average values for all employed individuals excluding VET graduates. Panels b and d correspond to the average values for VET graduates only. NR = Nonroutine. Cog = Cognitive.

*“The tasks performed by a VET graduate in 2019 were very similar to those performed by a VET graduate in 2004, while at the same time the tasks performed by the rest of workers changed significantly”*

The evolution of the task content of jobs is very different for workers with a VET degree, who represent a critical part of the labor force in Europe. The tasks performed by a VET graduate in 2019 were like those performed by a VET graduate in 2004 (Figure 4.10, panel b). This was also true for the average job of VET graduates aged 30 to 34, at the beginning of their professional life (Figure 4.10, panel d). There was no increase in the intensity of nonroutine cognitive tasks or the use of social skills, nor there was a decrease in manual tasks. These contrasting patterns between the changes in the task content of overall employment and that of VET graduates' employment suggest that the VET graduates are being left out of major trends in the labor market, including, as we will show below, technological progress.[52]

### 4.4.2 VET graduates do not perform tasks complementing new technology

Technology is changing the task content of jobs, increasing the demand for nonroutine cognitive analytical and personal tasks. Therefore, a technological shock will result in different labor market outcomes across educational groups. Individuals with skills that let them perform nonroutine cognitive tasks or social tasks—which complement new technology—will benefit from more firms adopting new technology, whereas workers with skills typically used to perform routine and manual tasks may experience a loss in labor market opportunities.

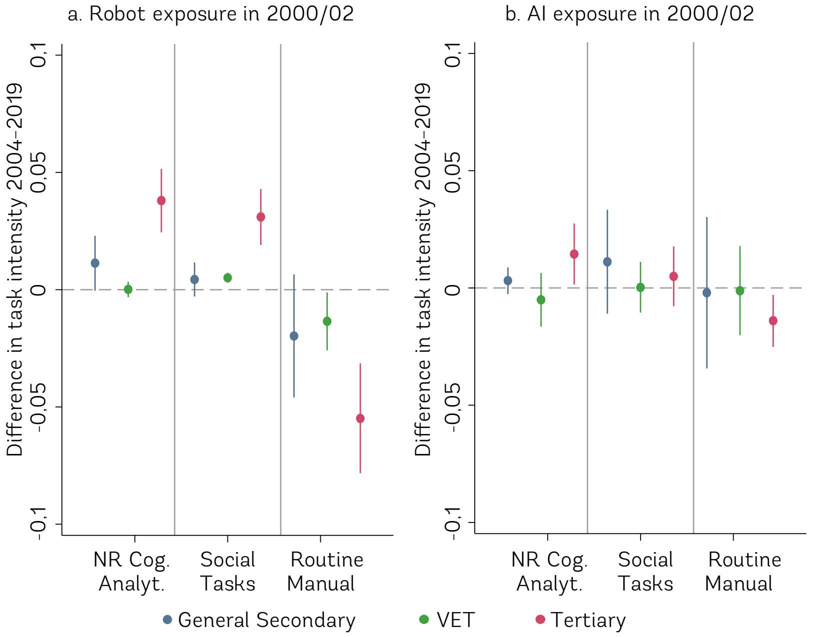
To test the impact of technology on tasks performed by different workers based on their education level, we correlate the changes in the task content of jobs of different educational groups over the period 2004–19 with the exposure to two technologies—robots and AI—in the early 2000s.[53] We carry out this exploratory analysis at the regional level, covering 95 regions across 8 EU countries for which information is available.[54] The results are summarized in Figure 4.11. Exposure to different technologies is correlated with a subsequent change in the task content of jobs, particularly for individuals with tertiary education: a higher exposure to operational technologies (such as robotization) in 2000–02 is correlated with an increase in nonroutine cognitive task intensity and the use of social tasks, and with a decrease in manual and routine tasks. These trends are expected because robots substitute for manual and routine tasks, and they indicate that tertiary graduates shift to jobs more intense in complementary tasks or that they remain with the same job, but it becomes more intensive in the performance of nonroutine tasks. A similar pattern is found for exposure to informational technologies such as software and AI, although the overall magnitude of the correlations is smaller. In the case of workers with a VET and general secondary education degree, they experience changes in task intensity that mirror the direction of those of tertiary graduates but are smaller in magnitude and in some cases, not statistically significant. The changes are even less significant for lower secondary graduates in most cases (not shown in Figure 4.11).

[52] It is important to note that the occupational composition of VET graduates' jobs in terms of ISCO 1-digit groups has changed, as shown by Vandeweyer and Verhagen (2020). In particular, VET graduates are increasingly likely to be employed as services and sales workers and decreasingly likely to work as clerical support workers. However, when occupations are decomposed into tasks, this change is strongly attenuated. This suggests that, while VET graduates may have nominally changed occupations, the tasks they do remain mostly the same.

[53] Exposure to technology is defined using the measure created by Webb (2020), which estimates the exposure of each occupation (in the US SOC classification) to a given technology using patent information. This measure was adapted to the European occupational classification (ISCO-08, ISCO-88), see Box 1.4 for details. The values of all occupations are aggregated to the relevant unit of analysis (sector, region, or country) using employment weights of year 2000/02 (that is, the number of individuals employed in a given occupation in the unit of analysis in 2000/02). Technological exposure is thus defined as the share of employment exposed to a given technology in year 2000/02.

[54] Belgium, the Czech Republic, France, Hungary, Italy, Poland, Sweden, and the Slovak Republic.

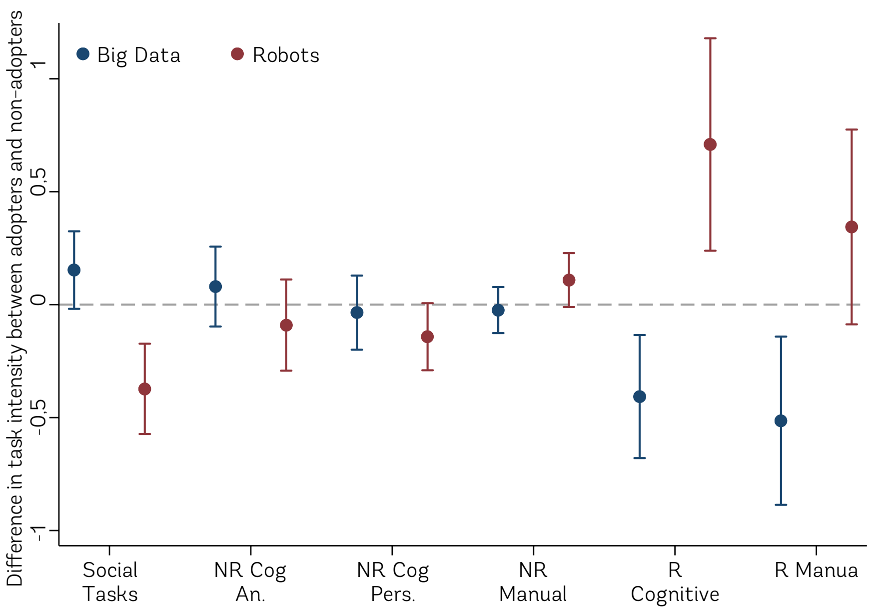
**FIGURE 4.11.** Exposure to technologies and change in task content of jobs by educational group




Note: this graph plots the partial correlation coefficients (and the associated 95 percent confidence interval) of a simple univariate regression where the dependent variable is the change in the task intensity in the period 2004–19 and the independent variable is an index of exposure to a given technology in 2000–02 (Robots in panel a and AI in panel b). For simplicity, results from only three tasks are included (nonroutine cognitive analytical, social tasks, and routine manual). The unit of analysis is an educational group (lower secondary graduates, general secondary graduates, VET graduates, and tertiary graduates) in a region (95 regions in eight countries). Standard errors are clustered at the country level. NR Cog. Analyt. = Nonroutine Cognitive Analytical.

The results in Figure 4.11 are correlations between the regional exposure to technology and task contents of jobs rather than the actual adoption of technology (see Box 1.4 above). What types of jobs that VET graduates do in firms that adopt new technologies? Evidence from the matched employer-employee database and the ICT survey of Italy shows that, in firms that adopt informational technologies (like big data), VET graduates tend to be employed for slightly more social and less manual tasks than in firms of the same size and sector that do not adopt such technologies. There are no significant differences in terms of cognitive tasks, both routine and nonroutine (Figure 4.12).

**FIGURE 4.12. Difference in task intensity among VET graduate hires between firms adopting and not adopting new technology in Italy**




Note: this graph plots the coefficient associated with using each type of technology (big data in blue, robots in maroon) from a firm-level regression which has task intensity among VET graduate hires as the dependent variable. Controls include the size and sector of the firm. The sample of firms correspond to the Italian 2018 ICT survey. NR Cog An. = Nonroutine Cognitive Analytical; NR Cog. Pers. = Nonroutine Cognitive Personal; R Cognitive = Routine Cognitive; R Manual = Routine Manual; NR Manual = Nonroutine Manual

Firms that use robots tend to hire VET graduates for jobs less intense in social and nonroutine cognitive tasks—and more intense in routine manual tasks—than firms of the same size and sector that do not use them. This result seems counterintuitive because it would have been expected that robots substitute for routine manual tasks and complement social and nonroutine cognitive tasks. But it is important to underline that this is a cross-sectional, correlational analysis: what it shows is that the use of robots is correlated with a job structure that is more intensive in routine manual tasks for VET graduates. How does this change over time? Unfortunately, the limited sample size of the ICT survey precludes doing a meaningful event study on the task intensity of VET graduate hires over time. More research will be needed to understand the long-term implications of technology adoption on VET graduates' jobs at the firm level.

The analysis in this section shows that tertiary graduates "take the lead" in the transformation of jobs following technological change, whereas other education groups, including workers with a VET degree, lag. This evidence supports the idea that workers with a VET degree do not have the skills to perform tasks complementing recent technological progress. As technology advances and is adopted by more firms, and the demand for skills to perform social and nonroutine cognitive tasks increases, VET graduates might experience lower labor market outcomes (lower employment or wages).

### 4.4.3 *How green are the jobs performed by VET graduates?*

There is also evidence that VET graduates perform jobs that are ***pollution intensive*** and less green and hence are at risk of disappearing with the green transition. The transition to a low-carbon economy entails massive investments in technology, infrastructure, innovation in production models, and will also imply strong changes in the labor market as new jobs will emerge, whereas others will be adjusted or replaced (ILO 2016). The green transition has the potential to create new and decent jobs while protecting the environment (Ruppert Bulmer & Rutkowski 2021; ILO 2016; 2018; World Bank 2021). But, the green transition will inevitably destroy employment, mainly in fossil fuel and particularly the coal mining sector (ILO 2016).

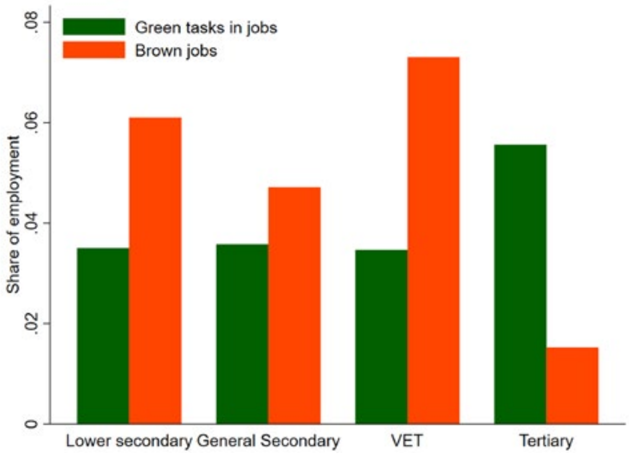
The transition to a greener economy will not affect European educational groups similarly. Garrote Sanchez and Makovec (2022) provide country-level estimates of the share of "green tasks" in jobs and the share of "brown jobs" across countries in the region. Using their methods, these same indicators can be estimated for workers with different education levels.

Following Vona et al. (2018)'s methodology, the share of green tasks is defined as the share of time spent working on tasks complying with environmental sustainability; these tasks are those specific to green occupations as defined by the O*NET Green Economy program. The share of brown jobs is defined as the share of occupations in industries in the United States' 95$^{th}$ percentile of pollution intensity (according to six air pollutants and $CO_2$ emissions). These two indicators, although not mutually exclusive, can illustrate how far ahead in the greening process different educational groups' jobs are and how many are expected to be directly hit as emissions constraints become more stringent.

*"VET graduates in the EU have the highest share of brown jobs among all educational groups."*

VET graduates in the EU have the highest share of brown jobs among all educational groups—about 7.4 percent of jobs by VET graduates in 2020 were in very polluting industries, compared to 6 percent of the jobs of lower secondary graduates, 5.1 percent of the jobs of general secondary graduates, and 1.6 of tertiary graduates' jobs (Figure 4.13). On the other hand, the share of green tasks in jobs is lowest for VET and lower secondary graduates at 3.6 percent, whereas it is highest for tertiary graduates at 5.6 percent. In this sense, the VET graduates' jobs seem to be the ones lagging in the green transition process, with a higher share of brown jobs than the rest of educational groups and the lowest share of green tasks in their occupations. This puts jobs performed by workers with a VET degree at risk of disappearing because of the green transition.

**FIGURE 4.13. Green tasks and brown jobs, by educational group, 2020**



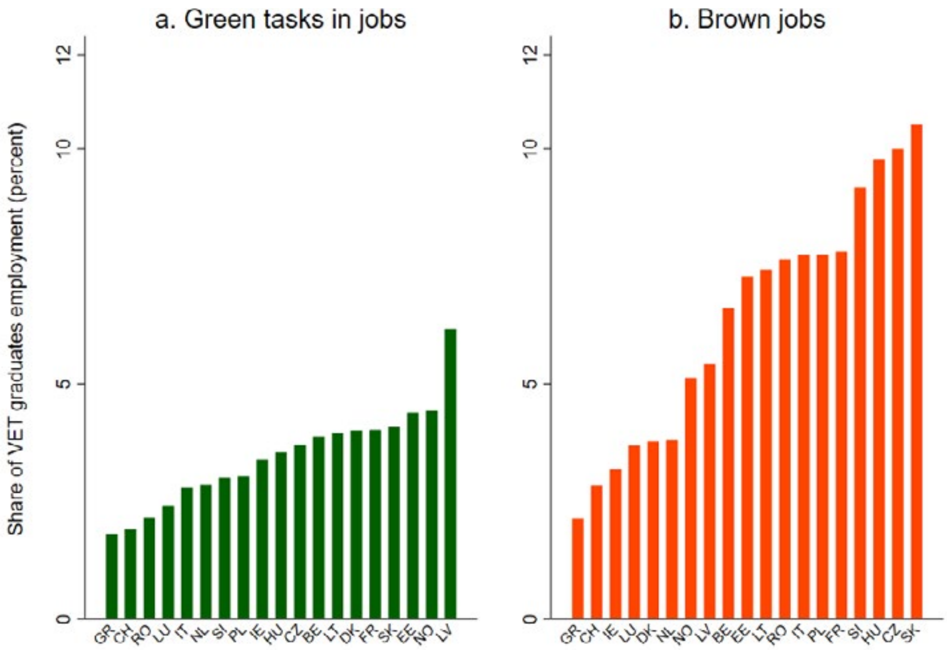

Source: authors' estimates using EU-LFS.

Note: This graph plots the share of green tasks in jobs (green bar), and the share of brown jobs among the employed (orange bar) across educational groups. The values correspond to all employed individuals in 2020 in 19 EU countries.

This broad pattern of green tasks and brown jobs across educational groups is similar across countries in the EU, although the magnitudes are different in all of theme. Figure 4.14 plots the share of green tasks (panel a) and the share of brown jobs (panel b) for VET graduates by country. The countries where VET graduates perform more green tasks in their jobs are in Northern Europe—Latvia, Norway, and Estonia. The countries where VET graduates perform the least these tasks are Greece, Switzerland, and Romania. When looking at the share of brown jobs among VET graduates, Central European countries stand out: in the Czech and Slovak Republics the share of VET employed in brown jobs is at or above 10 percent, and in Hungary and Slovenia the share exceeds 9 percent. The opposite situation happens in Greece, Switzerland, and Ireland, where the share of brown jobs among VET graduates is at 3 percent or below. In countries such as Greece or Switzerland, VET graduates' jobs seem to be not particularly "brown." Rather, they have a low share of green tasks, whereas in Poland and Slovenia, VET graduates' jobs are both quite "brown" and not very "green."

This heterogeneity in the green/brown dimension of VET graduates' jobs suggests that the policies to accommodate the labor market consequences of the greening of the economy may need to be country specific. Policies that help labor mobility across sectors may be best suited in those countries where the largest exposure is on the brown job dimension, whereas policies that emphasize skill training may be best suited in those countries where the largest exposure is on the green task dimension.

**FIGURE 4.14.** Green tasks and brown jobs among VET graduates, by country, 2020




Note: This graph plots the share of green tasks in jobs (panel a), and the share of brown jobs (panel b) among employed VET graduates, by country. The values correspond to all employed VET graduates in 2020 in 19 EU/EEA countries.

Source: authors' estimates using EU-LFS.

Note: This graph plots the share of green tasks in jobs (panel a), and the share of brown jobs (panel b) among employed VET graduates, by country. The values correspond to all employed VET graduates in 2020 in 19 EU/EEA countries.

## 4.5 Why are VET graduates not benefiting from technological progress?

The task content of jobs in the economy is trending in a direction different to that of VET graduates' jobs. However, not in all countries did the task content of VET graduates' jobs differ from that of overall employment in the same way (See Appendix D for country-level patterns of the task content of jobs). This heterogeneity in cross-country patterns allows for the exploration of its relationship with the characteristics of VET systems across countries, or the role played by foundational skills—numeracy, literacy, and socioemotional skills.

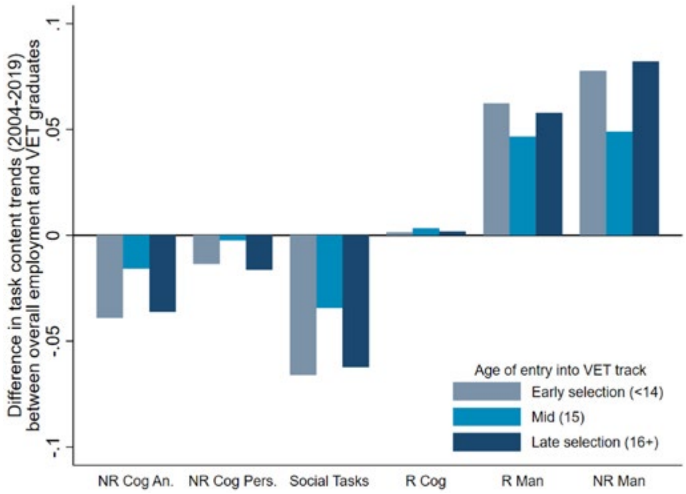
### 4.5.1 *The evolution of task content of VET jobs and the characteristics of the system*

VET systems in the EU differ in many dimensions—two of them being the age of entry into the system and the share of work-based learning in the curriculum.[55] Figure 4.15 and Figure 4.16 present the average difference in task intensity trends, calculated as the difference between the change in task intensity from 2004 and 2019 for overall employment and the same change for VET graduates' employment, for countries grouped by characteristics of their VET system. These figures summarize the differences in trends between VET and non-VET graduates presented in Figure 4.10 but distinguishing between VET systems with different age of entry and the share of work-based learning, respectively. We restrict here to the employment of individuals aged 30

55 Other dimensions are the route of entry into the system (whether voluntary, by selective exam, or by recommendation), the degree of integration with non-vocational tracks, the possibilities of continuing into tertiary education, the duration of the programs, and the degree of involvement of social partners (business chambers, trade unions, non-government organizations).

to 34, as this reflects better the nature of jobs that individuals have at the beginning of their professional life, when differences attributable to the type of education may be clearer. A negative value shows that VET graduates' jobs have become less intense in a task when compared to overall employment, whereas a positive value shows the opposite. In other words, if the task contents of jobs performed by VET graduates evolved on par with those of non-VET workers, the value of the bars in Figure 4.15 and Figure 4.16 would be zero. Therefore, smaller bars in Figure 4.15 and Figure 4.16 capture a smaller divergence on the task intensity of jobs performed by VET graduates, and larger bars represent a larger divergence.

**FIGURE 4.15. Difference in task intensity trends by age of entry into VET, age 30-34**




Source: authors' estimates using EU-LFS.

Note: this figure plots the difference between the change in task intensity over the period 2004–19 for overall employment and the change in task intensity over the period 2004–19 for VET graduates' employment, restricting the sample to individuals aged 30 to 34. The change over the period 2004–19 is expressed respect to an index of task intensity with a value of 1 for 2004 and is calculated using EU-LFS microdata. A negative value shows that the change for overall employment is higher than for VET graduates' employment, whereas a positive value shows the opposite. The values are calculated for each country in the sample separately and then are aggregated (as a simple average) into three groups based on the age of entry into the VET track: i) early selection, for those where entry occurs at age 14 or younger, ii) mid-age selection, for those where entry occurs at age 15; iii) late selection, for those where entry occurs at age 16 or older. NR Cog An. = Nonroutine Cognitive Analytical; NR Cog. Pers. = Nonroutine Cognitive Personal; R Cognitive = Routine Cognitive; R Manual = Routine Manual; NR Manual = Nonroutine Manual

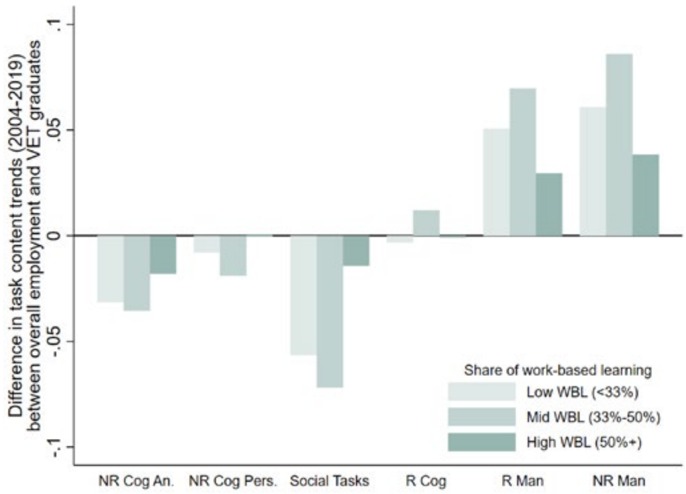
Figure 4.15 distinguishes three groups of countries based on the age of entry into the VET system: early selection at age 14 or younger, mid selection at age 15, and late selection at age 16 or later.[56] No clear pattern emerges, except that the difference between the trends of overall employment and VET graduates' employment seem to be smaller in absolute value for those countries where entry occurs at age 15.

Figure 4.16 groups countries based on the share of work-based learning of their VET system: less than 33 percent, between 33 percent and 50 percent, and over 50 percent. The share of work-based learning appears to be related to the difference in task content trends. In countries where the share of work-based learning in VET is highest—more than 50 percent of the average

[56] The list of countries in the three age-at-entry categories and share of work-based learning can be found in Table 4.1.

curriculum—the difference is smaller, whereas in countries where work-based learning represents less than 33 percent of the average curriculum of VET education, the difference is larger in absolute value. In this sense, in countries where VET systems have a high share of work-based learning, the task content of jobs of VET graduates has followed more closely the evolution of the task content of jobs of the overall employment. This finding resonates with Adao et al. (2023)'s analysis of the enrollment in apprenticeships—the type of VET education with the highest share of work-based learning—in the German VET system. Their analysis shows that VET students enroll in apprenticeships have occupations in high demand in the economy. In this sense, VET systems that give students the possibility to learn in the workplace seem to be more effective in allowing graduates—at least initially—to access the jobs that the economy is creating. VET systems that give a larger role to classroom-based learning may not be as effective in that dimension.

**FIGURE 4.16. Difference in task intensity trends by share of work-based learning in VET, age 30-34**




Source: authors' estimates using EU-LFS.

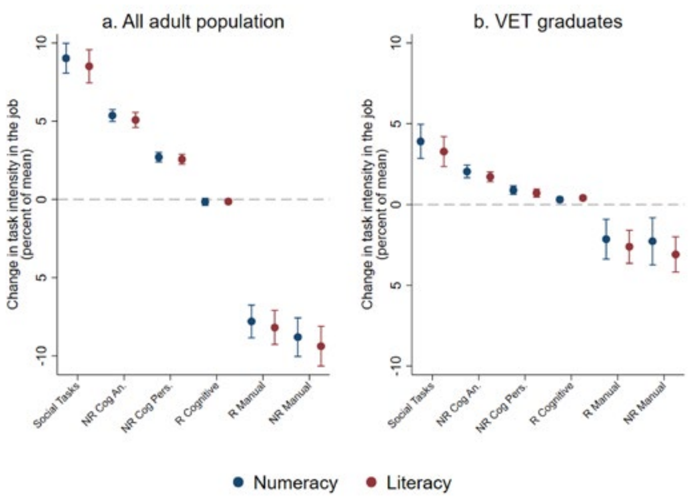
Note: this figure plots the difference between the change in task intensity over the period 2004–19 for overall employment and the change in task intensity over the period 2004–2019 for VET graduates' employment, restricting the sample to individuals aged 30 to 34. The change over the period 2004–2019 is expressed with respect to an index of task intensity with a value of 1 for 2004 and is calculated using EU-LFS microdata. A negative value shows that the change for overall employment is higher than for VET graduates' employment, whereas a positive value shows the opposite. The values are calculated for each country in the sample separately, and then are aggregated (as a simple average) into three groups based on the average share of work-based learning in VET students' curriculum: i) low, where the average VET has a share of work-based learning below 33 percent of the curriculum, ii) mid, where the average VET has a share of work-based learning between 33 percent and 50 percent of the curriculum; iii) high, where the average VET has a share of work-based learning above 50 percent of the curriculum. NR Cog An. = Nonroutine Cognitive Analytical; NR Cog. Pers. = Nonroutine Cognitive Personal; R Cognitive = Routine Cognitive; R Manual = Routine Manual; NR Manual = Nonroutine Manua

### 4.5.2 *The importance of foundational skills: literacy and numeracy*

Individuals with higher numeracy and literacy scores in the PIAAC survey are employed in jobs with higher nonroutine cognitive task intensity, a higher use of social skills, and a lower manual task intensity (Figure 4.17, panel a). A one standard deviation increase in the numeracy score is associated with an increase in social task intensity of about 9 percent of the mean, an increase in nonroutine cognitive analytical task intensity in the job of about 5.4 percent of the mean, an increase in nonroutine cognitive personal task intensity of about 2.7 percent of the mean.

The effect on routine cognitive task intensity is close to zero but there is also a strong, negative association with the intensity of manual tasks—both routine and nonroutine—of a magnitude exceeding 7 percent of the mean. A similar pattern is seen with the association between the literacy score and the task content of jobs: a higher proficiency in literacy is associated with a higher intensity of nonroutine cognitive tasks in the job and particularly social tasks, and a lower intensity of manual tasks. The same pattern emerges when focusing on VET graduates: although the magnitudes are smaller, a higher numeracy or literacy is associated with a higher intensity in social and nonroutine cognitive tasks, and a lower intensity in manual tasks. Cognitive skills are thus a fundamental correlate to the employment in jobs intensive in the tasks becoming more demanded in the labor market. This applies to all the population—VET graduates as well as general secondary and tertiary graduates.

**FIGURE 4.17. Change in task intensity in the job associated to a standard deviation increase in skill proficiency**



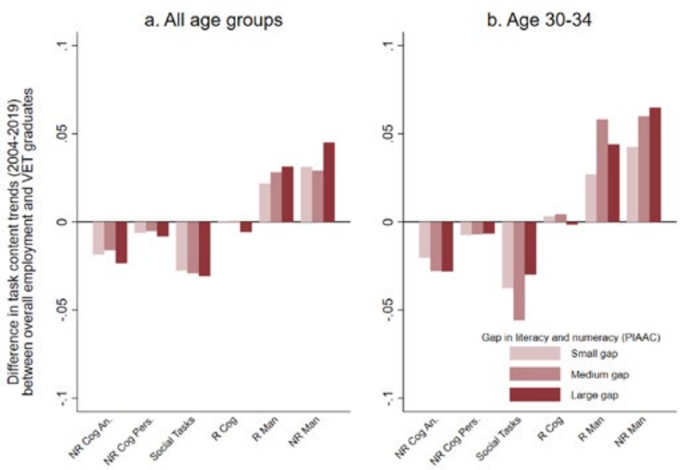

Note: this graph plots the change in the task intensity in the job (expressed as percent of the mean intensity) for a one standard deviation increase in the numeracy and literacy scores in the PIAAC survey. Panel a corresponds to all the adult population, whereas panel b corresponds only to VET graduates. Each value is calculated from a regression of task intensity on skill proficiency including country fixed effects. The sample for panel a includes 43,907 individuals from 12 EU countries in the PIAAC survey, whereas the sample for panel b includes 13,165 individuals in the same sample of countries. NR Cog An. = Nonroutine Cognitive Analytical; NR Cog. Pers. = Nonroutine Cognitive Personal; R Cognitive = Routine Cognitive; R Manual = Routine Manual; NR Manual = Nonroutine Manual

Source: authors' estimates using PIAAC.

The divergence between VET graduates' jobs and overall employment is largest in those tasks used in the job by individuals with better foundational skill proficiency, such as social tasks and nonroutine cognitive tasks (as shown earlier in Figure 4.9). It is worthwhile exploring whether the country-level divergence in the task content of VET graduates' job is associated with the gap in cognitive foundational skills (numeracy and literacy) between VET graduates and the average adult population. To this purpose we will use data from the PIAAC survey, classifying countries into three groups based on the gap (small, medium, and large) in the numeracy and literacy scores between VET graduates and the average adult population in the survey. The patterns of job task divergence are plotted in Figure 4.18. In countries where the gap in literacy and numeracy was large, the divergence in manual task intensity between VET graduates' jobs and overall employment was largest, both when looking at all age groups (panel a) or only those age 30 to 34 (panel b). When looking at cognitive and social tasks, the divergence is smallest for countries where the gap in literacy and numeracy is smaller, whereas it is larger for countries where the gap is medium or large. This evidence suggests that gaps in cognitive foundational skills could play a role in the divergence of labor market trends between VET graduates and overall employment.

*"The evidence suggests that gaps in cognitive foundational skills could play a role in explaining the divergence of labor market trends between VET graduates and overall employment"*

**FIGURE 4.18.** **Difference in task intensity trends by gap in literacy and numeracy between VET and average adult population**




Source: authors' estimates using EU-LFS.

Note: this figure plots the difference between the change in task intensity over the period 2004–19 for overall employment and the change in task intensity over the period 2004–19 for VET graduates' employment (panel a corresponds to all employees aged 18–65, panel b corresponds to employees age 30 to 34). The change over the period 2004–19 is expressed respect to an index of task intensity with a value of 1 for 2004 and is calculated using EU-LFS microdata. A negative value shows that the change for overall employment is higher than for VET graduates' employment, whereas a positive value shows the opposite. The values are calculated for each country in the sample separately, and then are aggregated (as a simple average) into three groups based on the average gap in literacy and numeracy scores between VET graduates and the average adult population at the country level in PIAAC: i) small, where the average gap is less than five points, ii) medium, where the average gap is between 5 and 10 points; iii) large, where the average gap is larger than 10 points. The country sample is restricted to those countries where there is a sufficient sample of VET graduates in PIAAC.

### 4.5.3 *The importance of foundational skills: socioemotional skills*

The tasks that imply the use of social skills (namely, the ability to work with others) have increased the most in the EU during the last decade and a half (as shown earlier in Figure 4.10). This coincides with a similar trend also observed in the United States (Deming, 2017). The reasons for this increase are linked to the complementarity of these tasks to the current wave of technological change—because both the exposure to operational and informational technologies are correlated with the increase in using these tasks (as shown earlier in Figure 4.11). This is also supported by case studies of ICT implementation that show it leads to reallocation of workers into flexible, team-based settings that facilitate adaptive responses and group problem solving (Autor et al., 2002; Bresnahan et al., 2002; Bartel et al., 2007). Social skills, in turn, improve team performance (Weidmann and Deming 2021).

With the increased demand for social skills, there is evidence from the United States that wage and employment returns to social skills have also increased. Deming (2017) finds that, between the 1980s and the early 2010s, the association between social skills and the probability of full-time work has increased more than fourfold, whereas the association with wage gains has almost doubled. Experimental evidence shows that better social skills are associated with better labor market outcomes (Algan et al., 2022).

Different from numeracy and literacy, for which the technology to teach and develop them is understood, there is still no consensus on how to develop social skills (Deming, 2022). However, training programs implemented by VET institutions seem to be able to improve individuals' soft skills. Acevedo et al. (2020) analyze a soft skills training program implemented by VET institutions in the Dominican Republic and find that the training improved the soft skills of female participants even three and a half years after program completion—particularly in perseverance, organization, and social skills—although not necessarily for men. In the short run, soft skill training successfully increased employment in higher quality jobs for women but not for men. A similar program carried out in Colombia was evaluated by Barrera-Osorio et al. (2023), who find that individuals that received training emphasizing social skills maintained a job for a longer time than individuals that received a training emphasizing technical skills. These findings apply for both men and women. These two studies are, however, among the very few that look into the possibility of developing social skills among adults. Algan et al. (2022) analyze a school-based intervention for children aged 7–9 and show that social skills can be improved earlier in life.

Deming and Noray (2020) analyze the earning dynamics of college graduates and find those majoring in technology-intensive subjects such as computer science, engineering, and business tend to have an early earnings premium in their career that dissipates quickly over time, thus lowering their return to experience and flattening their age-earning profile—just like the analysis for VET graduates using PIAAC data showed before (see Figure 4.5 in Section 4.3 above). The main reason for this is that the jobs in which these graduates are employed at the beginnings of their careers are also jobs that have a fast rate of skill change, that is, where the skill demands of the job change quickly, making any given job-specific skill (say, the ability to use of a particular type of software) obsolete quickly. These findings are similar to those of Cnossen et al. (2022), who find that VET degrees with a high share of technical content are associated with lower earnings. Deming and Noray show that how college graduates with these field specializations react to the quick obsolescence of their technical skills is by moving to occupations where these skills are less important—namely, managerial occupations. Because performance in managerial jobs is correlated with better soft skills, it is crucial for individuals with a technical educational background to learn soft skills to ensure better labor market prospects in the long term. The study by Cnossen, Piracha and Tchuente shows that VET graduates in the Netherlands from degrees with a high curriculum content of social skills have earnings that increase over time, as they gradually sort into industries which reward these skills as they go along in their professional life. The analysis of Langer and Wiederhold (2023) also points to the increasing returns of social skills taught in vocational training, particularly in the last decades. Preliminary evidence from a survey among upper-secondary students in Greece shows that vocational education does not seem to help the development of soft skills (see Box 4.3), potentially putting vocational track students at a disadvantage in a labor market that increasingly values social skills.

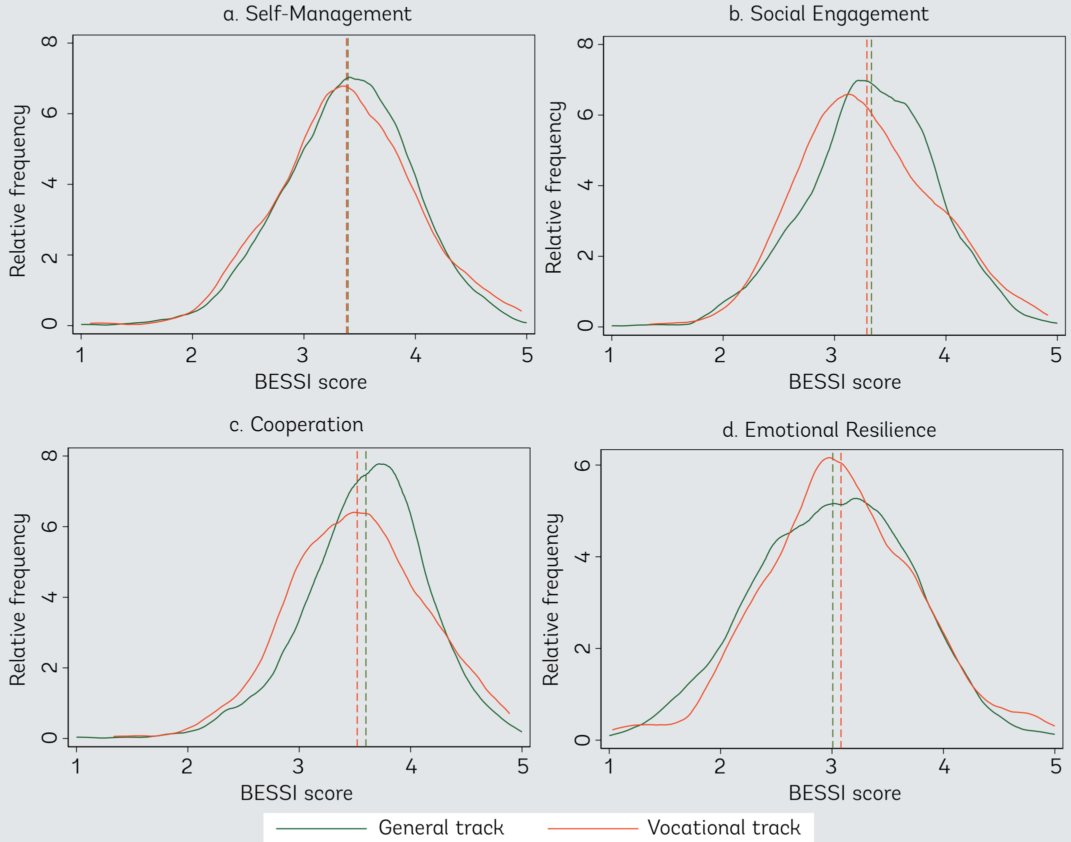
**BOX 4.3. Soft skills among upper-secondary vocational students in Greece**

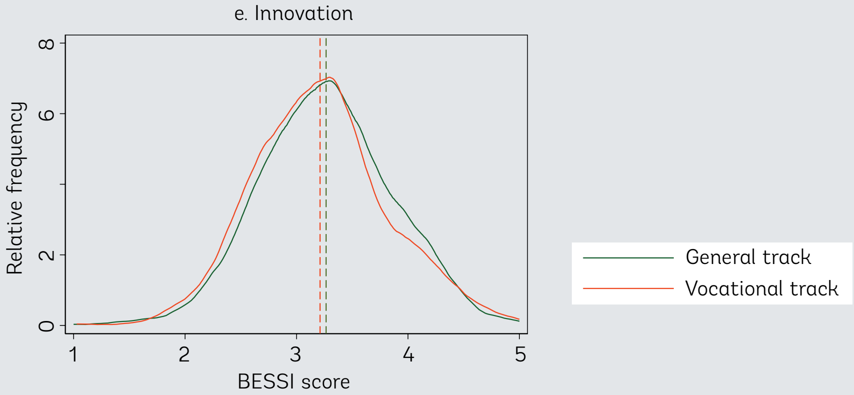
Greek employers across sectors increasingly value soft skills (EOPPEP, 2021) including teamwork, interpersonal and communication skills. Yet VET programs—which are designed specifically to increase graduates' employability—rarely target such skills. Students are not adequately equipped with other than professional skills, as generic skills—such as literacy, working with numbers, teamwork, computer literacy, and communication skills—are neither part of the course content nor included in extra-curricular activities of VET structures. A recent survey, covering over 400 employers and around 4,800 VET graduates, was conducted by the National Organization for the Certification of Qualifications and Vocational Guidance (EOPPEP), to monitor the progress of vocational education graduates in the Greek labor market. This study indicated that the highest skills mismatch is in soft rather than in professional and technical skills (EOPPEP, 2021). However, little is known about the actual proficiency in soft skills among vocational graduates.

To fill this knowledge gap, as part of this report, the World Bank and the Foundation for Economic and Industrial Research (IOBE) carried out a survey to assess the proficiency in socioemotional skills among 1,400 upper-secondary students in vocational and general tracks in the metropolitan areas of Athens and Thessaloniki during March–May 2023 (IOBE, 2023). The survey relied on a Greek adaptation of the Behavioral, Emotional, and Social Skills Inventory (BESSI) instrument created by Soto et al. (2022). By way of a self-assessment, this instrument allows to measure the proficiency in five social, emotional, and behavioral skill domains: self-management, social engagement, cooperation, emotional resilience, and innovation.

Preliminary results of the survey show that vocational and general students have a similar self-assessed proficiency in self-management (Figure B4.3.1, panel a) and social engagement (Figure B4.3.1, panel b), whereas statistically significant differences exist in cooperation (Figure B4.3.1, panel c), emotional resilience (Figure B4.3.1, panel d), and innovation (Figure B4.3.1, panel e). In particular, cooperation and innovation among vocational track students seems to be lower than among general track students, whereas emotional resilience seems to be higher.

**FIGURE B4.3.1. Self-assessed proficiency in social, emotional, and behavioral skills among upper-secondary students in Greece**






Source: World Bank-IOBE survey on socioemotional skills in upper-secondary students in Greece. Preliminary data.

Note: this figure plots the distribution of the BESSI score (on a 1–5 scale, where 1 indicates lowest proficiency and 5 indicates highest proficiency) in five domains for general track students (green line) and vocational track students (orange line). The vertical dashed lines indicate the mean score for the general track (green) and for the vocational track (orange). The asterisks indicate whether the difference in the means is statistically significant (* at the 10 percent level, ** at the 5 percent level, *** at the 1 percent level). The preliminary data used for this analysis includes 1,410 students (799 students in the general track and 611 students in the vocational track) from the first and third grade of upper secondary (781 students in the first grade and 632 students in the third grade).

Part of these differences could be explained by the gender composition of the students in each track—girls make up 48 percent of the students in the general track and 37 percent of the students in the vocational track—and differences in their social backgrounds—vocational track students tend to have lower socioeconomic status than students in the general track. When controlling for these factors, the average differences between both tracks disappear in most domains.

The survey results show, however, an important difference between the vocational and general track: in the vocational track, the soft skill scores are not different between students in the first and the last year of upper secondary; in the general track, the scores in most domains are higher in the last year than in the first one. These patterns suggest that a general track education seems to help the development of soft skills among students, whereas a vocational track education has no effect.

## 4.6 The long-term effects of school track choice: evidence from the academic literature

As seen in the previous sections of this chapter, the choice of school track—either general/academic or vocational/technical—can be associated with significant differences in labor market outcomes. However, differences in school track can simply reflect differences in socioeconomic background or cognitive abilities, which may be ultimately the driving factors of labor market outcomes. Several studies have aimed at understanding whether school track per se has a causal effect on earnings and employment in the long term. Because of the method used, which requires controlling for many factors that affect school choice, these studies focus on specific country settings and cannot explain differences across countries.

A first set of studies looks at the long-term impact of school choice on marginal students, that is, students on the margins or indifferent between going to the general or the vocational tracks. Dustmann et al. (2017) look at the case of Germany and study the long-term education and labor market outcomes of students on the margin between general and vocational tracks because of their date of birth. Students born before the cutoff date for school enrollment reach the end of primary school at an earlier age than students born right after the cutoff date. This, in turn, translates into a lower probability of attending a general track school in middle school, and a higher probability of attending a vocational track. Their analysis shows that, for these students, the school track choice does not have a long-term impact on their educational attainment and labor market outcomes. They explain this null effect on the school system in Germany being flexible enough to allow for changes in track choice during middle and high school, and that students who are "misallocated" at the beginning of middle school can change tracks later on. Birkelund and van de Werfhorst (2022) look at the case of Denmark and study the effect of going into a vocational track for those students whose choice of track responds to their peers' track choice. In particular, they study the effect on two types of marginal students—those on the margin between an academic and a vocational track, and those on the margin between a vocational track and dropping out of school. They find that, for the first set of students, choosing an academic track over a vocational track does not lead to higher earnings or higher employment rates at age 40, but only affects the occupation—less intensive in manual work than for vocational track students. For the second set of students, they find that choosing a vocational track over dropping out of school leads to higher earnings and higher employment rates at age 40. Matthewes and Ventura (2022) look at the same two choices—between academic and vocational, and between vocational and drop out—in England but using a different margin—that of geographical distance. Differently to the study in Denmark, they find that enrolling in a vocational track school (as opposed to an academic track school) substantially decreases earnings at age 30, whereas for those that enroll in a vocational track instead of dropping out the impact on earnings is positive but small. Silliman and Virtanen (2022) analyze the pool of students in the margin between general and vocational tracks in Finland (where tracking occurs at a late stage, at age 16) and find that those who end up in the vocational track because of oversubscription of their preferred choice see a positive difference in earnings but no difference in employment at least until age 37 vis-à-vis those students of the same pool who end up in the general track. The authors claim that one reason for the lack of a negative effect of vocational track on earnings is marginal vocational track students enrolling in higher education at the same rate as marginal general track students, something that is possible in the Finnish education system (which allows vocational graduates to go into university) Last, Borghans et al. (2019) look at school track choice in Netherlands for students who are around the cutoff score of the achievement test that places students in different tracks. In their setting there are four tracks, which are ordered from a "lowest" vocational track to a "highest" academic track (pre-university) with two middle tracks (lower general and higher general) in between. They find that students that end up in a higher track (either at the lowest end of the track choice, between vocational and lower general, or at the top end of the track choice, between higher general and pre-university) have higher earnings in the long run, whereas students that end up in the higher track in the middle rank of track choices (that is, they attend the higher general instead of the lower general track) have lower earnings in the long run.

A second set of studies look at inframarginal students, that is, students who a priori are set to choose a specific track in a given educational system rather than being indifferent between them. These studies rely mostly on institutional differences in the educational system as the source of exogenous variation to identify the long-term effects of school track choice. Malamud and Pop-Eleches (2010) look at the case of Romania, where an educational reform in 1973 delayed entrance to vocational schools and extended general education. They find that, in the long run, men with more years of general education than vocational because of the reform were less likely to work in manual or craft-related occupations, but had similar levels of labor market participation and earnings (similar results hold for women, who were otherwise not affected substantially by the reform). Their analysis still does not include information on the labor market outcomes of the first fifteen years of professional life. Zilic (2018) analyzes the long-term effects (over thirty years later) of a reform in 1975–78 in Croatia (which was at the time part of socialist Yugoslavia) that extended the general curriculum for students attending vocational training. He finds no long-term effects on labor market outcomes but does find heterogeneous effects across genders in terms of educational attainment: men in vocational training that received more general education saw a reduced educational attainment in the long term, whereas for women there were no effects. The 1999 educational reform in Poland, which delayed tracking by a year, was shown to improve student academic performance—as measured by PISA scores—particularly among vocational students (Jacubowski et al., 2016)and increased employment probability by 3 percent and earnings by 4–5 percent on average (Drucker et al., 2022). A similar reform that delayed the separation into vocational and general education by two years in France is studied by Canaan (2020). She finds that the reform raised individuals' level of education and increased their wages by 6 percent at ages 40 to 45, and that these effects are concentrated among men and individuals from low socioeconomic backgrounds. Guyon et al. (2012) look at the effect of a reform in Northern Ireland's educational system that increased the number of students that could attend the secondary school track that leads to university (grammar schools). By comparing cohorts of students affected and not affected by this reform, they identify the effect of attending an academic track school for students who would previously could not go to one because of their academic achievement. They find that, for these students, attending an academic track increases their educational attainment in the long run. Matthewes (2021) exploits institutional differences across German states to investigate the effects of going into a single, comprehensive non-academic track vs. going into an intermediate or a lower non-academic track—the former providing further access to the academic track, and the latter only providing access to the intermediate, non-academic track. He finds that students with low achievement in primary school have a higher achievement later in their education when they go to a single, comprehensive track that when their placed into a lower track. Higher achieving students are not affected by attending a single, comprehensive track instead of a differentiated one.

***"The literature shows that, in most contexts, attending an academic track school may improve educational achievement and long-term labor market outcomes for those students whose ability would have otherwise placed them in a vocational track"***

Last, it is worth mentioning the study of Golsteyn and Stenberg (2017), who look at the lifetime earnings and employment profile of vocational and general track graduates in Sweden. Although their study is descriptive, their correlational analysis controls for academic achievement and family background and follows individuals over more than 30 years after finishing high school. It shows that graduates from vocational tracks have higher earnings than general track graduates at the beginning of the professional life but lower earnings later in time, and that this cannot be easily dismissed on the grounds of endogeneity because this would require confounding factors to generate bias in different directions over time.

Overall, the literature shows that, in most contexts, attending an academic track school may improve educational achievement and long-term labor market outcomes for those students whose ability would have otherwise placed them in a vocational track. For students who are marginally indifferent between tracks because of factors not related to their ability (such as geography, date of birth, slot availability, or social circle), the difference between attending an academic track school and a vocational one is not clear because some factors are associated with a positive difference and others with a non-significant or negative one. In this sense, the differences in labor market outcomes between general and academic track graduates cannot be fully explained by selection into tracks on the basis of ability but, rather, they may be partly explained by the school tracks themselves.

## 4.7 Summary

VET systems are critical for productivity and inclusion in Europe. Almost half of the students enrolled in upper secondary in EU member states attend a VET institution—most of these students have a disadvantaged background. European countries invest considerable resources in VET systems—more than for the average general track student—mostly under the assumption that these systems provide better labor market opportunities for their graduates.

The analysis presented in this chapter raises serious doubts about this assumption. VET graduates have an initial employment advantage vis-à-vis general track graduates who do not pursue further education, but they lose this advantage a few years after entering the labor market. The earning profile of VET graduates as they age is flatter than that of general secondary graduates, suggesting lower returns to experience, and leading overall to lower labor market earnings. The task content of VET graduates' jobs is not a complement to recent technological progress because they are more intensive in manual tasks and less intensive in social and nonroutine cognitive tasks. This lack of complementarity with technology is clear in the increased divergence of the task content of VET graduates' jobs from that of the rest of the economy: VET graduates' jobs have not changed in more than a decade and a half, whereas the rest of the employment—including general secondary graduates' jobs—has become more intensive in social and nonroutine cognitive tasks and less intensive in manual tasks.

The divergence in the patterns of task contents of VET graduate jobs with respect to the rest of the economy is smaller in countries where the VET system has a large share of work-based learning. But cognitive foundational skills explain also this divergence: the wider the gap in literacy and numeracy (and, possibly, in socioemotional skills) between VET graduates and the rest of the adults in the population, the larger the divergence in the task content of jobs.

Although the analysis in this chapter is based on conditional correlations, and the results cannot be interpreted as causally driven by enrollment into either general or vocational track, the emerging patterns coincide with the academic literature providing causal evidence on the effects of school track choice at the country level, which indicate that vocational track students do not necessarily have better long-term prospects than if they had attended a general or academic track school.

As in any regional analysis, the patterns found at the aggregate level may not represent specific country contexts. VET systems across and within countries are heterogeneous, and in some cases their performance may be better than in others. However, the regional patterns are indicative of general trends and point to the dimensions where policy reforms are needed.

# CHAPTER 5 Policy Recommendations

*"The best way to predict the future is to invent it"*

Alan Kay

Technological advances have constantly disrupted the economy since the industrial revolution. With every advance, old methods are replaced by new and better ways of doing things, resulting in ***creative destruction*** and economic growth. However, the transition from the old to the new state of the economy inevitably creates winners and losers, affecting how income is distributed between labor and capital, across different regions, and among workers with varying skills. The distributional impacts of technology can cause anxiety among those who are likely to be negatively affected. This report aims to enhance our comprehension of the distributional effects of technological progress by identifying how it affects firms' productivity, market concentration, regional disparities, and differences in labor market outcomes among workers with varying education levels.

This report brings together two areas of research that rarely intersect: the analysis of the effect of technology on firm productivity and the demand for different skills, and the influence of education systems on the supply of skills needed in the technological transition. By combining these fields, we can pinpoint the crucial role that human capital plays in technology adoption and the significant impact that technology has on rendering specific skills obsolete or in demand.

This report addresses two specific challenges brought about by technological progress in the EU:

1. *Market concentration*: creative destruction enhances a company's productivity and market share, paving the way for further technological advancements. Unfortunately, this process often leaves small businesses in less developed areas behind and can increase market concentration. Workers receive a smaller portion of the national income when a few large companies control a larger market share. Those who own capital in those large firms profit from this equilibrium, but it may not benefit the average worker. In addition, technology adoption usually concentrates in better-off areas with better conditions. This results in a disparity in income distribution, leaving less developed regions behind.

2. *Income dispersion*: Technology affects firms by changing their organization, workers' tasks, and the workforce's required skills. Individuals with more education have skills that complement technological advancements, enabling them to benefit from the changes. However, those with less education do not have this advantage, increasing income disparities between people with different education levels. The novel results in this report show that, through the channels described above, technology stimulates economic growth in the EU but at the cost of more income disparities.

Relying on market forces to drive technology adoption and addressing its challenges through redistribution policies like taxes and transfers may seem theoretically sound but is ultimately unrealistic and naive. To achieve a fair and inclusive process of technological change, policies must ensure an equal distribution of technology's benefits. Simply relying on ex post redistribution will not be enough to overcome the challenges posed by the latest technological innovations. Economic systems that provide equal opportunities for all individuals to participate in and benefit from markets—what Acemoglu and Robinson (2012) define as ***inclusive institutions***—create a virtuous cycle of technology, shared prosperity, and innovation. The main point conveyed in this report is the pressing necessity to formulate and execute supplementary policies that guarantee widespread and equitable advantages from technological advancements.

In this section, we present policy recommendations to promote inclusive institutions and optimize technology's positive impact on human wellbeing. We categorize these recommendations into two groups: those that directly stem from the empirical findings of this report and those that are informed by other relevant studies but still pertain to the two challenges mentioned above.

## Promoting technology adoption among small and younger firms with a focus on lagging regions

Our analysis, based on data from Italy's firms, reveals that larger and more productive companies in more advanced areas with available financial resources and human capital are more likely to adopt new technologies. This adoption of technology increases the productivity and size of the firms, and this can exacerbate market concentration. To prevent further market concentration and reduce the impact of technology on regional gaps, both the EU and governments of EU member states could introduce policies that promote the adoption of new technologies among small businesses, with a special focus on those in lagging regions. We identify four main policy recommendations.

***"Policies should not just promote "technology drops" but must address the deficiency of complementary inputs, specifically managerial capabilities and organizational structure."***

First, policies must address the deficiency of complementary inputs, specifically managerial capabilities and organizational structure. A weakness prevalent especially among smaller enterprises, many of which tend to be family instead than professionally managed (Iacovone et al, 2019; Bloom et al 2021). An emerging literature pioneered by Bloom and Van Reenen (2007) has pointed to the importance of managerial and organizational capabilities as crucial conditions for taking advantage of the opportunities offered by modern information technologies (Bloom, Sadun and Van Reenen 2012). In line with this idea, Brynjolfsson et al. (2021) have recently shown how intangible investments (for example, in managerial capacities and workers' skills) play a crucial role in enabling the benefits from general-purpose technologies such as IT. The consequent policy recommendation is that policies should not just promote "technology drops" but create incentives for making these complementary investments, such as improving managerial practices and organization. More at the regional level, our analysis points to the importance of external factors as key drivers of technology adoption. Based on the Italian case study, we find how adoption is much weaker in lagging regions, regions characterized by deficiencies in those key external factors that drive technology adoption: access to finance, availability of skilled workers, enabling business environments. The policy agenda to promote technology adoption, especially in lagging regions, needs to focus on addressing these enabling and complementary factors.

***"Market fragmentation in Europe presents a substantial barrier, especially for SMEs, and requires renewed attention"***

Second, market fragmentation in Europe presents a substantial barrier, especially for SMEs, and requires renewed attention. Despite strides toward market integration, the European market remains notably fragmented, particularly in the service sectors upon which many manufacturing businesses are dependent. (For example, the retail sector is key for firms producing for final consumers.) This fragmentation is due to a mix of regulatory and non-regulatory hurdles. As suggested by the recent European Single Digital Market report, Europe's critical agenda is enhancing integration to ensure a fully operational single market. This integration is especially important for SMEs because their smaller scale makes the fixed costs of transacting across borders especially onerous. The key message is that the complexities and uncertainties arising from disparate market rules, regulatory barriers, and standards across countries can deter SMEs from embracing new technologies.

Third, EU governments need to carefully promote competition and market contestability. The new digital economy, particularly with the advent of advanced AI, requires a renewed focus on antitrust policy. As discussed by Goolsbee (2018), the concentration of market power in technology-driven industries can resemble the consolidation of industries during the original Gilded Age. To prevent the emergence of monopolistic or highly concentrated markets, policymakers should prioritize competition policy interventions. First, policymakers need to carefully assess the impact of fixed costs, economies of scale, and network externalities on market concentration. Although these factors can lead to winner-takes-all outcomes, it is crucial to identify potential anticompetitive behavior and make sure market power does not hinder competition or innovation. This initiative may involve targeted regulations or guidelines to promote fair competition and market contestability. Second, maintaining a competitive landscape in the modern information economy, especially in the context of the quick emergence of advanced AI, requires ongoing scrutiny of dominant players and potential antitrust violations. Policymakers should actively monitor mergers and acquisitions, ensuring they do not result in monopolistic control or anticompetitive practices. Additionally, competition authorities should have the resources and expertise to analyze complex information and technology-driven markets effectively.

A complement to the focus on competition and contestability is a novel approach to safeguarding data rights and consumers' privacy. Because the information economy relies heavily on data, policymakers must address concerns surrounding access and of personal information. In line with the ideas proposed by Goolsbee (2019), we suggest that it is crucial to establish regulations that restrict certain behaviors and practices driven by asymmetric market power. First, policymakers should consider implementing restrictions on access to consumers' information and determine what are acceptable ways in which companies can collect, store, and use customer information by focusing on keeping an even playing field between larger companies, with the capacity to generate and obtain large quantities of data on consumers and demand, and smaller firms or startups that may lack these capacities and be unable to compete. Clear guidelines are needed to define the ownership and sharing of consumers' data while safeguarding privacy. Second, policymakers should explore policies against various forms of price discrimination. Discriminatory pricing practices, enabled by big data processing and AI algorithms, can lead to market distortions and unfair treatment of consumers, plus exacerbate market power asymmetries. Regulators should develop frameworks to make sure price discrimination does not result in discriminatory outcomes or hinder competition.

Last, there is a pressing need for improved measurement of technology adoption. The status quo is highly unsatisfactory because current statistical information available (the Survey for ICT Usage among Enterprises) treats firms as black boxes and provides generic information on technology adoption at the extensive margin (for example, whether a firm adopts a certain technology or not) but does not provide information on how this technology is used (for example, technology for what? For managing customers or suppliers? Or internal processes?) and does not tell us the intensity with which this technology is used. The World Bank's Technology Adoption Survey (TAS) could serve as an instrumental tool in this context. As implemented already in two EU member states (Poland and Croatia), the TAS offers detailed firm-level data on the extent of technology adoption and usage, thereby facilitating the creation of a comparable measure of technology sophistication. The survey identifies the purpose of technologies adopted by a firm, measures the technologies the firm adopted and uses most frequently, and can be aggregated by country, region, sector, or specific business function. The TAS builds on global best practices in terms of surveys to measure technology in a granular way such as the Advanced Technologies Adoption and Use by Firms implemented by the US Census Bureau.[57],[58]

## Adapting technology to meet the needs of society

Our research indicates that companies in Europe that implemented technology have increased the demand for nonroutine cognitive tasks while decreasing the demand for routine and manual tasks. Highly educated employees have reaped the benefits of technological adoption, as their skill sets enable them to perform nonroutine cognitive tasks effectively. However, workers with VET degrees have not seen significant changes in their job tasks in the past two decades. Although we have treated technological innovations as exogenous in this report, they are actually shaped by context, incentives, and government intervention. Therefore, policymakers can shape technological progress to complement, rather than replace, workers with low levels of education (including VET graduates).

***"To promote job creation and good employment opportunities, it is crucial to remove disincentives that prioritize capital investment over investment in workers."***

To promote job creation and good employment opportunities, it is crucial to remove disincentives that prioritize capital investment over investment in workers. Several countries in the EU have tax policies that unintentionally subsidize capital and investment while placing a burden on employment. These policies make automation more lucrative, leading to increased use of machines and research. By readjusting tax incentives to favor labor-intensive investment, we can create a more conducive environment for quality employment and job growth.

In addition, it is important for policies to focus on redirecting technological advancements toward activities that integrate labor back into the production process. Autor (2022) highlights the significance of public policies in shaping innovation and technology to complement the skills of the workforce. Countries can make sure their innovation systems benefit a wider range of individuals and regions by increasing and targeting investments in research and development (R&D) and reviving their programs (Gruber & Johnson, 2019). Furthermore, aligning tax policies with the interests of workers and addressing social challenges can further enhance the impact of innovation on job creation and inclusive growth.

The impact of technology on markets, firms, and society is greatly shaped by the policies and institutions in place. According to Autor et. al. (2022c), the adverse effects of technological change on labor markets in Europe are less severe compared to those in the United States, partly due to their different labor market policies and institutions. Labor unions and stricter minimum wage requirements give workers more bargaining power and help moderate the negative effects of technology on labor markets.[59] Additionally, social insurance and assistance programs for unemployed workers can aid in navigating job transitions and mitigate the negative effects of technology adoption. Tax systems also play a crucial role in driving technological development and its impact on society, as they provide incentives for labor and capital.

57 More information on this survey is provided online here.
58 For more details see World Bank Group (2022).
59 Focusing on workers that mainly perform routine tasks, Parolin (2020) shows that union membership affects the likelihood that a routine worker (1) remains employed in a routine job for a longer duration of time, (2) avoids unemployment, and (3) achieves higher earnings over time relative to non-unionized routine workers.

## Youth must have the skills to adapt and reinvent themselves

Based on our findings, individuals with a VET degree are more likely to work in companies that need updating, are relatively old, and are unproductive. The task content of the VET graduates' jobs has remained essentially unchanged over the past two decades and involves many manual tasks susceptible to being replaced by automation. Moreover, only a small fraction of VET graduates are employed in environmentally sustainable roles, whereas a significant percentage work in industries with high CO2 emissions, leaving them vulnerable to job loss during the green transition.

Modernizing VET systems is essential to promote Europe's growth and inclusion agendas. Half of the future workforce in Europe is enrolled in VET schools, a group mostly comprising disadvantaged youth with inadequate foundational skills (numeracy, literacy, and socioemotional skills). These limitations restrict their capacity to perform nonroutine cognitive tasks, ultimately reducing their potential gains from technological advancements. It is critical that European education systems provide all graduates, regardless of their chosen path, with fundamental skills. This can be done by implementing a basic core curriculum shared among all upper-secondary education tracks, including VET programs. The practice of tracking, which involves placing students into either VET or general secondary school based on an examination, should be reassessed. Studies show that relaxing the tracking restriction and increasing the number of students pursuing the academic track could have positive effects on their education and employment prospects.

According to our research, the cost of producing a VET graduate is 15 percent higher than that of a general secondary education graduate. However, VET graduates only have an advantage in employment for the first 5–7 years after entering the workforce. Our findings also reveal that the task content of jobs held by VET graduates has remained largely unchanged over the past 20 years, which can be attributed in part to lower levels of numeracy and literacy among VET graduates.

***"VET systems face the challenge of preparing students with relevant professional skills that will remain useful in a fast-changing job market."***

In today's job market, the importance of foundational skills cannot be overstated. With rapid advancements in technology and increased global trade, job turnover is high, and job tenure is low. Staying in the same job for an extended period is increasingly rare. As a result, VET systems face the challenge of preparing students with relevant professional skills that will remain useful in a fast-changing job market. Balancing the supply and demand of skills is challenging, and predicting the skills that will be in demand in the future is nearly impossible.

Improving foundational skills can be expensive, but effective policies can enhance cognitive foundational skills like numeracy and literacy. Research shows that smaller class sizes, better school facilities, and more instructional time have reliable impacts on cognitive skill development (Deming, 2022). The most effective inputs include high-dosage tutoring, extra instructional time, personalized instruction, teaching to the right level, and structured pedagogy for teachers). These interventions are cost-effective and do not require reinventing the learning process (Akyeampong et al., 2023). However, it is crucial for any intervention aiming to improve foundational skills to have coherence in approach among different actors and policies in the educational system (World Bank, 2018).

Having foundational skills is essential for continuing to learn, adapting to changes in the job market, and reinventing oneself. Although general secondary graduates are in a better position than VET graduates, low foundational skills are still a relevant challenge in many EU member states, especially lagging ones. Although it is important to equip workers with professional competencies demanded by the labor market through ALMPs, the absence of foundational skills may limit their benefits. Research shows that most ALMPs have a modest effect on labor market outcomes (see Box 5.1); however, making sure all beneficiaries have minimum foundational skills could increase the effectiveness of ALMPs. Additionally, if foundational skills are adequately taught in collaboration with business associations and prospective employers, a shift away from classroom-based learning toward work-based learning could help VET graduates follow labor market demand more closely. Foundational skills are also necessary for lifelong learning and upskilling, enabling workers to adapt to rapidly evolving technologies and changing job requirements.

**BOX 5.1. Policies beyond formal education: ALMPs**

ALMPs refer to a set of public policies with the common goal of enhancing the labor market participation and opportunities of beneficiaries (that is, their employment or earnings). ALMPs can be classified into three types according to the side of the labor market which their interventions address: i) labor supply side interventions (for example, skills training); ii) labor demand-side interventions (for example, wage subsidies); iii) labor market intermediation interventions (for example employment services).

Among supply-side interventions, one of the most popular are short-term vocational/professional skills trainings. These vocational trainings are often delivered in combination with non-vocational trainings (for example, soft skills). These programs take place outside the educational system, usually after completion (or drop-out) of secondary school. Common interventions within these programs are subsidized classroom-based training and placement in workplace-based training (including firm-based training and internships). A systematic literature review and meta-analysis by Kemper et al. (2022) covering 89 studies globally finds that youth-targeted vocational training tends to have an economically meaningful impact on labor market outcomes. The size of the impact does not depend on country income level, implying that well-designed interventions can work irrespective of labor market challenges. Another qualitative literature review of 28 randomized evaluations of apprenticeships and skills training programs in LMIC reports overall mixed impacts (JPAL 2023). The reviewers find that programs which included practical experience, soft skills training, and job referrals increased hours worked and earnings. Card et al. (2018) find that training programs tend to have larger, positive average effects in the medium and longer run, whereas they may have small or negative effects in the short run.

Another common type of supply-side interventions is entrepreneurship promotion programs. These programs typically provide nascent or recent entrepreneurs support through business skill training, business advice, access to finance, and access to markets or value chains. A literature review and meta-analysis by McKenzie (2017) finds that the standard entrepreneurship training programs yield, on average, only modest increases in profits and sales.

Labor market intermediation interventions aim to improve the match between labor supply and demand. The most common labor market intermediation interventions are employment service programs. Evidence reviews suggest that employment services tend to have stronger effects in the short run (Vooren et al., 2019, ILO & World Bank, 2023). Programs that emphasize "work first" by providing incentives to enter work quickly tend to have a similar effect both in the short and in the long run (Card et al., 2018). Caliendo and Schmidl (2016) find that job search assistance programs show a similar effectiveness for youth as they do for the overall working population. However, Kluve et al. (2019) and ILO & World Bank (2023) find that impacts on youth labor market outcomes are rather small relative to other ALMPs. At the same time, employment services programs tend to be the least costly ALMPs (Levi Yeyati et al., 2019). This suggests that low-cost intermediation programs could be cost-effective, despite their small overall effects.

Among labor demand-side interventions, private sector employment and public sector employment incentives are the most common. Private sector employment incentives are typically provided as wage subsidies, paid to either the firm or the worker. Evidence reviews suggest that private sector employment programs have only a small effect on labor market outcomes in the short run, but the impact increases over time (Card et al., 2018, Vooren et al. 2019). A more positive assessment of subsidized employment is given in the meta-analysis by Levi Yeyati et al. (2019), who find that wage subsidies have the largest positive effect among 102 ALMP interventions analyzed.

Public sector employment programs (often called public works programs (PWPs)) are mostly short-term direct employment programs and sometimes longer-term employment guarantee programs. Evidence reviews suggest that public sector employment programs have the least positive impacts on labor market outcomes of participants relative to other ALMP. Vooren et al. (2019) find that PWPs only have a positive effect on labor market outcomes after 36 months. According to Card et al. (2018), PWPs are ineffective at all time horizons.

Overall, the evidence from impact evaluations suggests that ALMPs have moderate impacts on average (Kluve et al., 2019; Card et al., 2018). Comparing among the range of ALMPs, labor supply-side interventions seem to have the most positive effects (especially skills training programs) followed by private sector employment incentives. At the same time, these programs also tend to be the costliest on average (McKenzie, 2017; ILO & World Bank, 2023). Labor market intermediation interventions (for example, employment services) tend to have small or negligible effects, especially in the longer term. But they are also often less costly than other ALMPs. Public work programs seem to have a zero or negative impact on labor market outcomes and often comparatively high costs.

The evidence of ALMPs suggests that tailoring specific design elements to the context matters more than the type of ALMP (Kluve et al., 2019). Evidence suggests that multi-pronged programs, combining different intervention types, have a higher chance of success (Kluve et al., 2019). However, there is a lack of comparable rigorous cost-benefit studies that would allow for a comparison of cost-effectiveness across different types of ALMPs.

## The future holds many possibilities yet to be defined

Technology, much like the Roman god Janus, has two faces. One represents its endless ingenuity which has historically led to unprecedented levels of human wellbeing and opened up possibilities for our societies that were previously unthinkable. Technology expands our productive capabilities and generates new tasks and jobs. It can complement our abilities, enhance our capacities and overcome our human limitations. However, the other face of technology represents its destructive power, which can lead to the substitution of workers and the elimination of jobs, occupations, firms, or entire sectors.

**BOX 5.2. Promoting technology in an inclusive manner**

The choice that societies make determine crucially how technology is incorporated by firms and how it shapes society. One example of a country that has succeeded at achieving a virtuous cycle between technology, shared prosperity, and innovation is Estonia. Despite its size, Estonia has emerged as one of the most technologically advanced societies in the world by making significant progress in its levels of digital technology adoption. Estonia ranked first in 2021 and 2022 based on the Emerging Europe's IT Competitiveness Index[60] which ranks 23 countries across Central and Eastern Europe, and the Caucasus. Three key areas should be highlighted to understand the success of Estonia. First, its education system with a strong focus on foundational skills, math and science, which has led to a high and equitable performance based on the recent PISA scores. Relatedly, Estonia has integrated use of technology into education from early age making technology a force for equalizing access and providing opportunities. Second, the digitalization of government services has provided a strong incentive and led the way for promoting the adoption of digital technologies. Third, its promotion of innovation and entrepreneurial activity, which have led Tallin, its capital, to be named the "Silicon Valley of Europe," as shown by the creation of globally well-known startups such as Skype and TransferWise. Estonia with its policies has made its tech sectors an engine of growth and job creation, that critically contributes to its shared prosperity.

Like any human creation, technology's dual nature is not inherent. We shape its evolution, define its goals, and consider its impact on society. We must also determine the speed at which technological advancements will reshape markets and affect income distribution among regions, households, and individuals—making sure disadvantaged groups do not bear the burden of unregulated technology solely governed by the market. Estonia, for instance, provide an example of a European country that has deployed proactive policies that have promoted the diffusion of digital technology in a manner that also supports inclusion and equity (See box 5.2).

Although it is important to focus on improving fundamental skills and optimizing the effectiveness of ALMPs, these endeavors may require significant time. Meanwhile, technology will continue to advance. Therefore, social assistance policies, particularly implementing a guaranteed minimum income (GMI), will be crucial in mitigating the negative effects of technology's disruptive impact. The EU's social rights framework marks a significant advancement in establishing inclusive institutions, but several member states, particularly those that are less developed, still have inadequate coverage of vulnerable populations and insufficient cash transfer amounts in their GMI programs.

To advance the modernization of VET systems, enhance the efficacy of ALMPs, and reinforce GMIs, any required reforms must be grounded in evidence and exhibit the intended impact. Despite the EU's demonstrated political dedication to establishing inclusive institutions and allocating adequate resources for carrying out social policies and interventions, there is not enough evidence regarding the effectiveness of these policies and interventions. It is vital to demonstrate the effectiveness of social policies to make sure everyone is included in the digital transition and that technology does not worsen the already prevalent income inequality.

Neglecting to prioritize technology's role in addressing urgent social needs or failing to improve social services for disadvantaged groups due to poorly designed policies or lack of concern for measuring its impact may exacerbate income disparities. Such distributional tensions could aggravate political polarization, ultimately putting both the technological shift and the larger liberal agenda at risk.

[60] https://emerging-europe.com/future-of-it/

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# APPENDIX A
# Additional Methods and Results, Chapters 2 and 3

**TABLE A.1. Countries in the EU-wide analysis of chapters 2 and 3**

| Region | Countries | Region | Countries |
|---|---|---|---|
| Western Europe | Belgium<br>Netherlands<br>Luxembourg<br>France<br>Germany<br>Austria<br>Ireland<br>United Kingdom | Eastern Europe | Estonia<br>Lithuania<br>Latvia<br>Czech Republic<br>Slovakia<br>Poland<br>Hungary<br>Slovenia |
| Northern Europe | Denmark<br>Finland<br>Norway<br>Sweden | South-Eastern Europe | Bulgaria<br>Romania<br>Greece<br>Croatia<br>Cyprus<br>Turkey<br>Serbia<br>Bosnia and Herzegovina |
| Southern Europe | Italy<br>Spain<br>Portugal<br>Malta | | |

**TABLE A.2. Sectors in the EU-wide analysis of chapters 2 and 3**

| NACE Rev. 2 | Description |
|---|---|
| C 10-12 | Manufacture of food products; beverages and tobacco products |
| C 13-15 | Manufacture of textiles, wearing apparel, leather and related products |
| C 16-18 | Manufacture of wood, paper, printing and reproduction |
| C 19-23 | Manufacture of coke, refined petroleum, chemical and basic pharmaceutical products, rubber and plastics, other non-metallic mineral products |
| C 24-25 | Manufacture of basic metals and fabricated metal products, except machinery and equipment |
| C 26 | Manufacture of computer, electronic and optical products |
| C 27-28 | Manufacture of electrical equipment, machinery and equipment n.e.c. |
| C 27-28 | Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment |
| C 29-30 | Manufacture of furniture; jewelry, musical instruments, toys; repair and installation of machinery and equipment |

| NACE Rev. 2 | Description |
|---|---|
| C 31-33 | Electricity, gas, steam and air conditioning supply; water supply; sewerage, waste management and remediation activities |
| C 31-33 | Transportation and storage |
| D-E | Construction |
| F | Wholesale and retail trade; repair of motor vehicles and motorcycles |
| G | Accommodation and food service activities Information and communication |
| H | Real estate activities |
| I | Professional, scientific, and technical activities |
| J | Administrative and support service activities. |

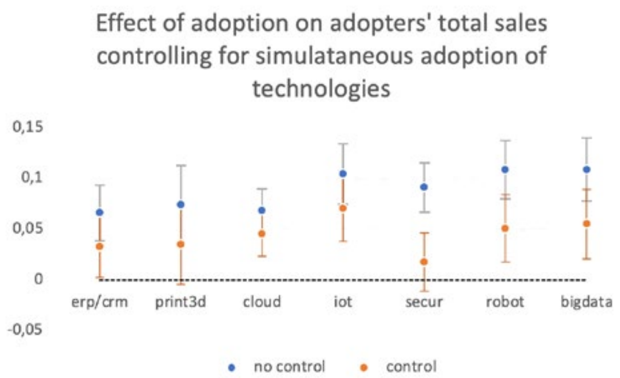
## Additional results on determinants of technology adoption

| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
|---|---|---|---|---|---|---|---|---|
| | Adoption of | | | | | | | |
| | Big data | ERP/CRM | Cloud | IoT | Augmented reality | Robots | 3D printing | Cybersecurity |
| **Intensity of nonroutine cognitive tasks** | 0.0199*** (0.00811) | -0.0211 (0.0385) | 0.0191 (0.0229) | 0.0233*** (0.0135) | 0.00702** (0.00727) | 0.0195*** (0.0120) | 0.0198*** (0.0121) | 0.0204 (0.0285) |
| | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Adoption of | | | | | | | |
| | Big data | ERP/CRM | Cloud | IoT | Augmented reality | Robots | 3D printing | Cybersecurity |
| **Share of graduates** | 0.0374* (0.0197) | 0.0867 (0.0548) | 0.0305 (0.0247) | 0.00942 (0.00834) | 0.00339 (0.00303) | 0.0153* (0.00784) | -0.000575 (0.00531) | 0.0222 (0.0204) |
| | | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Adoption of | | | | | | | |
| | Big data | ERP/CRM | Cloud | IoT | Augmented reality | Robots | 3D printing | Cybersecurity |
| **Productivity _** | 0.117* (0.0630) | 0.703** (0.325) | 0.308* (0.160) | 0.0887 (0.0947) | 0.0242 (0.0381) | 0.234*** (0.0703) | -0.00353 (0.0538) | 0.776** (0.303) |

## Controlling for the simultaneous adoption of multiple technologies

Controlling for the simultaneous adoption of multiple technologies reduces the magnitude of the effects but does not change the qualitative conclusions drawn from the analysis. As firms increase their technological sophistication, they can sometimes simultaneously adopt a bundle of technologies. A simple difference-in-difference estimate built around the adoption of single technology can thus pick up the effect of other technologies being adopted simultaneously by the firm. The estimated effect of adoption changes when the difference-in-difference estimate controls for the simultaneous adoption of multiple technologies. Figure A.1 shows that, even after controlling for simultaneous adoption, for most technologies the estimated effect of adoption on sales remains strong and qualitatively similar. The only exception is cybersecurity. The effect of this technology effectively disappears after controlling for the simultaneous adoption of other technologies. The magnitude of effect of the adoption of other technologies is reduced by between 33 and 53 percent but remains strong and statistically significant—except for 3d printing technologies. Figure A.2 also shows that, by 2019, the difference in the estimated effect with and without simultaneous adoption controls loses importance in relative terms. In 2019, the point estimate with controls is only 4 percent and 10 percent lower for the adoption of big data analytics and robots, respectively.

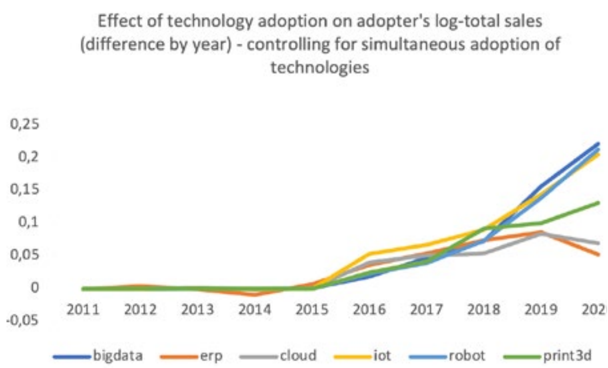
**FIGURE A.1. Effect of adoption on adopters' total sales, controlling for simultan ous adoption of technologies**




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relationship management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

**FIGURE A.2. Effect of technology adoption on adopter's log-total sales (difference by year), controlling for simultaneous adoption of technologies**




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relationship management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

## The direct effect of technology adoption on the average age of employees

**FIGURE A.3.** Effect of technology adoption on the average age of workers in adopting firms (difference by year)

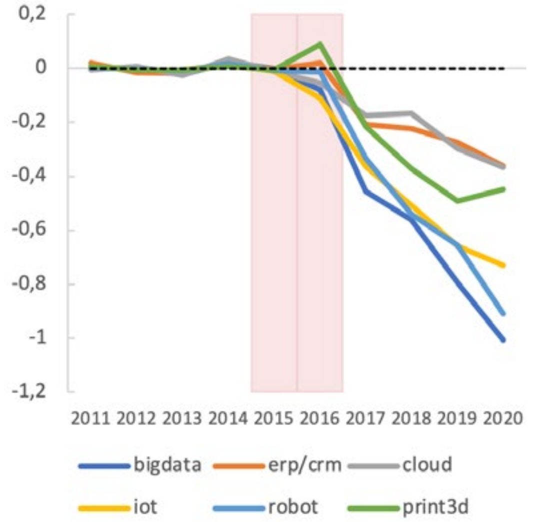
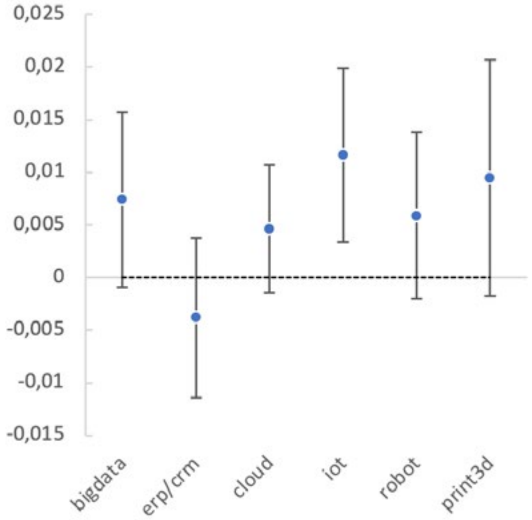



**FIGURE A.4.** Effect of technology adoption on the average age of workers in adopting firms (diff-in-diff estimate 2011–20)




Source: Italian administrative data, ISTAT firm census, EUROSTAT ICT Survey (Italy), and authors' calculations.

Note: erp/crm = enterprise resource planning and consumer relationship management; iot = Internet of Things; print3d = 3d printing; bigdata = big data analysis. Shaded area in panel b identifies treatment periods.

## Estimating the effects of technology adoption at the country-sector level

We estimate the effect of the change in technology adoption share on the change in some outcome of interest, for each technology separately:

$$\Delta y_{ci[t_1,t_N]} = \alpha + \beta \, \Delta \, Tech_{ci[t_1,t_N]} + Controls'_{c(i),t_1} + SectorFE + \varepsilon_{ci}$$

- $\Delta y_{ci[t_1,t_N]}$ change in the (log) outcome variable between the first and the last year in the sample, for country **c**, sector ***i***
- $\Delta \, Tech_{ci[t_1,t_N]}$ change in the share of firms that have adopted a technology between the first and the last year in the sample, for country **c**, sector ***i***
- $Controls'_{c(i),t_1}$ country-sector level: log average wage, log employment, log investment per person, log sales; country-level: log real GDP per capita, share of human resources in technology & science in the labor force, in the first year in the sample
- $SectorFE$ Sector fixed effects

# APPENDIX B
# Data Sources and Definitions for Chapter 4

The empirical analysis of Chapter 4 relies on three data sources: the PISA, the PIAAC, and the European Union Labor Force Survey (EU-LFS). This appendix details the definitions used to classify individuals by educational group in each of these three sources.

## PISA

PISA is the OECD's Programme for International Student Assessment. PISA measures 15-year-olds' ability to use their reading, mathematics and science knowledge and skills to meet real-life challenges. 78 education systems (70 countries and eight cities/autonomous regions) participated in the last round of PISA, which was carried out in 2018.

For the purpose of this report, we use the survey data corresponding to countries with a sufficient sample of vocational track students in the EU. Because the survey measures skill proficiency of 15-year-olds, it will not include vocational track students in countries where vocational studies only start at age 16 and later. The sample of countries used in our analysis thus includes these countries: Belgium, Bulgaria, Croatia, Czech Republic, France, Greece, Hungary, Italy, Luxembourg, Portugal, Romania, and Slovenia.

## PIAAC

The PIAAC is a survey that assesses the proficiency of adults in three information-processing skills essential for full participation in the knowledge-based economies and societies of the 21st century: literacy, numeracy and problem solving in technology-rich environments. The survey is run by the OECD. The target population for the survey consisted of the population aged 16–65 years, residing in the country at the time of data collection. Twenty-four countries participated in Round 1 of the Survey of Adult Skills (PIAAC), with data collection taking place from 1 August 2011 to 31 March 2012 in most countries. Nine countries participated in Round 2 of the assessment, with data collection taking place from April 2014 to end-March 2015. Six countries participated in Round 3, with data collection taking place from July to December 2017.

For the analysis in this report, we use the survey data corresponding to 14 EU countries in Round 1 (except where noted): Belgium, Czech Republic, Denmark, Finland, France, Greece (Round 2), Hungary (Round 3), Ireland, Italy, Netherlands, Poland, Slovak Republic, Slovenia (Round 2), and Spain.

The survey identifies explicitly the adults with a vocational degree through the variable ***vet*** in the microdata. We use this variable to identify upper secondary (ISCED 3) and postsecondary (ISCED 4) graduates with a vocational degree.

In terms of the variables used to measure skill proficiency, we focus on the plausible values of literacy ***pvlit1*** and numeracy ***pvnum1***. Our results are robust to the use of alternative plausible values.

## EU-LFS

The EU-LFS is a quarterly labor force survey run in the 27 European Union countries and in other participating countries (Iceland, Montenegro, North Macedonia, Norway, Serbia, Switzerland, and Türkiye). It covers the resident population of working age (15 years and above) in each country, and it is aimed at assessing the employment status of the target population. The quarterly rounds of the survey include only a subset of the variables in the annual rounds of the survey, and for the analysis in this report, only the annual rounds are used.

To classify individuals by educational group, the information recorded in three variables is used:

- The variable "Highest educational attainment level" (***HATLEV***)
- The variable "Orientation of the highest educational attainment level" (***HATVOC***)
- The variable "Field of the highest educational attainment level" (***HATFIELD***)

The variable ***HATLEV*** is asked to all the individuals aged 15 years and above. In the years 1998 to 2013 this variable was recorded using the ISCED 97 classification, whereas in the years 2014 and after the ISCED 11 classification was used. These two classifications, in the abridged versions used in the EU-LFS, distinguish upper-secondary students who follow tracks that provide access to tertiary education (codes 3A and 3B in ISCED 97; code 304 in ISCED 11) or that provide access only to nontertiary education (code 3C in ISCED 97; codes 302 and 303 in ISCED 11). Postsecondary nontertiary education is distinguished in two groups in ISCED 97 based on whether it provides access to tertiary education (codes 4A and 4B) or not (code 4C), but the version of ISCED 11 used in EU-LFS does not distinguish this (code 400 is used for all tracks of postsecondary nontertiary education).

The variable ***HATVOC*** was included in EU-LFS starting from 2014, and it indicates whether the orientation of the highest attainment level is "general" or "vocational." This variable is only recorded for individuals who report their higher attainment level being upper secondary (codes 300, 302, 303, and 304 in ISCED 11) or postsecondary nontertiary (code 400 in ISCED 11) and it is only recorded for individuals who are 34 years or younger, or older than 34 years but have attained that level of education in the last five years.

The variable ***HATFIELD*** was included in EU-LFS starting from 2003, and it indicates the field of the highest attainment level within a classification of 16 fields (for the survey rounds of years 2003 to 2015) or a classification of 11 fields (for the survey rounds of year 2016 and later). This variable is only recorded for individuals who report their higher attainment level to be upper secondary or higher (ISCED 97 levels 3 and above, and ISCED 11 levels 300 and above). As ***HATVOC***, this variable is only recorded for individuals 34 years or younger, or older than 34 years but have attained that level of education in the last five years.

Critical to our report is the identification of vocational education graduates in the survey data. Strictly, the EU-LFS only allows to unambiguously identify vocational education graduates among the population age 15 to 34 in the years 2014 and later. To identify vocational education graduates of older age groups and in earlier years we follow two procedures. We start by following Vandeweyer and Verhagen (2020) to identify vocational education graduates between ages 15 to

34 in the period 2004–13. They find that, in the period after the variable ***HATVOC*** was included (2014 and after), an almost one-to-one match can be done between the variable ***HATVOC*** and ***HATFIELD***—individuals that indicate that they pursued a vocational degree in ***HATVOC*** indicate a specific set of fields in the variable ***HATFIELD*** and vice versa.[61] They use this match to attribute an imputed value of ***HATVOC*** for the period 2004–13 based on the values of ***HATFIELD*** reported for those years. We extend this procedure to other age groups, noting that, within the population age 15–34, certain educational codes in the variable ***HATLEV*** in the period 2004–20 are associated unambiguously to a vocational degree. The assumption we use is that individuals older than 34 who report these educational codes in ***HATLEV*** also hold a vocational degree. The combination of these two procedures lets us identify vocational education graduates among the population 15 years and older in 17 countries in the period 2004–20 and in three countries in the period 2014–20. Ambiguities remain in certain cases which do not let us completely identify the whole universe of vocational graduates, a portion of which may remain included in the "general secondary" category—particularly those graduates from a vocational track that allows access to tertiary education. Also, and following Vandeweyer and Verhagen (2020), in many cases we group upper-secondary vocational education graduates with postsecondary nontertiary vocational education graduate into a single group which we call "VET graduates." The reason for this is that, due to the heterogeneity of VET systems in the EU, in some countries the students that pursue secondary studies in a vocational track graduate with a postsecondary degree, whereas in others they graduate with an upper-secondary degree.

We note in Table B.1 the codes of the variable ***HATLEV*** that we use to identify VET graduates and in each country. For the case of Austria, Cyprus, Finland, Portugal, Spain, the United Kingdom, it is impossible to substantially identify vocational graduates of all age groups in any time period.[62]

**TABLE B.1. Identification of educational groups in EU-LFS**

| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| Belgium | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | 100% of the 15–34 age group with code 32 indicate generic fields in ***HATFIELD***. |
| | | 2014–2020 | 304 | 100% of the 15–34 age group with code 304 indicate general education per ***HATVOC*** |
| | VET graduates | 2004–2013 | 31, 43 | 100% of the 15–34 age group with code 31 indicate vocational fields in ***HATFIELD***. 43 corresponds to postsecondary education, entirely vocational |
| | | 2014–2020 | 303, 400 | 100% of the 15–34 age group with code 303 indicate vocational education per ***HATVOC*** |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

[61] Among the possible fields in ***HATFIELD*** is "General programmes"/ "Generic programmes and qualifications" (code 000). In the case of individuals with upper secondary education with no access to tertiary education (code 304 in ISCED 11), 100 percent of respondents which indicated a field other than code 000 indicated that their degree was vocational in 21 countries. The same was true for individuals with upper secondary education with access to tertiary education (code 305 in ISCED 11) in 20 countries.

[62] For Finland, Spain, Portugal, and the United Kingdom, it is only possible to identify them in the 15-34 age group.

| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| Czech Republic | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | |
| | | 2014–2020 | 304 | |
| | VET graduates | 2004–2013 | 31, 43 | 100% of the 15–34 age group with code 31 indicate vocational fields in *HATFIELD*. 43 corresponds to postsecondary education, entirely vocational |
| | | 2014–2020 | 303, 400 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Denmark | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | 100% of the 15–34 age group with code 32 indicate generic fields in *HATFIELD*. |
| | | 2014–2020 | 304 | 100% of the 15–34 age group with code 304 indicate general education per *HATVOC* |
| | VET graduates | 2004–2013 | 31 | 100% of the 15–34 age group with code 31 indicate vocational fields in *HATFIELD*. |
| | | 2014–2020 | 303 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Estonia | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | |
| | | 2014–2020 | 304 | 55% of the 15–34 age group with code 304 indicate general education per *HATVOC* |
| | VET graduates | 2004–2013 | 41 | Code 41 corresponds to postsecondary education, but it is the only code that captures exclusively vocational education students. |
| | | 2014–2020 | 400 | Code 400 corresponds to postsecondary education, but it is the only code that meaningfully captures vocational education students. 100% of the 15–34 age group with code 400 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| France | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes students in the "technological" track of academic upper-secondary schools (***voie technologique au lycée general et technologique***). |
| | | 2014–2020 | 304 | Includes students in the "technological" track of academic upper-secondary schools (***voie technologique au lycée general et technologique***). |
| | VET graduates | 2004–2013 | 31 | 100% of the 15–34 age group with code 31 indicate vocational fields in *HATFIELD*. Corresponds to the "professional" upper secondary (***lycée professionel***). |
| | | 2014–2020 | 303 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC*. Corresponds to the "professional" upper secondary (***lycée professionel***). |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Greece | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | |
| | | 2014–2020 | 304 | 74% of the 15–34 age group with code 304 indicate general education per *HATVOC*. |
| | VET graduates | 2004–2013 | 42 | Code 42 corresponds to postsecondary education, but it is the only code that captures exclusively vocational education students. *EPAL* (technical school) graduates are included in this code. |
| | | 2014–2020 | 400 | Code 400 corresponds to postsecondary education, but it is the only code that meaningfully captures vocational education students. 97% of the 15–34 age group with code 400 indicate vocational education per *HATVOC*. *EPAL* (technical school) graduates are included in this code. |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| Hungary | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | 100% of the 15–34 age group with code 32 indicate generic fields in *HATFIELD*. |
| | | 2014–2020 | 304 | 74% of the 15–34 age group with code 304 indicate general education per *HATVOC* |
| | VET graduates | 2004–2013 | 31 | 100% of the 15–34 age group with code 31 indicate vocational fields in *HATFIELD*. |
| | | 2014–2020 | 303 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Ireland | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | |
| | | 2014–2020 | 304 | 100% of the 15–34 age group with code 304 indicate general education per *HATVOC* |
| | VET graduates | 2004–2013 | 42 | Code 42 corresponds to postsecondary education. Vocational education in Ireland is classified as postsecondary. |
| | | 2014–2020 | 400 | Code 400 corresponds to postsecondary education. Vocational education in Ireland is classified as postsecondary. |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Italy | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes students all tracks of academic upper-secondary schools (*liceo*). |
| | | 2014–2020 | 304 | Includes students in all tracks of academic upper-secondary schools (*liceo*). |
| | VET graduates | 2004–2013 | 31 | 100% of the 15–34 age group with code 31 indicate vocational fields in *HATFIELD*. Corresponds to students in professional institutes (*istituto tecnico/istituto professionale*) |
| | | 2014–2020 | 303 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC*<br><br>(*istituto tecnico/istituto professionale*) |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| Latvia | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | |
| | | 2014–2020 | 304 | 62% of the 15–34 age group with code 304 indicate general education per ***HATVOC.*** |
| | VET graduates | 2004–2013 | 31, 41 | 100% of the 15–34 age group with codes 31 and 41 indicate vocational fields in ***HATFIELD***. |
| | | 2014–2020 | 303, 400 | 100% of the 15–34 age group with codes 303 and 400 indicate vocational education per ***HATVOC*** |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Lithuania | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | |
| | | 2014–2020 | 304 | 69% of the 15–34 age group with code 304 indicate general education per ***HATVOC***. |
| | VET graduates | 2004–2013 | 41 | Code 41 corresponds to postsecondary education, but it is the only code that captures graduates from VET institutions. |
| | | 2014–2020 | 400 | Code 400 corresponds to postsecondary education, but it is the only code that captures graduates from VET institutions. 100% of the 15–34 age group with code 400 indicate vocational education per ***HATVOC***. |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Luxembourg | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | |
| | | 2014–2020 | 304 | 71% of the 15–34 age group with code 304 indicate general education per ***HATVOC***. |
| | VET graduates | 2004–2013 | 31 | |
| | | 2014–2020 | 303 | 67% of the 15–34 age group with code 303 indicate vocational education per ***HATVOC***. |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| Netherlands | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes HAVO (*Hoger Algemeen Voortgezet Onderwijs*) and VWO (*Voorbereidend Wetenschappelijk Onderwijs*) graduates |
| | | 2014–2020 | 304 | Includes HAVO and VWO graduates |
| | VET graduates | 2004–2013 | 31, 41, 42 | 100% of the 15–34 age group with codes 31, 41 and 42 indicate vocational fields in *HATFIELD* |
| | | 2014–2020 | 303, 400 | 100% of the 15–34 age group with codes 303 and 400 indicate vocational education per *HATVOC*. |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Norway | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | n.a | Impossible to identify vocational/general graduates before 2014 |
| | | 2014–2020 | 304 | 100% of the 15–34 age group with code 304 indicate general education per *HATVOC* |
| | VET graduates | 2004–2013 | n.a. | Impossible to identify vocational/general graduates before 2014 |
| | | 2014–2020 | 303 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Poland | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes vocational students on the track that allows access to tertiary (*technikum*) |
| | | 2014–2020 | 304 | Includes vocational students on the track that allows access to tertiary (*technikum*) |
| | VET graduates | 2004–2013 | 31, 42 | 100% of the 15–34 age group with codes 31 and 42 indicate vocational fields in *HATFIELD* |
| | | 2014–2020 | 303, 400 | 85% of the 15–34 age group with code 303 and 100% of those with code 400 indicate vocational education per *HATVOC*. |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

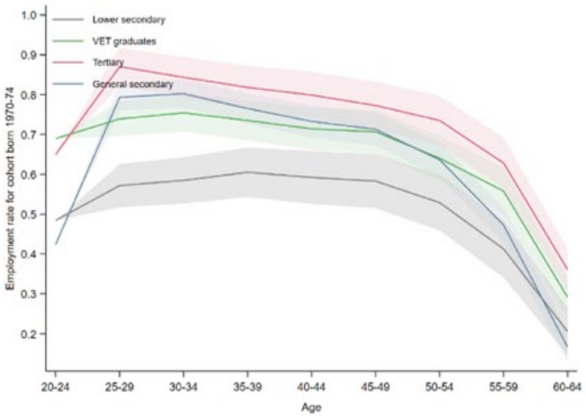
| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| Romania | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes vocational students on the track that allows access to tertiary (*Liceu filiera Teoretică/ Vocațională / Tehnologică*) |
| | | 2014–2020 | 304 | Includes vocational students on the track that allows access to tertiary (*Liceu filiera Teoretică/ Vocațională / Tehnologică*) |
| | VET graduates | 2004–2013 | 31, 41 | |
| | | 2014–2020 | 303, 400 | 96% of the 15–34 age group with code 303 and 100% of those with code 400 indicate vocational education per *HATVOC*. |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Slovak Republic | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes vocational students on the track that allows access to tertiary. |
| | | 2014–2020 | 304 | Includes vocational students on the track that allows access to tertiary. |
| | VET graduates | 2004–2013 | 31 | 100% of the 15–34 age group with code 31 indicate vocational fields in *HATFIELD* |
| | | 2014–2020 | 303 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Slovenia | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | n.a | Impossible to identify vocational/general graduates before 2014 |
| | | 2014–2020 | 304 | Includes vocational students on the track that allows access to tertiary. |
| | VET graduates | 2004–2013 | n.a | Impossible to identify vocational/general graduates before 2014 |
| | | 2014–2020 | 303 | 100% of the 15–34 age group with code 303 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

| Country | Educational group | Period | HATLEVEL Codes | Note |
|---|---|---|---|---|
| Sweden | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes vocational students on the track that allows access to tertiary |
| | | 2014–2020 | 304 | Includes vocational students on the track that allows access to tertiary |
| | VET graduates | 2004–2013 | 31, 41 | |
| | | 2014–2020 | 303, 400 | |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |
| Switzerland | Lower secondary | 2004–2013 | 10, 11, 21 | |
| | | 2014–2020 | 100, 200 | |
| | General secondary | 2004–2013 | 32 | Includes vocational students on the track that allows access to tertiary |
| | | 2014–2020 | 304 | Includes vocational students on the track that allows access to tertiary |
| | VET graduates | 2004–2013 | 31 | |
| | | 2014–2020 | 303 | 86% of the 15–34 age group with code 303 indicate vocational education per *HATVOC* |
| | Tertiary | 2004–2013 | 51, 52, 60 | |
| | | 2014–2020 | 500, 600, 700, 800 | |

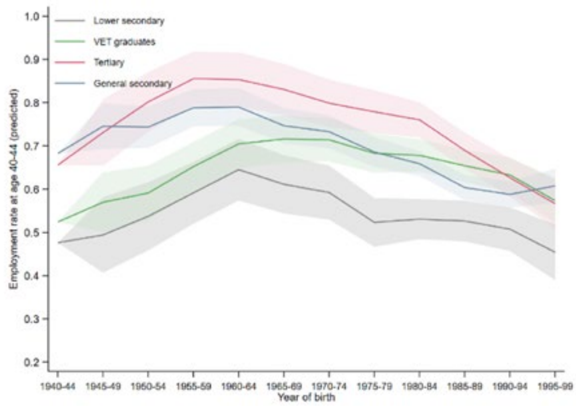
# APPENDIX C
# Age and Cohort Profile of Employment, by Country

***Belgium***

*Age*

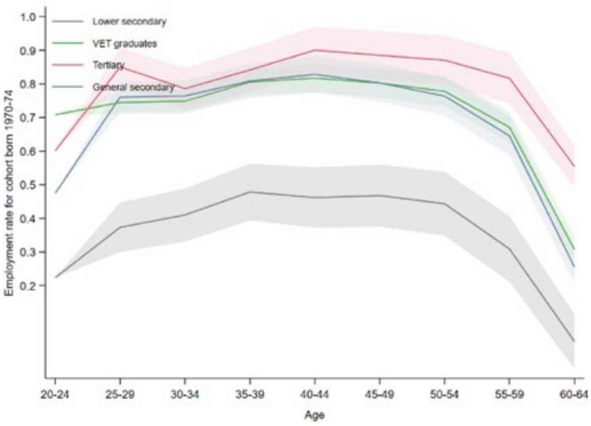



*Cohort*

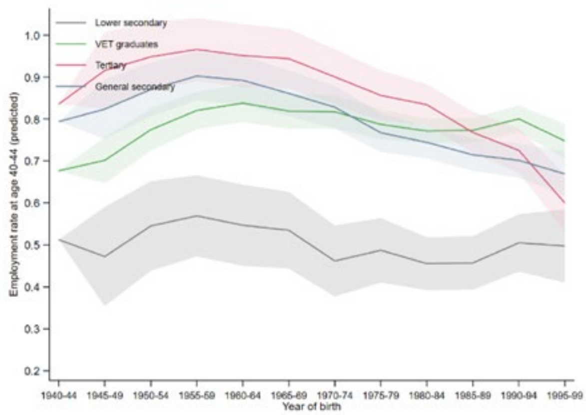



***Czech Republic***

*Age*

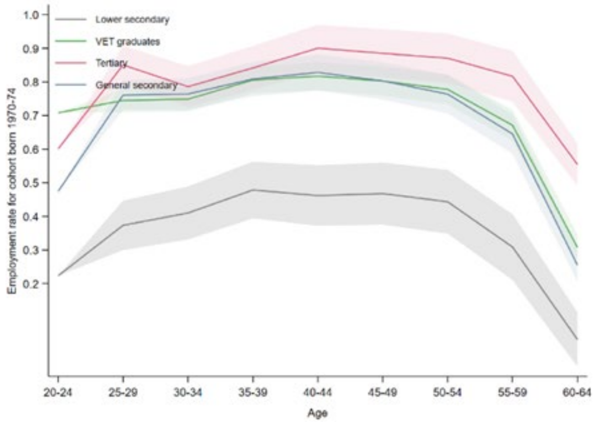



*Cohort*



***Denmark***

*Age*

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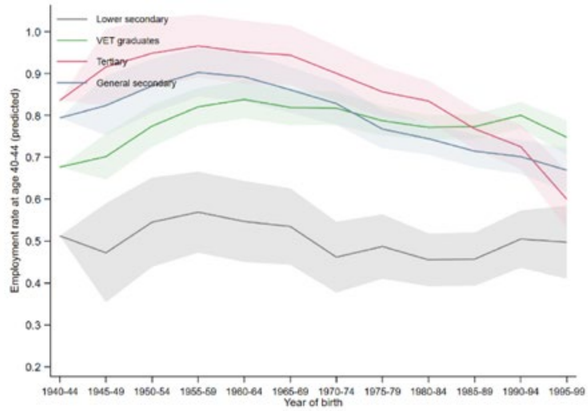
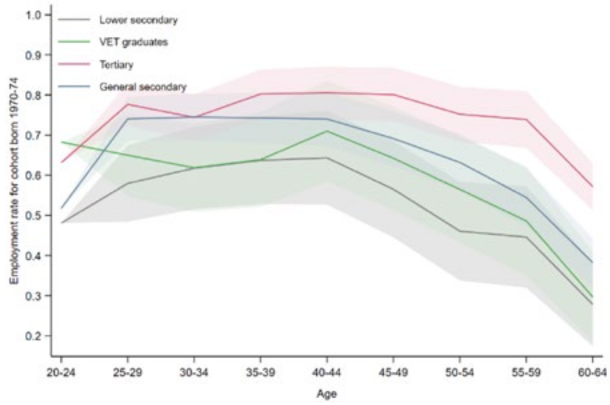



***Estonia***

*Age*

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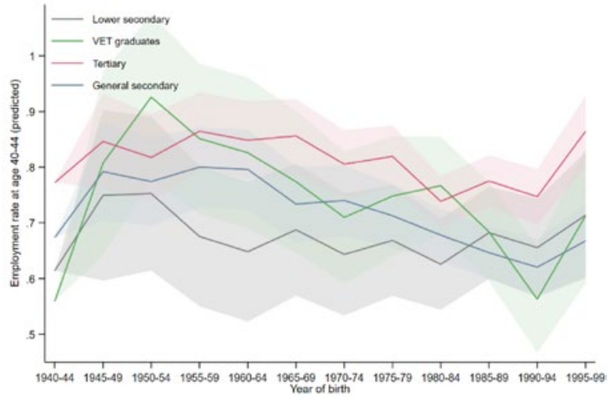
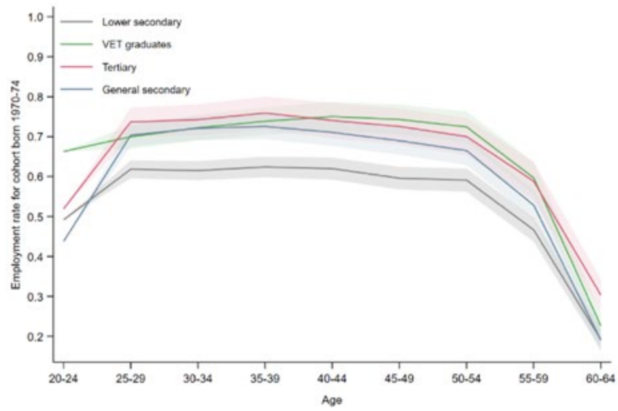



***France***

*Age*

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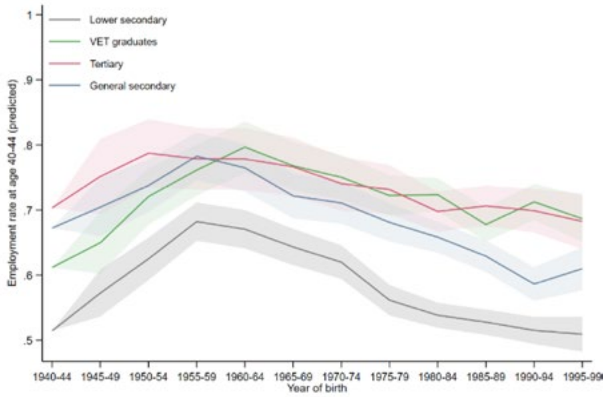
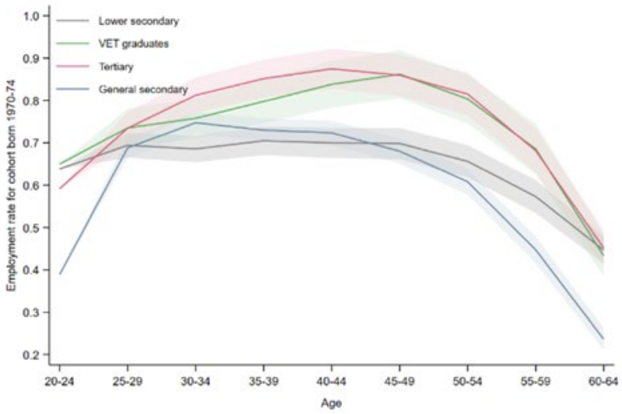


**Greece**

*Age*

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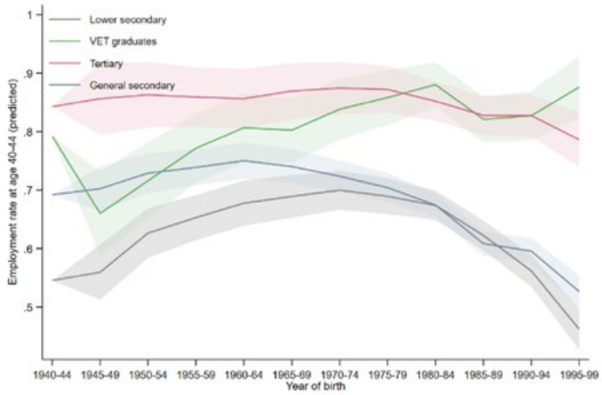
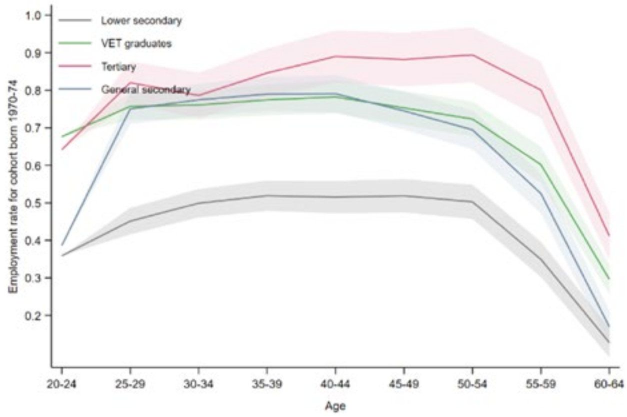



**Hungary**

*Age*

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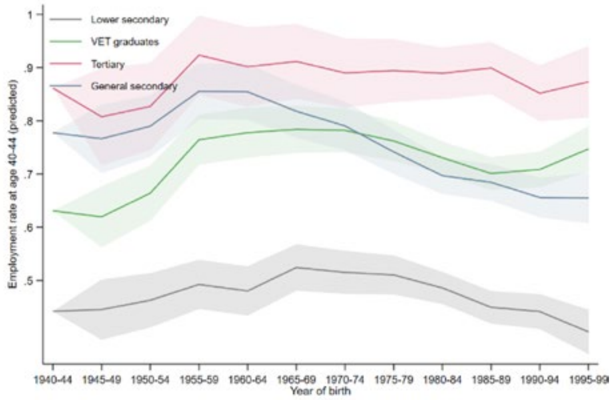
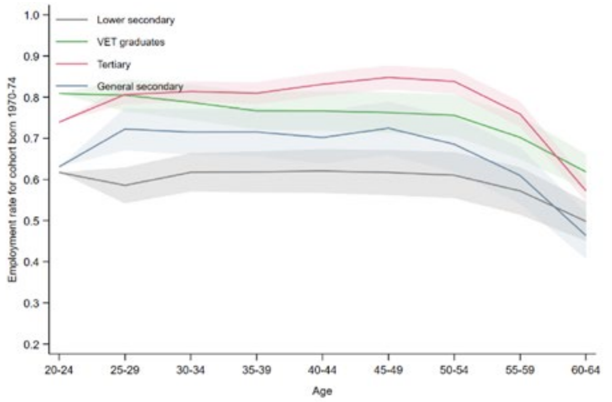



**Ireland**

*Age*

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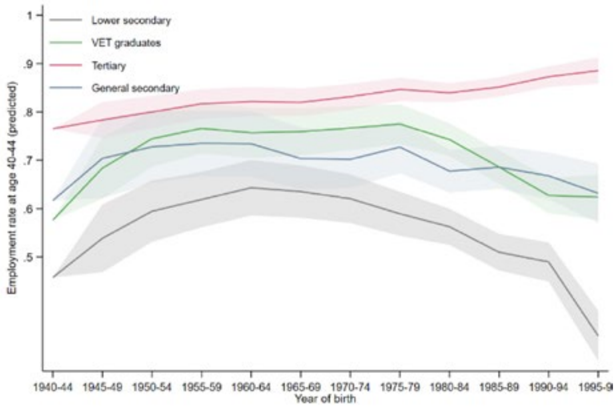
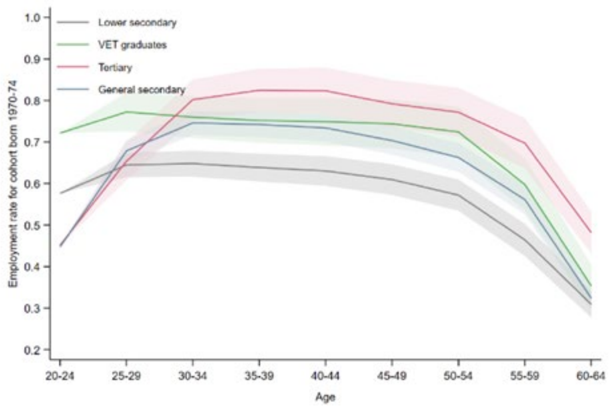


## Italy

Age

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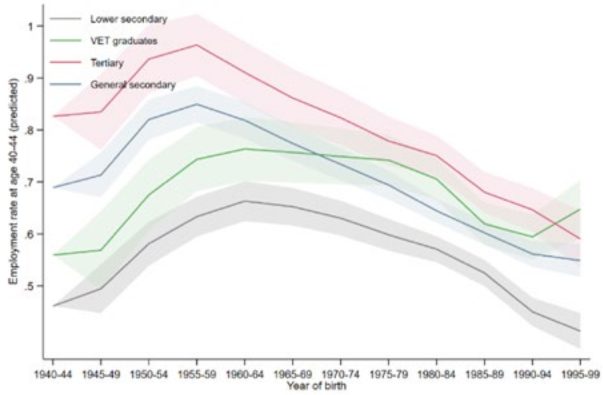
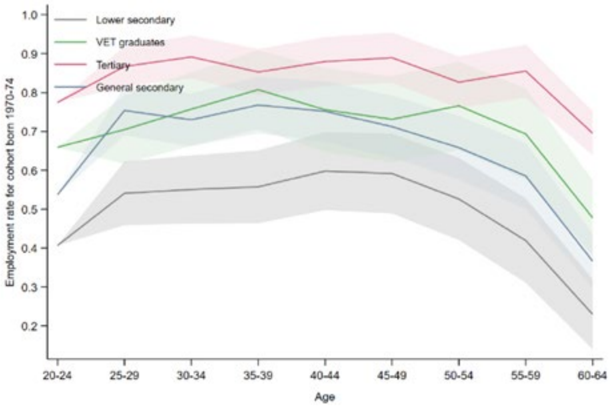



## Latvia

Age

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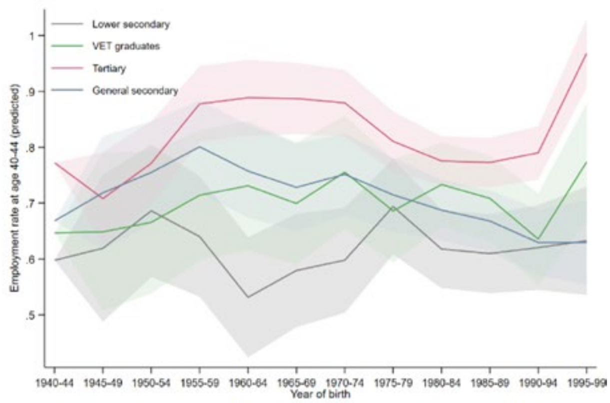
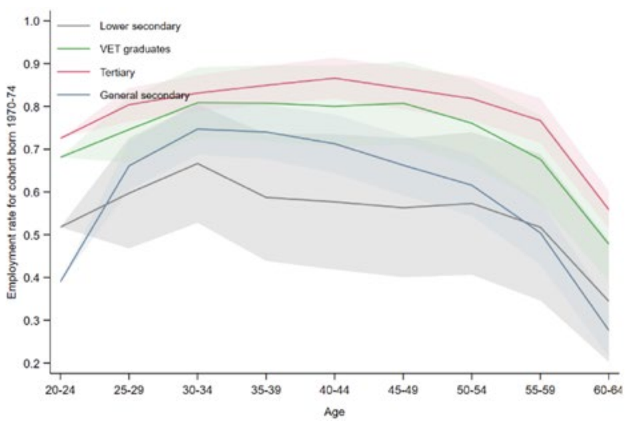



## Lithuania

Age

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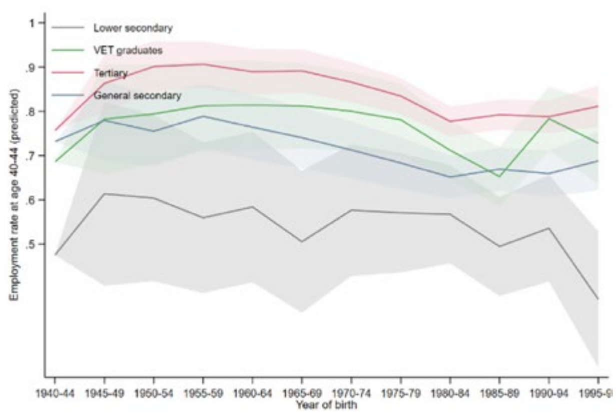
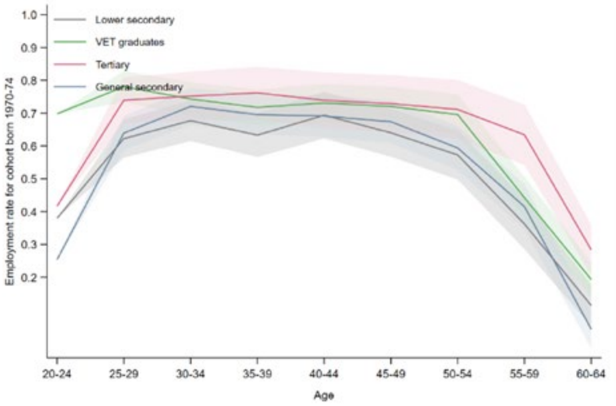


## *Luxembourg*

*Age*

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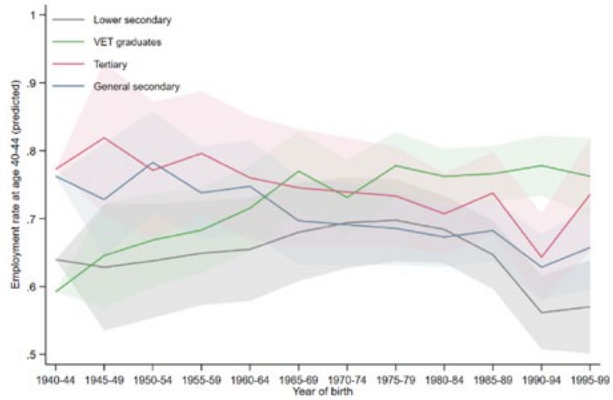
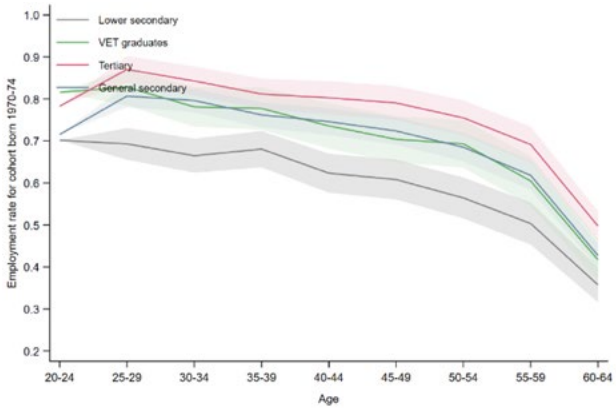



## *Netherlands*

*Age*

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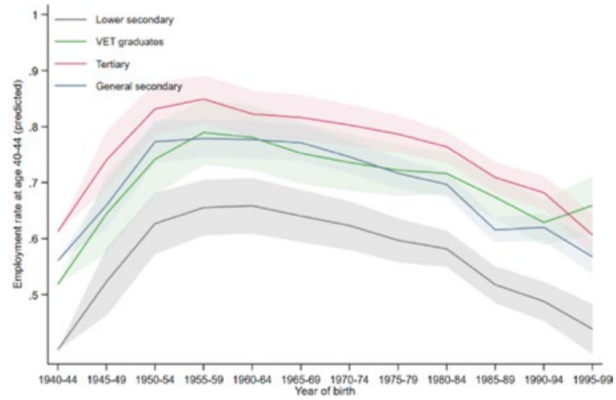
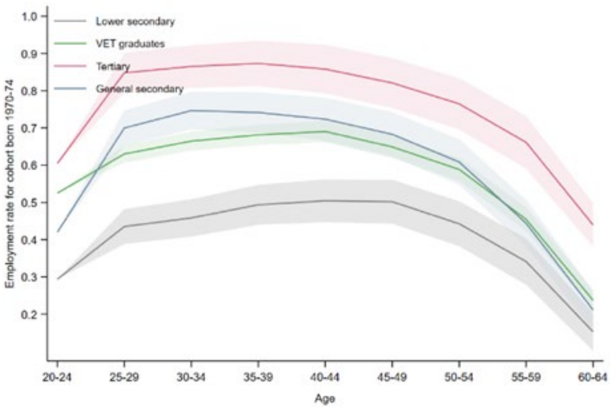



## *Poland*

*Age*

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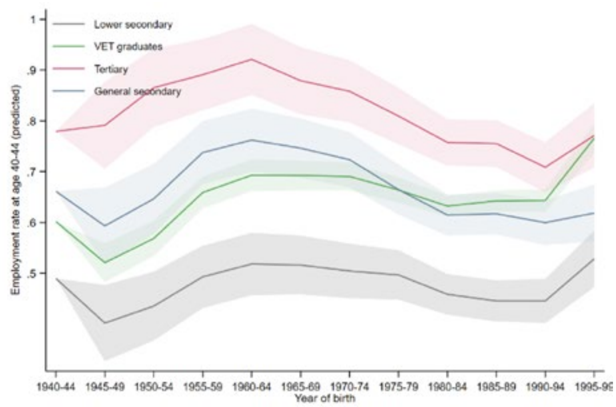
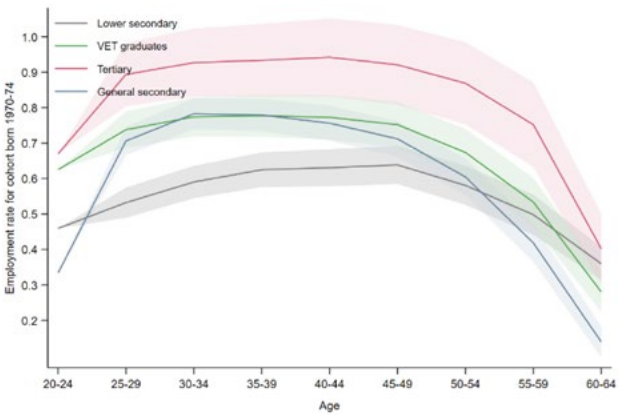


**Romania**

*Age*

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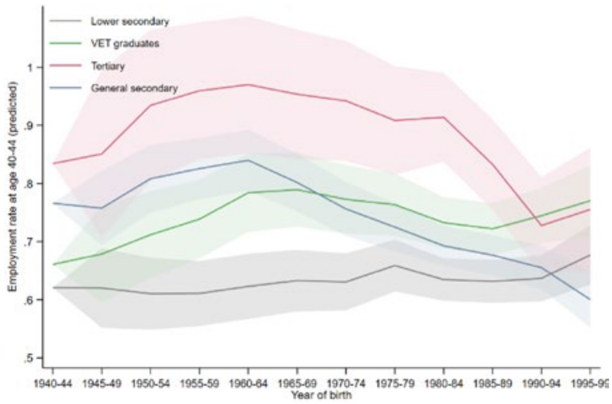
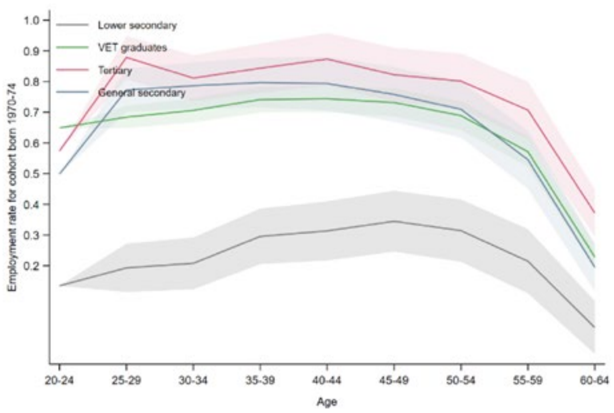



**Slovak Republic**

*Age*

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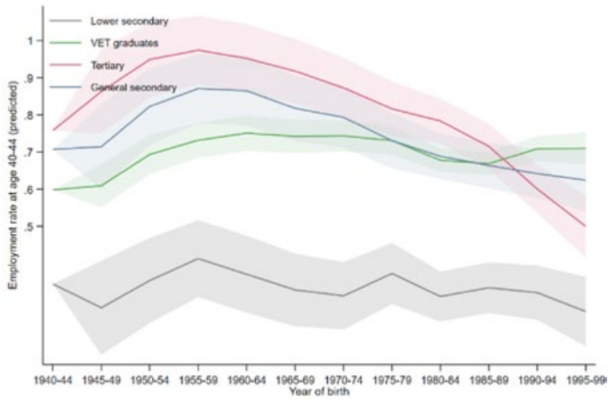
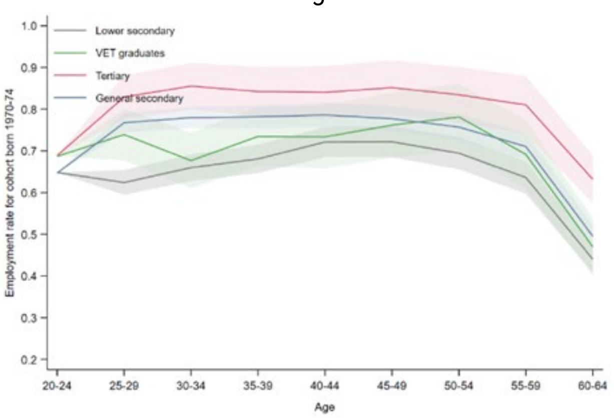



**Switzerland**

*Age*

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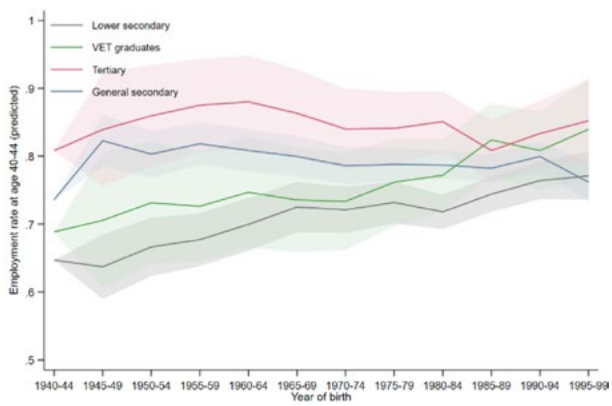
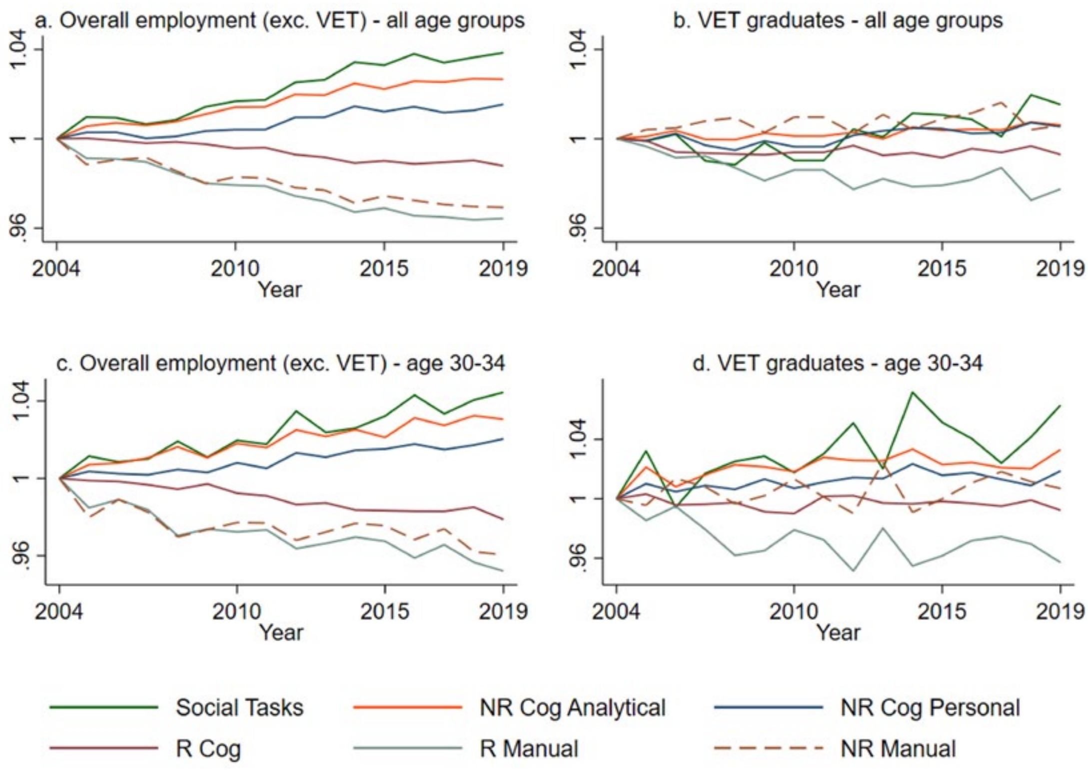


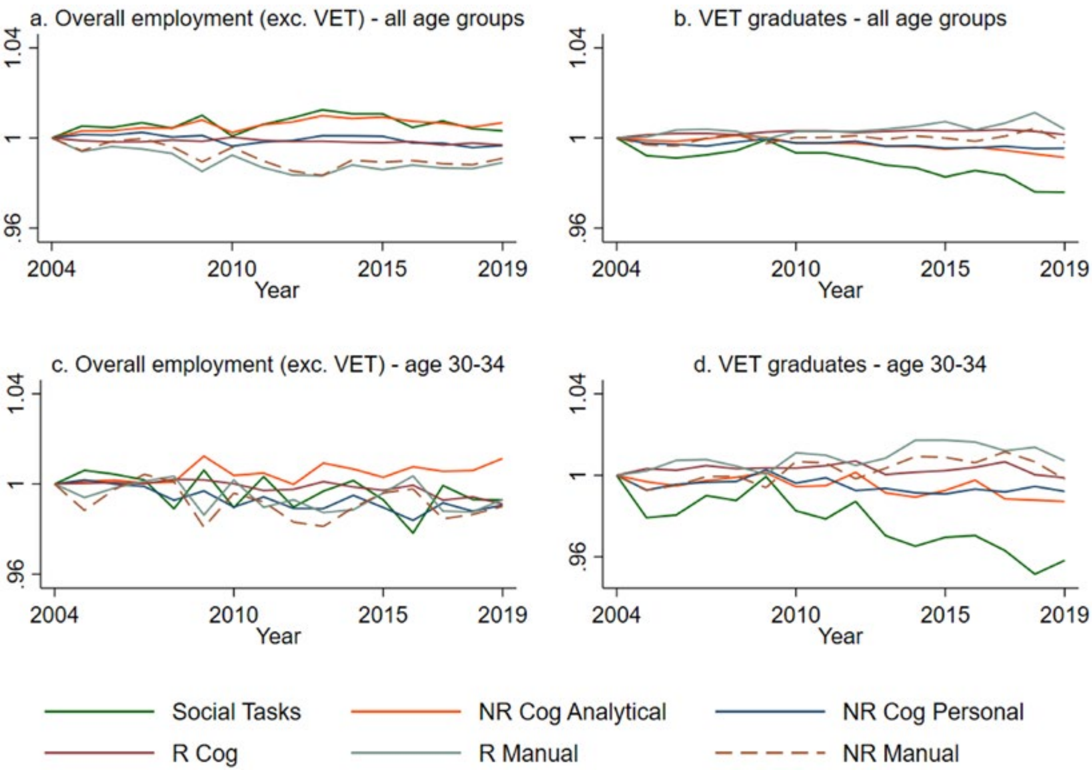
# APPENDIX D
# Trends in task content of jobs, by country

Note: NR = Nonroutine; R = Routine; Cog = Cognitive

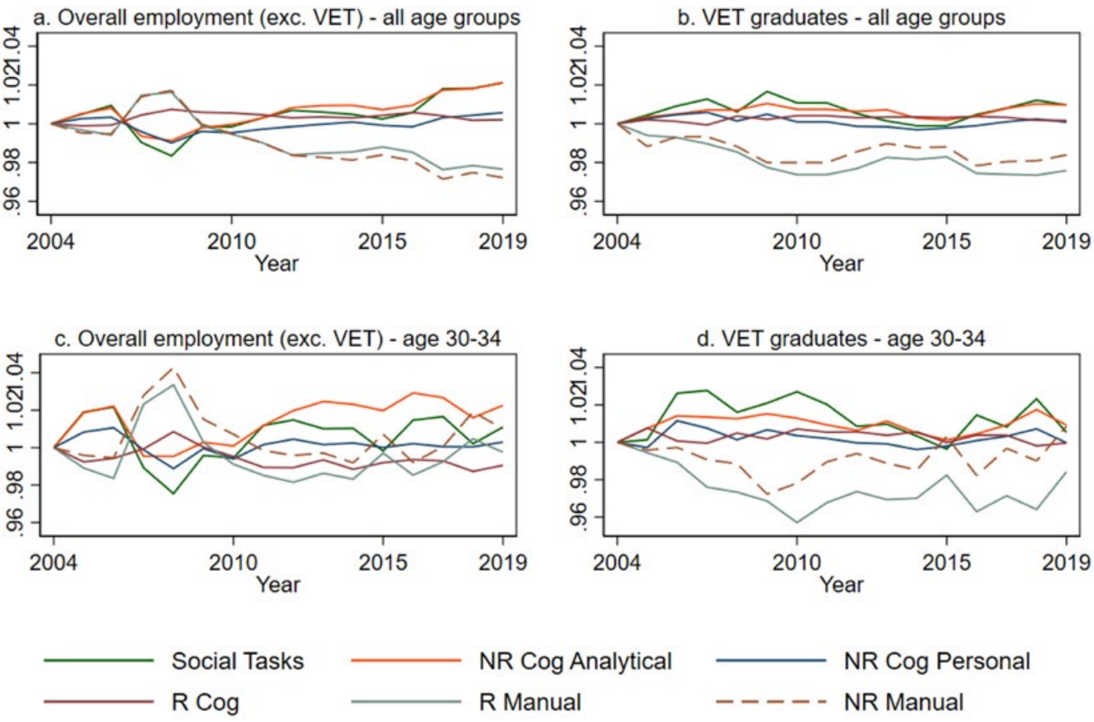
***Belgium***



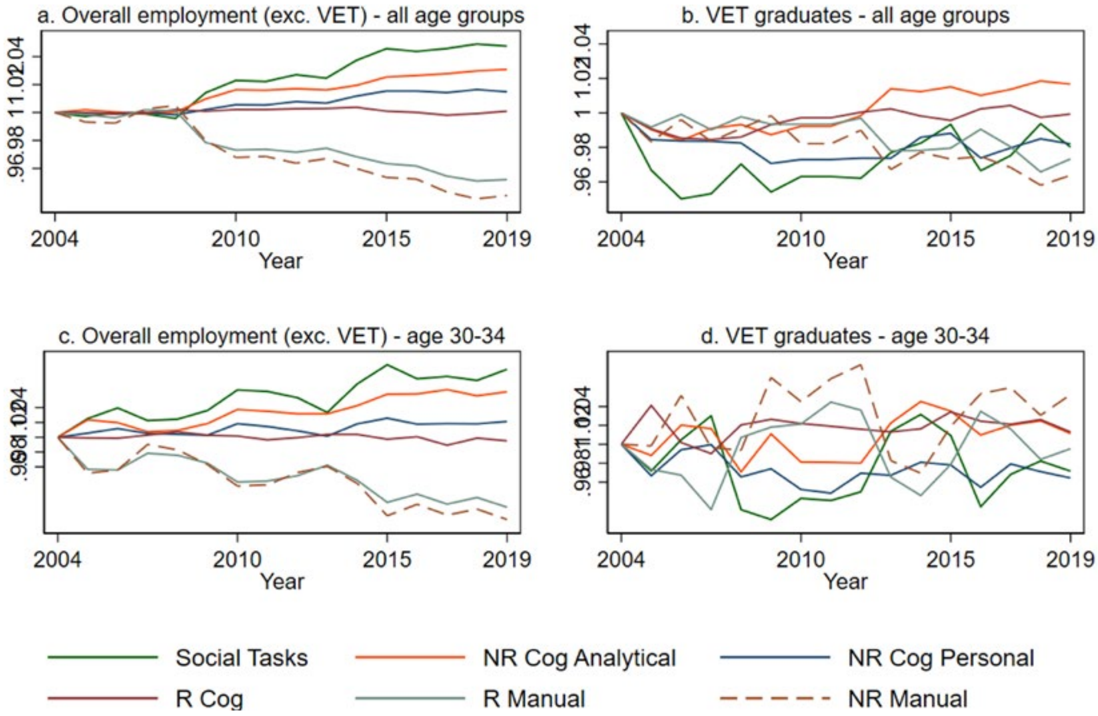
***Czech Republic***



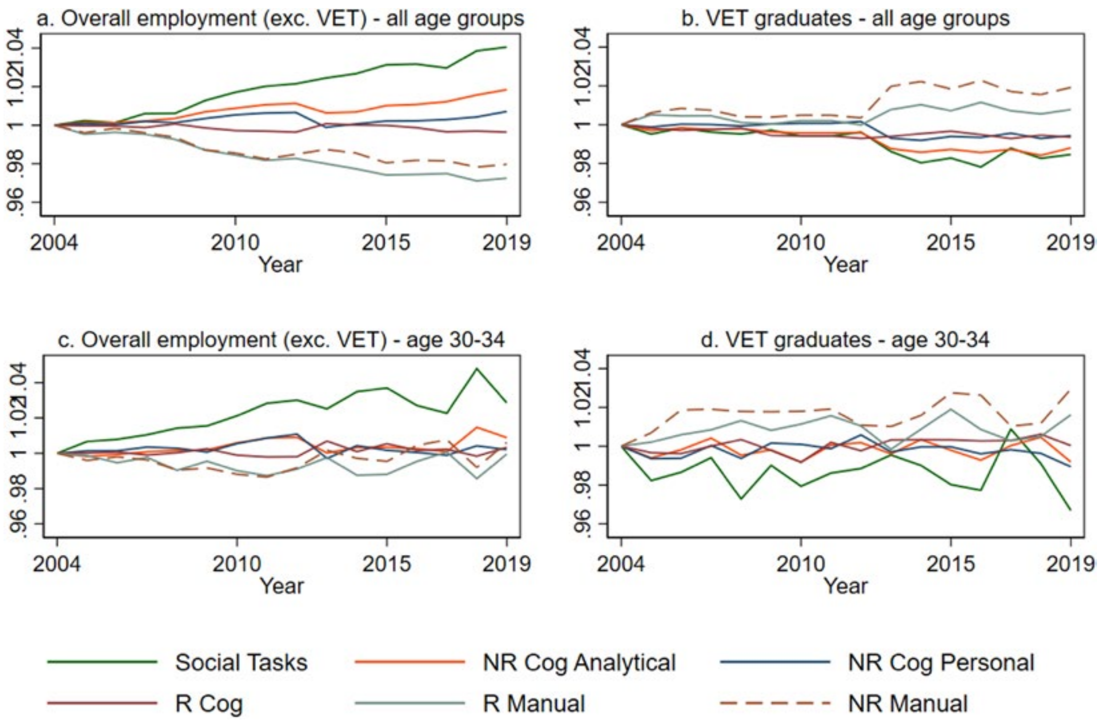

***Denmark***



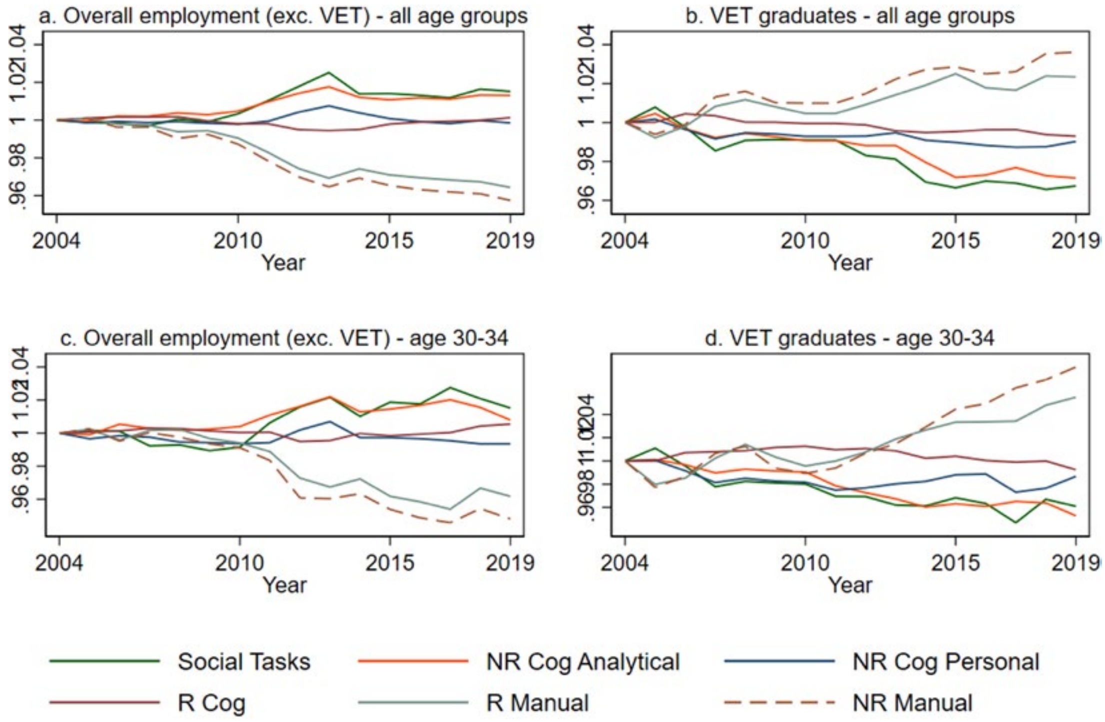
**Estonia**



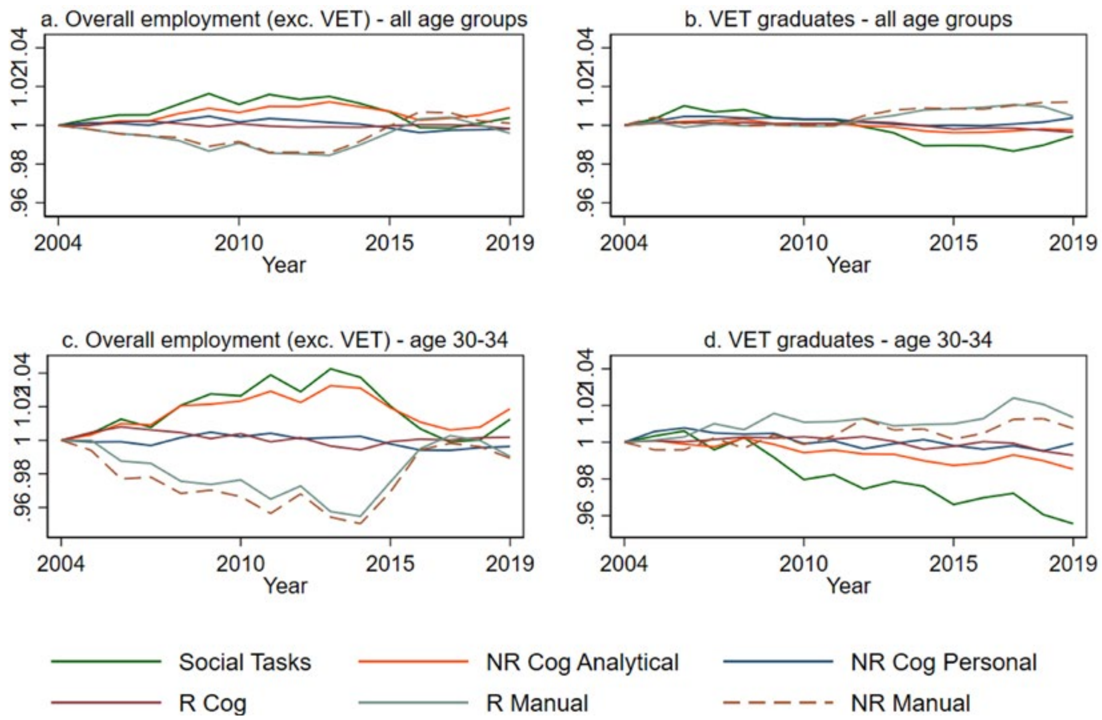

**France**



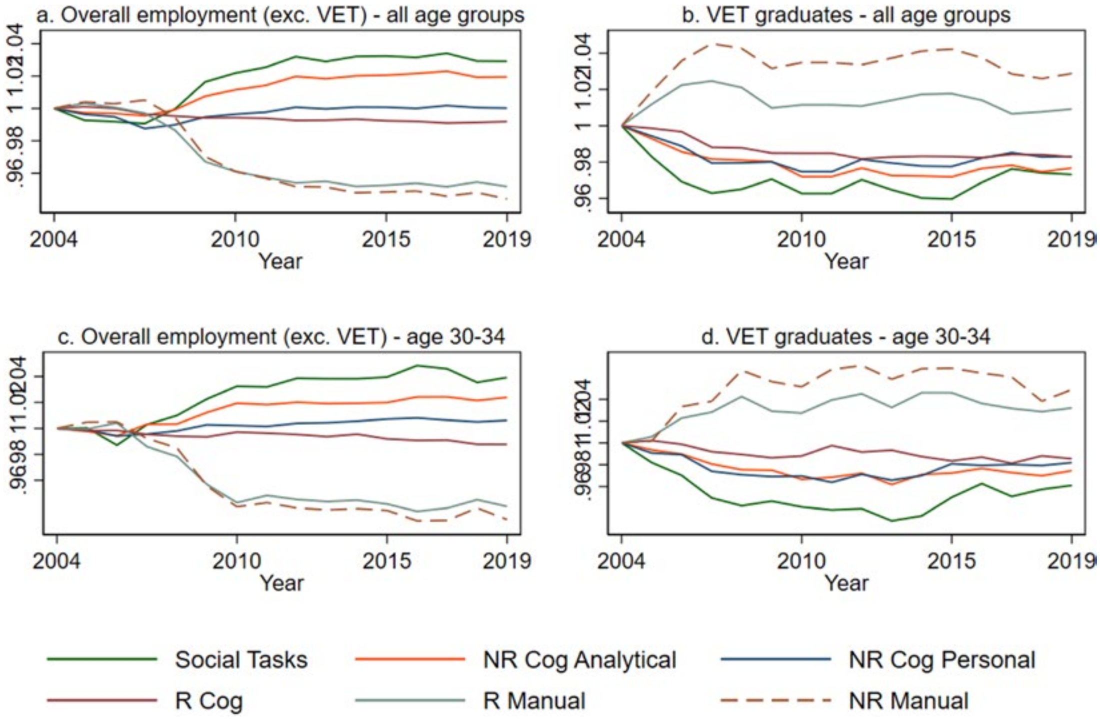
***Greece***



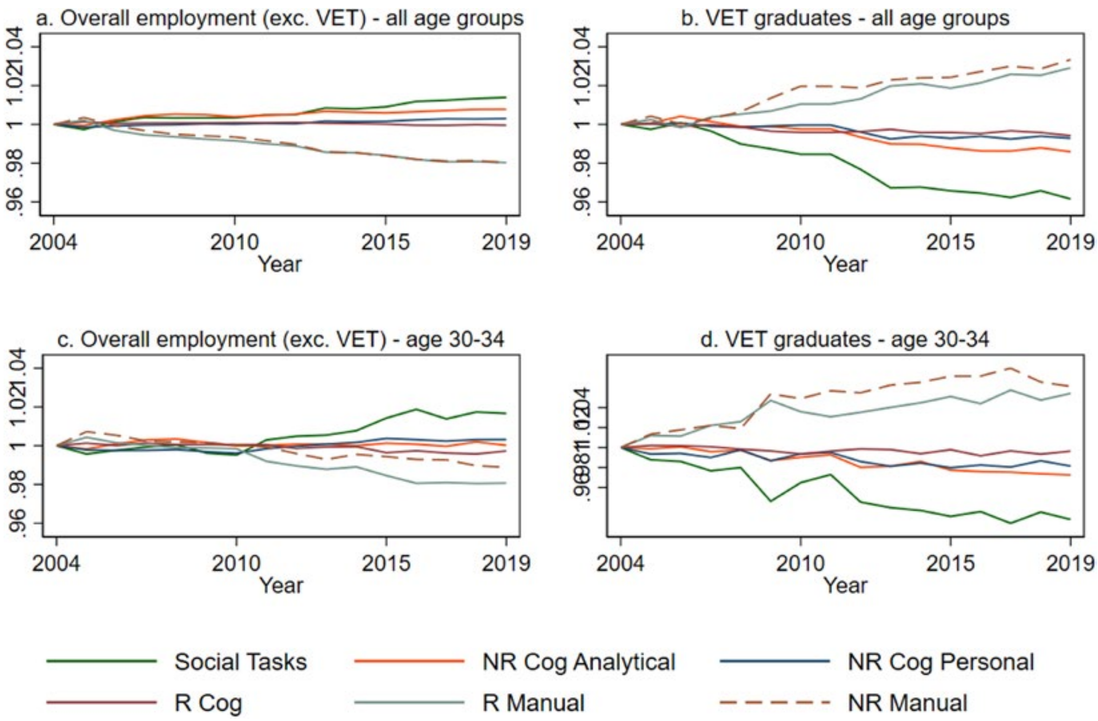

***Hungary***



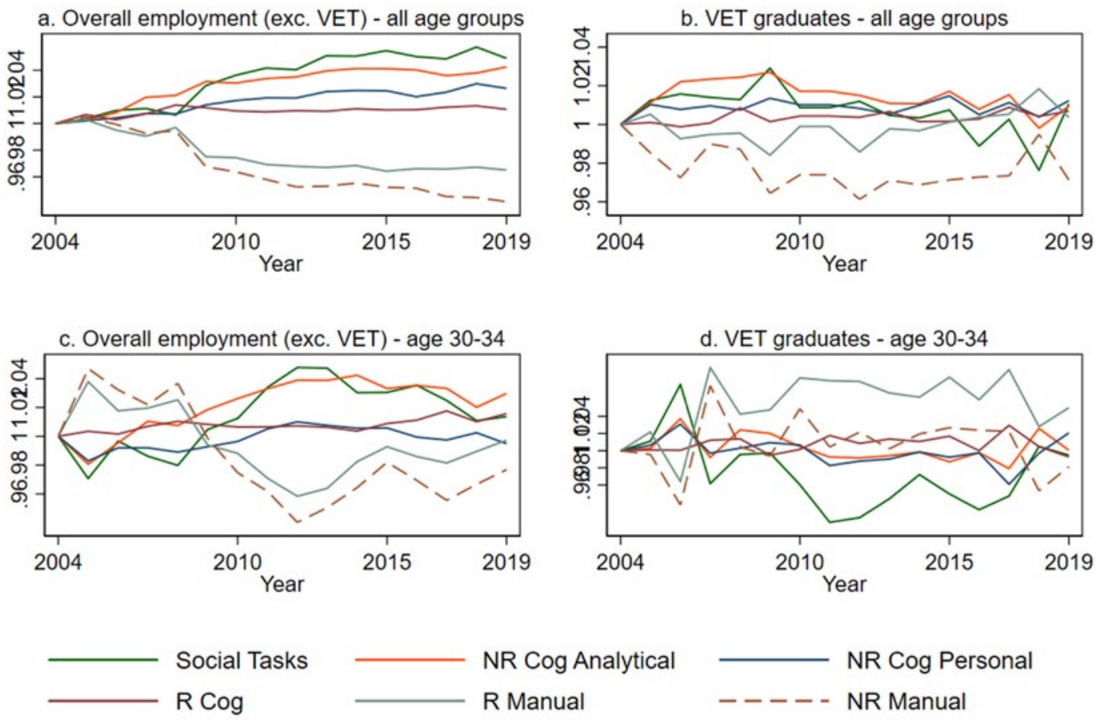
***Ireland***



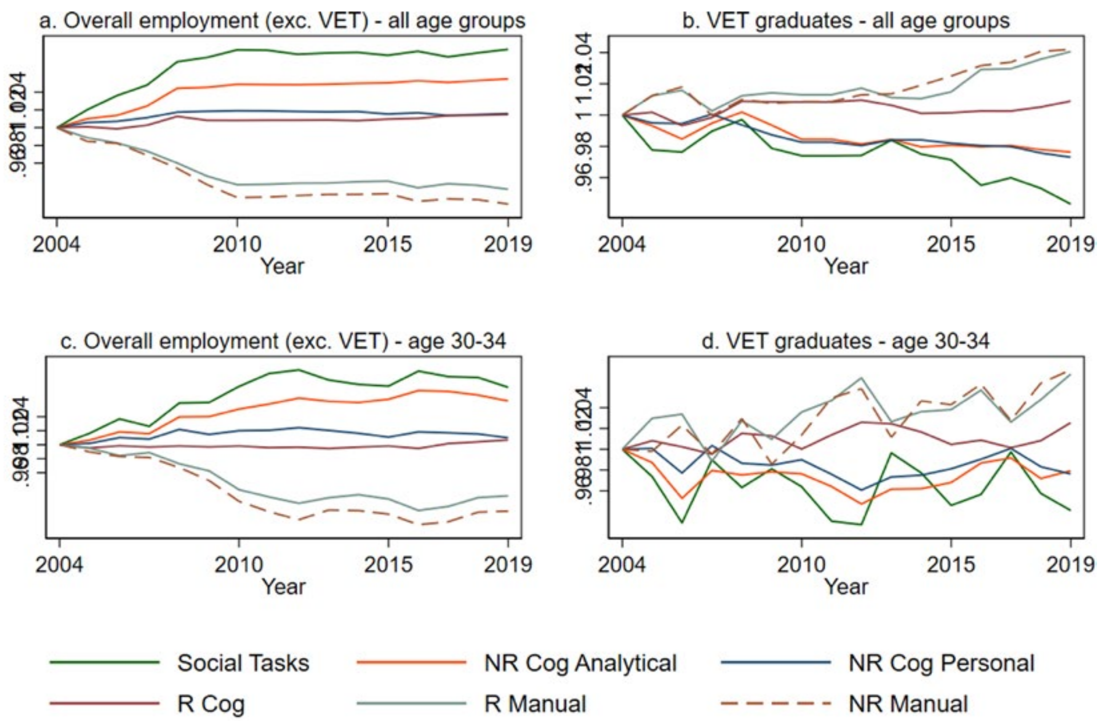

***Italy***



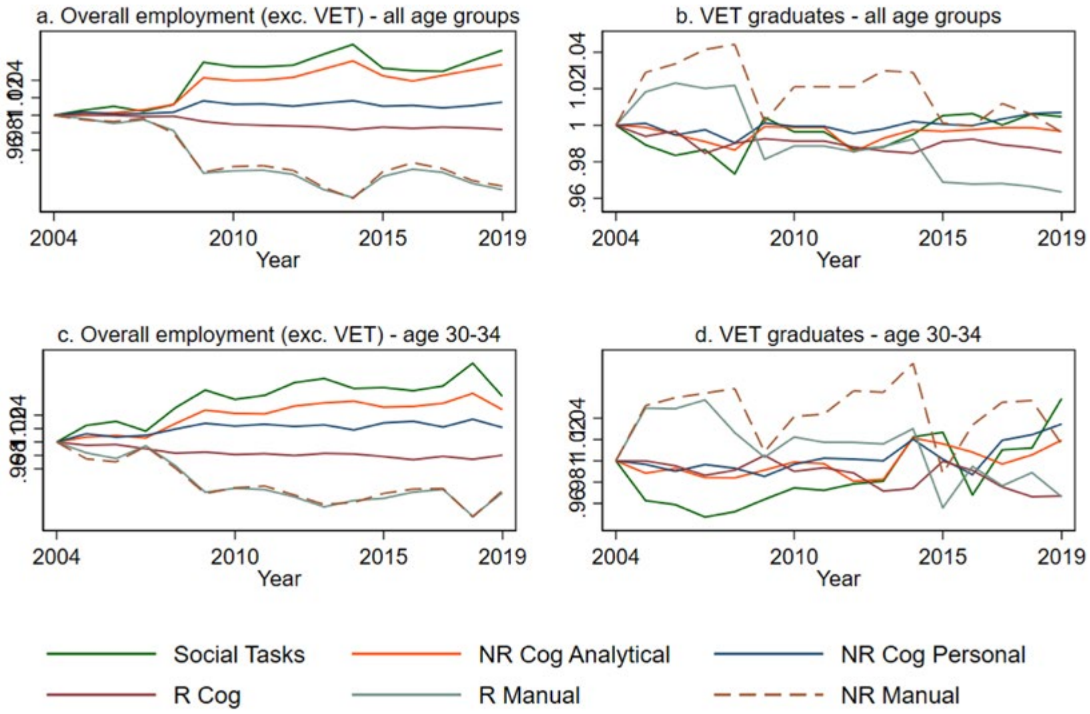
***Latvia***



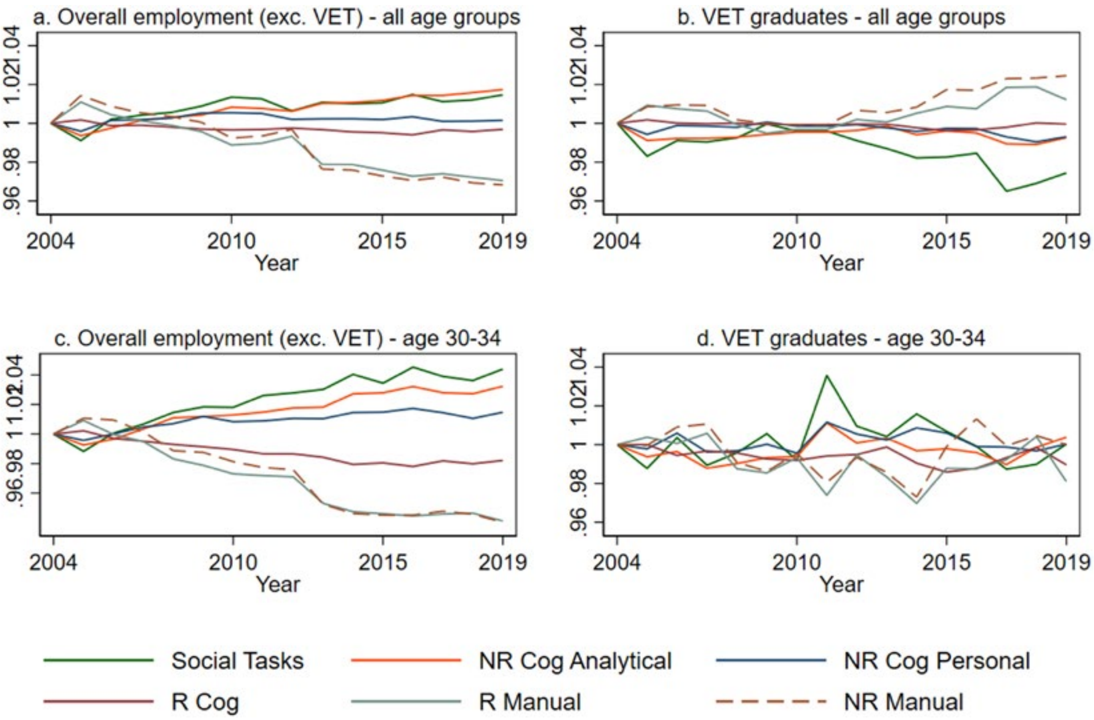

***Lithuania***



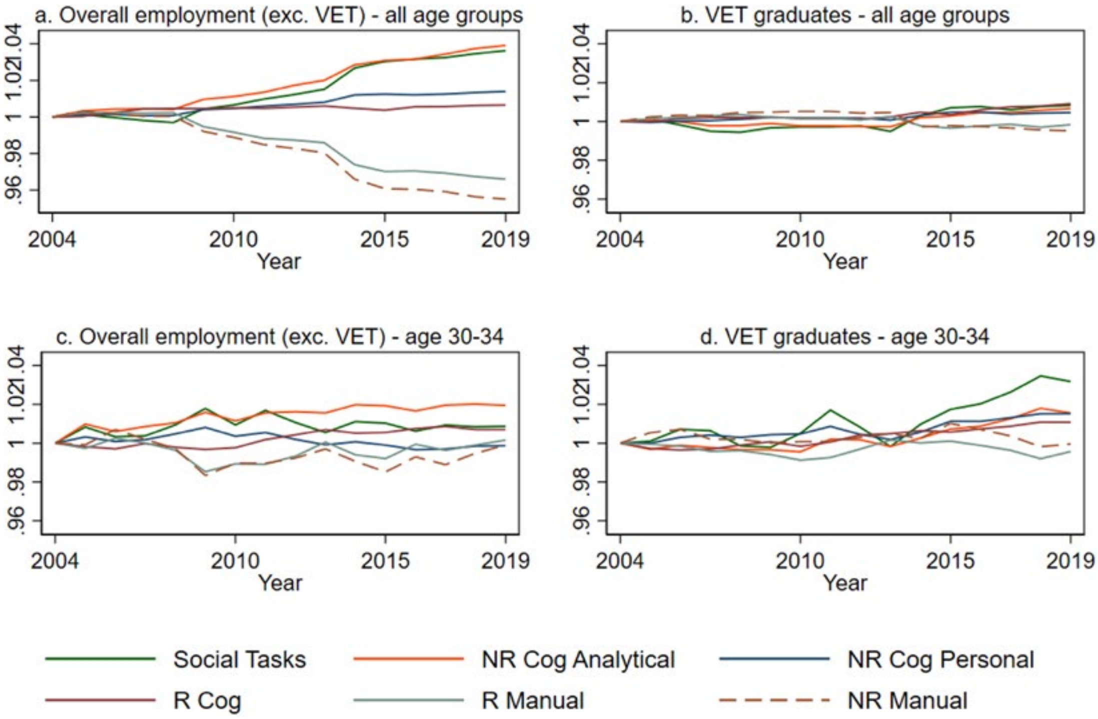
***Luxembourg***



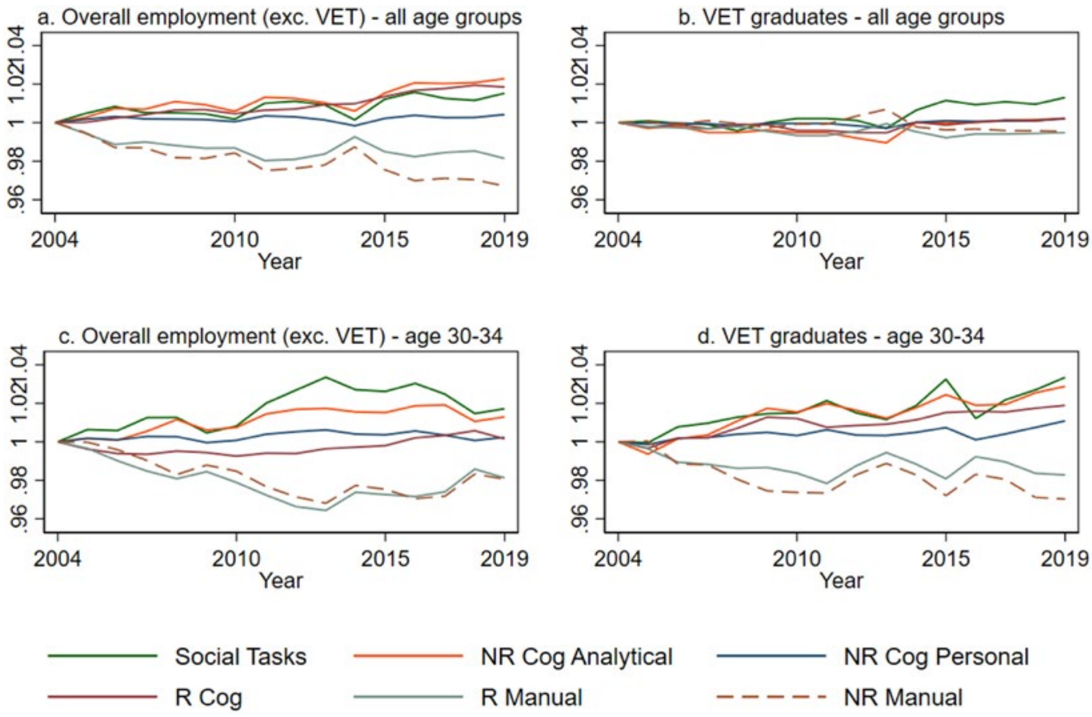

***Netherlands***



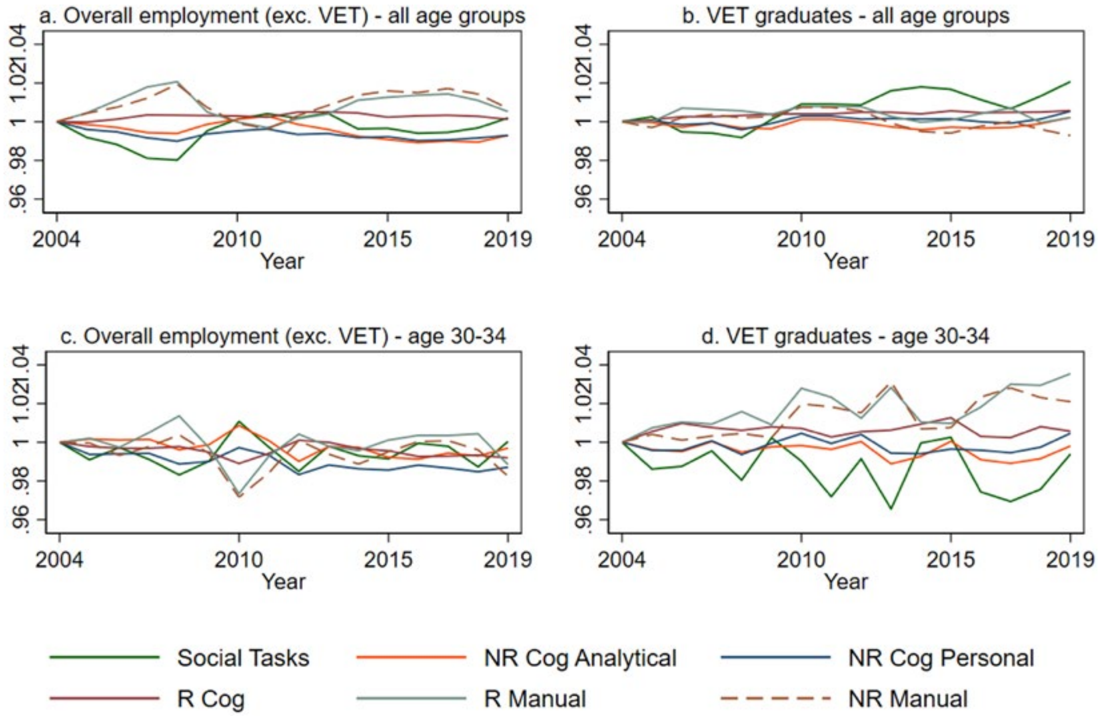
***Poland***




***Romania***



***Slovak Republic***




***Switzerland***