TRAILS

Enabling Data Analytics for Actions
Tackling Skills Shortages & Mismatch

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ACRONYMS

Acronym	Explanation
ESJS	European Skills and Jobs Survey
ESCO	European Skills, Competences, Qualifications and Occupations classification system
ISCO	International Standard Classification of Occupations
ISCED1997	International Standard Classification of Education (1997 version)
ISCED2011	International Standard Classification of Education (2011 version)
VET	Vocational Education and Training
ICT	Information and Communication Technology
CEDEFOP	European Centre for the Development of Vocational Training
NACE	Nomenclature of Economic Activities

Executive Summary

Technological change is impacting substantial numbers of employees in the EU labour market. This can have important consequences, depending on how technology interacts with jobs and tasks. For example, if technology substitutes employees or replaces tasks, jobs could be lost and skills could become obsolete. On the other hand, technology may complement or augment existing skills, allowing employees to upskill and improve productivity, potentially creating new opportunities and boosting employment. In this Deliverable, we examine these issues in three closely related chapters using two waves of the European Skills and Jobs Survey (ESJS). The ESJS captures unique information from employees across the EU relating to technological change, skills development, training and job security. Using this data, we examine the incidence of technological change across the EU and its association with skill change. We also examine how employees adapt to the introduction of new technologies, either through formal training or informal learning methods. In addition, we examine the relationship between organisational technological change and firm-level employment growth.

Our analysis reveals some notable findings. Across several measures, and over two time periods, we find consistent evidence that approximately half of all EU employees have been recently (in the previous 12 months) been impacted by technological change at work. In Chapter 1, we show that employees that experience technological change are more likely to have completed training, and that technological change is positively associated with upskilling. For example, one quarter of employees that were exposed to technological change at work report that their skills have increased significantly, compared to just 17 percent among employees not exposed to technological change. Chapter 1 also provides a detailed ranking of the potential effectiveness of different training and learning combinations. Employees that completed multiple training modes report the greatest degree of upskilling. Structured courses (e.g. classroom based or online) appear to be particularly effective, especially when combined with other types of training (e.g., learning from a supervisor). This emphasizes the importance of looking beyond a simple training incidence – it is not just the extensive margin that matters, but also the intensive margin that appears to matter when it comes to training.

While formal training courses are clearly important for adapting to technological change, informal learning also plays a role. Although there is a growing recognition of the importance of informal learning for employees' skill development, the literature in this area is underdeveloped (De Grip, 2024). In Chapter 2, therefore, we focus on the role played by informal methods when it comes to learning new software or computer programs. Our definition of informal learning includes self-guided learning (learning on your own), learning from family or friends, learning from colleagues and learning from a supervisor. A notable finding from Chapter 2 is that approximately five percent of employees that recently learned to use new software or computer programs did so using self-guided learning *only*, without the support of formal training from their employer, their supervisor or their colleagues. This highlights a feature of modern labour markets, in which technology is rapidly changing and advancing, and employees use their own initiative to adapt to new programs and software. It may also reflect the quality and widespread availability of resources which facilitate self-directed learning. For example, it is possible to learn new software or programming languages, such as Python, using online and freely available video tutorials. It is also possible to utilise massive open online courses (MOOCs) in a flexible and cost-effective way to learn new digital and technology skills.

The policy debate on technological change often focuses on its potential for replacing employees and leading to widespread job losses, even though this is often not supported by empirical evidence (McGuinness et al., 2023). In Chapter 3 we examine the relationship between organisational technological change and employment growth. Our definition of organisational technological change is based on a self-reported measure by employees who indicate that new computer systems, devices or programs were recently introduced into their workplace. Our results show that the introduction of new technology within an organisation is positively associated with employment growth; respondents that work in firms where new technology was recently introduced are approximately 10 percentage points more likely to report increases in employment within their workplace over the same period. However, despite this, employees in firms where new technologies are being introduced are more likely to fear losing their jobs. This underscores the uncertainty that exists among employees about the role that technology may play in the future.

Our findings are highly policy relevant. Several policies and initiatives across the EU, along with a considerable amount of funding, is focused on equipping individuals and businesses with the capabilities and skills to adapt to a rapidly changing technological and digital landscape.[1] Our results highlight the importance of these initiatives, given that we find almost half of all employees in the EU have experienced recent technological change. Our analysis shows that new technology can enhance employees' skills, especially when accompanied by training. Multiple modes of training are associated with the greatest increase in skills, particularly when this involves some combination of structured training courses and supervisor involvement. However, our results also show a strong role for informal learning when it comes to adapting to new computer software. Many employees learn how to use new software on their own using, for example using books or online video resources, without the support of formal or structured training. This may, to some extent, reflect the greater availability of free resources for high quality self-guided learning. However, for others it may be symptomatic of a particularly acute deficit in digital skills and / or a lack of adequate employer provided training. For example, our results show that those with low levels of education are far more likely to learn how to use new software or computer programs from family or friends.

Taken together, our findings indicate that the introduction of new technology in the workplace is often associated with positive outcomes, including skills development and an increase in employment. Nonetheless, it is difficult to predict how this will continue to develop. Those employees that have been recently exposed to technological change at work are more likely to fear

[1] For example, The Digital Europe Programme, the European Commission's Pact for Skills, the European Social Fund Plus funding instrument, among others.

future job loss, even if they report recent job growth within their firm. This highlights the uncertainties associated with ongoing technological advances in the labour market.

Purpose of the Deliverable

The overall purpose of Deliverable 3.2 is to examine "the interplay between technological change, training and upskilling Europe". To achieve this, the Deliverable examines several policy-relevant questions. In Chapter 1, we examine the incidence of exposure to technological change among EU employees, and examine the extent to which technological change is associated with employees' upskilling? In addition, we investigate whether employees that experience technological change are more likely to receive training compared to employees that did not experience technological change. Finally, Chapter 1 ranks the specific combinations of training that are most strongly associated with higher levels of upskilling.

In Chapter 2, the focus moves towards informal modes of training and learning. Specifically, we investigate the role played by informal learning methods, such as interactions with family and friends or through self-guided learning via books or online materials, when it comes to learning to use new software and computer programs. We then examine the relationship between different methods of informal learning and employees' perceptions of the effectiveness and usefulness of technology.

While Chapters 1 and 2 focus on the training and upskilling of existing employees, it is important to also recognize that technological change may impact overall employment in a firm, either positively or negatively. To investigate this, Chapter 3 examines the relationship between technological change, at an organisational level, and employment growth within the firm. It also examines how organisational technological change may impact employees' job security, and fears of future job loss.

Relation with Other Deliverables and Tasks

This deliverable builds on the work of several previous, closely related deliverables. Deliverable 1.1 provided a detailed summary of the existing literature on skills mismatch, including its determinants, impacts and the policies that can affect it. This provides a basis for reviewing relevant literature, both empirical and theoretical, relating to skills mismatch and skills development. Deliverable 3.1 examined how skill requirements within occupations have changed over time, and the role of training in enabling employees to keep pace with these changes. The most closely related Deliverable is Deliverable 5.1, which showed that most EU employees experience some type of technology-related skills deficit, emphasizing the need for adequate training to address this issue.

1. Chapter One: Training and Upskilling in the Presence of Technological Change

1.1 Introduction

Technological change continues to reshape job tasks and skill requirements across Europe. As automation, digital tools, and new production technologies become more prevalent, workers increasingly need to adjust their competences to keep pace with evolving job demands. These developments heighten concerns around skills mismatch, since technological upgrading can raise required skill levels while making some existing competencies obsolete. Adjustment to these changes can take different forms. Workers may upskill, by deepening or extending their competences within existing roles, or reskill, by reallocating tasks and adapting to new skill bundles as labour demand evolves. Recent research, particularly in the context of AI adoption, emphasises the importance of reskilling and task reorganisation as firms reorganise production and redeploy labour rather than simply intensifying existing skills (Tamayo et al., 2023). In practice, these processes are closely related and often occur jointly, with training and learning supporting both skill upgrading and task adaptation within jobs.

These issues are at the forefront of global economic policy (World Economic Forum, 2020; OECD, 2023) and have led to major policy initiatives, such as the European Year of Skills (European Commission, 2022), which recognises the critical need for upskilling to maintain competitiveness. Large shares of European workers report gaps between the skills they possess, and the skills demanded by their jobs demand (Cedefop, 2015), and such mismatches have been associated with lower productivity, reduced job quality, and constraints on labour mobility (Kampelmann et al., 2020; Brunello & Wruuck, 2019; McGuinness et al., 2018). Understanding how workers update their skills in response to technological change, and the role that different forms of training play in supporting this adjustment, has therefore become an important policy and research priority.

A large body of research shows that technological change can alter the skill content of work by reducing the importance of routine tasks and increasing demand for non-routine cognitive and interpersonal skills (Autor et. al, 2003; Acemoglu & Autor, 2011). Technology adoption is often accompanied by increases in training provision and on-the-job learning opportunities, implying that training acts as a complementary input to new technologies (Freel, 2005; Cobbenhagen, 2000). While some existing studies examine either the incidence of training or associations between technology and labour demand, we know less about how specific learning modes - formal courses, supervisor-led instruction, peer learning, self-directed learning, and experiential learning - relate to actual employee upskilling, or about which combinations of these modes are most effective. Evidence at the individual employee level, and across countries and industries, remains limited.

This chapter contributes to filling these gaps by analysing the relationship between technological change, training, and upskilling using microdata from the first wave of the European Skills and Jobs Survey (ESJS1) (Cedefop, 2014). While recent research emphasises reskilling and task reallocation as important responses to technological change, particularly in the context of advanced digital technologies, the ESJS is designed to capture skill development and learning within workers' current jobs. It therefore allows us to examine upskilling and the training mechanisms that support skill improvement among workers exposed to technological change. The ESJS provides detailed information on workers' exposure to technological change, the types of training and learning they receive, and the extent to which their skills improve while in their current job. Using this dataset, we address three questions. First, to what extent is technological change associated with employees' upskilling? Second, are employees that are exposed to technological change more likely to receive training? Third, which specific forms or combinations of training are most strongly associated with higher levels of upskilling.

Our findings can be summarised in four points. First, technological change is consistently and positively associated with employee upskilling: employees who report technology-related task changes are substantially more likely to report skill improvement. Second, employees exposed to technological change are more likely to receive training of all kinds, with particularly large increases in the probability of engaging in hybrid programmes that mix formal and informal learning. Third, training (particularly formal training and supervisor-led learning) is strongly associated with higher upskilling. Fourth, the combinations of learning modes are important. Employees who engage in multiple learning pathways, typically integrating courses with supervisor-led or peer-based learning, exhibit the highest levels of upskilling. Less structured or single-mode approaches yield weaker associations.

Taken together, these results improve our understanding of how employees adapt to technological change and highlight the importance of training design, rather than training incidence alone, for effective upskilling. By identifying which learning modes and combinations are most strongly associated with skill improvement, and by documenting substantial variation across countries, industries, and firms, the chapter provides evidence of direct relevance for labour-market and skills policies aimed at reducing skill mismatch and supporting employees in technology-intensive jobs.

1.2 Related Literature

Technological change in the labour market can alter the task content and the skill requirements of jobs. Theoretically, the impact depends on whether new technology complements or substitutes the existing skills of employees, and these effects could vary depending on the type of employee (see Goos (2018) for a review of the existing theoretical literature). For example, technological change could boost the productivity of high skilled employees more than low skilled employees, resulting in a widening wage premium for high-skilled employees (see, e.g., Katz and Murphy, 1992; Goldin and Katz, 2007). While technology can affect existing tasks, it also has the potential to create new tasks in which labour has a comparative advantage (Acemoglu and Restrepo, 2019).

McGuinness et al. (2023), who examine the incidence and impact of technological change that has the potential to make some employees' skills obsolete – they refer to this as skill displacing technological change (SDT). They find that SDT mainly affects high-skilled employees and is often accompanied by training. Furthermore, it is associated with greater task variety and job-skill complexity. However, it is also associated with a greater fear of job loss. McGuinness et al. (2023) argue that their findings provide direct survey evidence of the 'reinstatement effect', whereby new technologies can create tasks which complement and advantage the skills of existing employees.

A related strand of research specifically examines how firms respond to technological change through investment in training. Innovative and technology-intensive firms have been found to invest more heavily in training, and this can have positive associations with productivity (Freel, 2005; Cobbenhagen, 2000; Johnson, Love, & Gellatly, 1996). Using firm-level data for the US, Bresnahan et al. (2002) demonstrate the important link between IT adoption and training. The authors note that firms do not simply "plug in computers" and benefit from efficiency gains. Instead, new technology must be accompanied by organizational policies, including training.

With regard to training more generally, a meta-analysis by Arthur et al. (2003) finds that formal training leads to improvements in learning outcomes and job performance. However, the authors note that the effectiveness of training can vary depending on the method used and the evaluation criteria. Early work on the "transfer of training" problem shows that only a portion of skills learned in training settings translate into sustained changes in workplace behaviour (Baldwin & Ford, 1988; Georgenson, 1982). Key determinants of successful transfer include trainee motivation, managerial and peer support, opportunities for practice, and alignment between training content and job demands (Noe, 1986; Kontoghiorghes, 2001; Tracey & Tews, 2005; Gegenfurtner et al., 2009). Informal learning has also been shown to be important. Employees frequently acquire skills through daily interactions, observation, feedback, and problem-solving rather than structured courses (Boud & Middleton, 2003; Eraut, 2004). Many organisations explicitly recognise the complementary nature of formal and informal learning, reflected in frameworks such as the 70–20–10 model (Johnson, Blackman, & Buick, 2018), which says that effective learning comes roughly from 70% on-the-job experience, 20% coaching and feedback, and 10% from formal training. There is also evidence that combinations of learning modes (such as formal courses paired with supervised practice, peer learning, or self-directed exploration) produce stronger upskilling outcomes than single training channels (Arthur et al., 2003; De Grip & Sauermann, 2013; Blume et al., 2010). This literature demonstrates that looking at the broad incidence of training alone is not sufficient, as training effectiveness depends on the type of training being implemented.

The existing literature also points to heterogeneity when it comes to the relationship between technology, training, and upskilling. Industries vary in how and when technological change occurs, with sector-specific innovation patterns generating different training needs (Pavitt, 1984; Tidd, 2001; Oerlemans et al., 1998). High-tech sectors typically rely more on formal skill upgrading and R&D-related training, whereas traditional sectors may depend more on experiential and on-the-job learning. Firm size is another relevant dimension: large firms consistently offer more structured training opportunities than SMEs, which often face constraints such as limited resources, higher turnover risk, and fewer dedicated training mechanisms (van den Berg et al., 2020; Kitching, 2008). Cross-country differences in vocational education systems, labour-market institutions, and training incentives further shape how employees acquire skills and how firms respond to technological change (Hall & Soskice, 2001; Estevez-Abe et al., 2001; Dieckhoff, 2008).

Overall, the literature establishes three points that are central to this chapter: (1) technological change shifts job task requirements in ways that typically increase the need for upskilling; (2) firms commonly respond by expanding training provision, often combining formal and informal modes of learning; and (3) training effectiveness is heterogeneous and depends on the mode of learning, workplace environment, and institutional context. These insights motivate the empirical analysis that follows, which examines how technological change, training behaviours, and different learning modes shape upskilling outcomes among European employees.

1.3 Data and Descriptive Statistics

Our analysis draws on microdata from the first wave (2014) of the European Skills and Jobs Survey (ESJS), a cross-country survey conducted by Cedefop that collects harmonised information on employees' skills, job tasks, training, and learning behaviour across EU labour markets. The ESJS samples employed adults aged 24–65 across all EU Member States and contains rich information on sociodemographic characteristics, job attributes, job-skill requirements, and perceived skill mismatches. Crucially for our purposes, the 2014 wave records detailed information on employees' exposure to technological change, whether they experienced upskilling, whether they completed training, and the specific type of training methods that they completed.[2] Table 1 provides some descriptive statistics for the full sample of employees.

[2] The detailed information on training type and upskilling is not available in the later (2021) wave of data.

Table 1: Descriptive Statistics

Variable	Mean	St. dev.	N
Age	42.44219	10.1045	47969
Tenure	10.26191	9.263509	47657
>1 workplace location	0.594132	0.491064	47969
Male	0.517506	0.499699	47969
Low education	0.139528	0.3465	47969
Middle education	0.490688	0.499919	47969
High education	0.369785	0.482751	47969
Part-time	0.165251	0.371411	47385
Private	0.639553	0.480135	47969
Temporary contract	0.117951	0.322553	47969
Occupations			
Managers	0.070691	0.256311	47969
Professionals	0.192824	0.39452	47969
Associate professionals	0.162198	0.368636	47969
Sales employees	0.149263	0.356352	47969
Clerical employees	0.212486	0.409071	47969
Agricultural employees	0.007872	0.088375	47969
Builders and tradespeople	0.081788	0.274045	47969
Machine-operators and drivers	0.070777	0.256455	47969
Industries			
Administration and support services	0.127851	0.333928	47969
Agriculture	0.018736	0.135593	47969
Gas or electricity, mining or quarrying	0.02145	0.144881	47969
Supply, management or treatment of water	0.01175	0.10776	47969
Manufacturing or engineering	0.156078	0.362933	47969
Construction or building	0.068735	0.253005	47969
Retail, sales, shop work or wholesale	0.106525	0.308511	47969
Accommodation, catering or food services	0.03322	0.179212	47969
Transportation or storage	0.057189	0.232206	47969
ICT	0.057159	0.232149	47969
Financial, insurance, or real estate services	0.048499	0.21482	47969
Professional, scientific or technical services	0.058289	0.234291	47969
Services relating to education or health	0.144445	0.351544	47969
Cultural industries	0.019335	0.137701	47969
Social and personal services	0.059448	0.236464	47969

Other	0.011292	0.105662	47969
Firm-size			
1-9	0.221546	0.415292	47969
10-49	0.275123	0.446581	47969
50-99	0.123763	0.329314	47969
100-249	0.122294	0.327629	47969
249-499	0.074311	0.262279	47969
500 and over	0.152036	0.35906	47969

Source: ESJS1 (2014).
Note: Descriptive statistics. Weighted. Based on authors calculations.

To derive our measure of technological change, we use the following question:

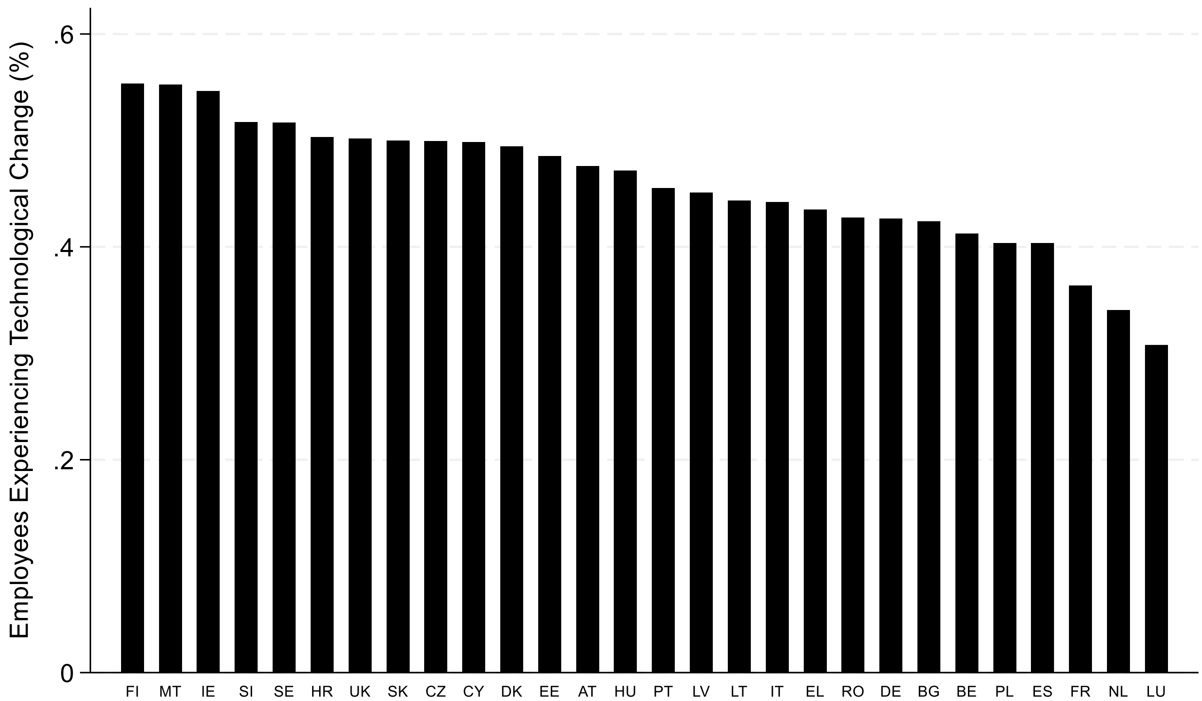
"In the last 5-years or since you started your main job, have any of the following changes taken place in your workplace/organisation - Changes to the technologies you use (e.g. machinery, ICT systems)?"

If an employee answers yes to this question they are classified as having experienced tech change.

Overall, approximately 45% of European employees report experiencing changes to the technology that they use in their workplace. However, the incidence of technological change varies substantially across countries, as shown in Figure 1. Finland, Malta and Ireland have the highest rates of technological change, at over 50 percent, whereas France, the Netherlands, and Luxembourg report the lowest, ranging from approximately 30 to 35 percent.

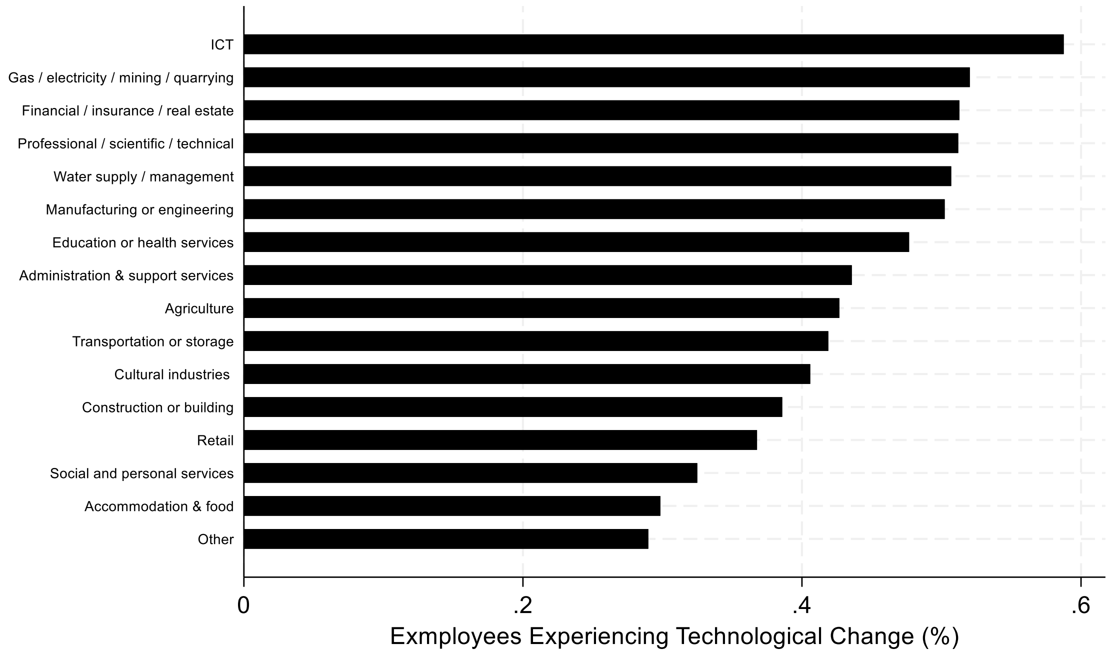
There are also substantial differences in the incidence of technological change across industries, as shown in Figure 2. High-skilled and tech-intensive sectors such as ICT, Finance and Professional Services show a relatively high incidence of technological change, while Accommodation & Food, Retail and Social Services report the lowest. In relation to firm-size (Figure 3), there is a clear monotonic relationship; employees in large firms are more likely to report technological change than those in small firms. This is consistent with existing evidence that larger firms adopt new technologies earlier and at greater scale (Freel, 2005; Bresnahan et al., 2002).

Figure 1: Incidence of Technological Change by Country



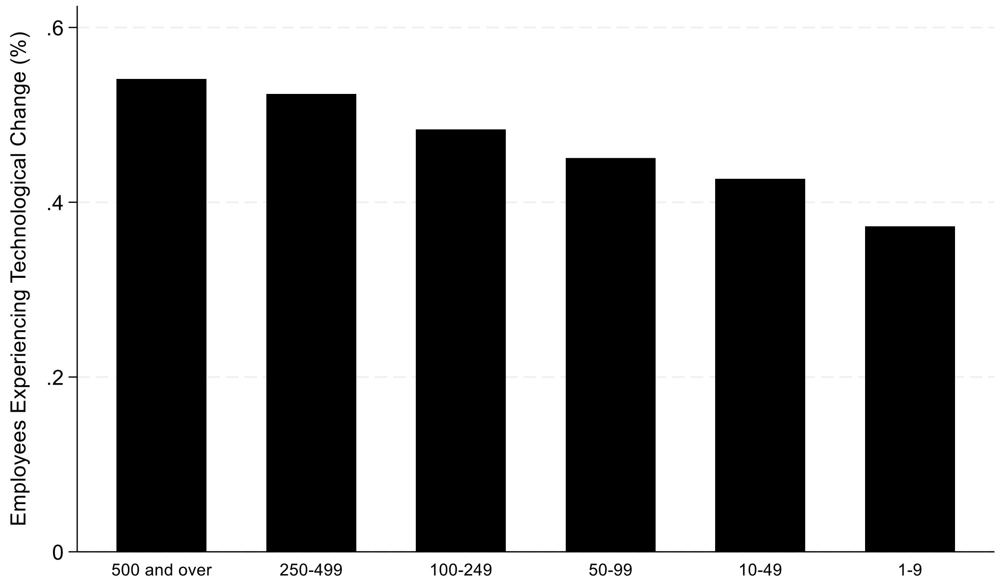
Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

Figure 2: Incidence of Technological Change by Sector



Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

Figure 3: Incidence of Technological Change by Firm Size



Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

To capture upskilling, we use the following question:

"Compared to when you started your job with your current employer, would you say your skills have now improved, worsened or stayed the same? Please use a scale of 0 to 10 where 0 means your skills have worsened a lot, 5 means they have stayed the same and 10 means they have improved a lot."

The vast majority (86 percent) of employees report some degree of upskilling – that is, they report a value between 6 and 10. Just 14 percent report that their skills have gotten worse or have stayed the same (0 to 5). Therefore, to capture the intensity of upskilling in a clearer and more concise way, we create a new upskilling scale that ranges from 0 to 5. A value of zero indicates that an employees' skills have either worsened or stayed the same (0 to 5 on the original scale). Values of 1 to 5 indicate upskilling, with a value of 5 corresponding to the greatest degree of upskilling (equivalent to 10 on the original scale, meaning skills have improved a lot).

Table 2 overleaf shows the incidence of each category in the 0-5 skill change scale for all employees, those that experienced technological change, and those that did not experience technological change. It is clear that the degree of upskilling is higher for the group that experienced technological change. For example, 44 percent of the tech-change group report a high degree of skills improvement (category 4 or 5), compared to 37 percent of all employees and just 32 percent of the no-tech change group.

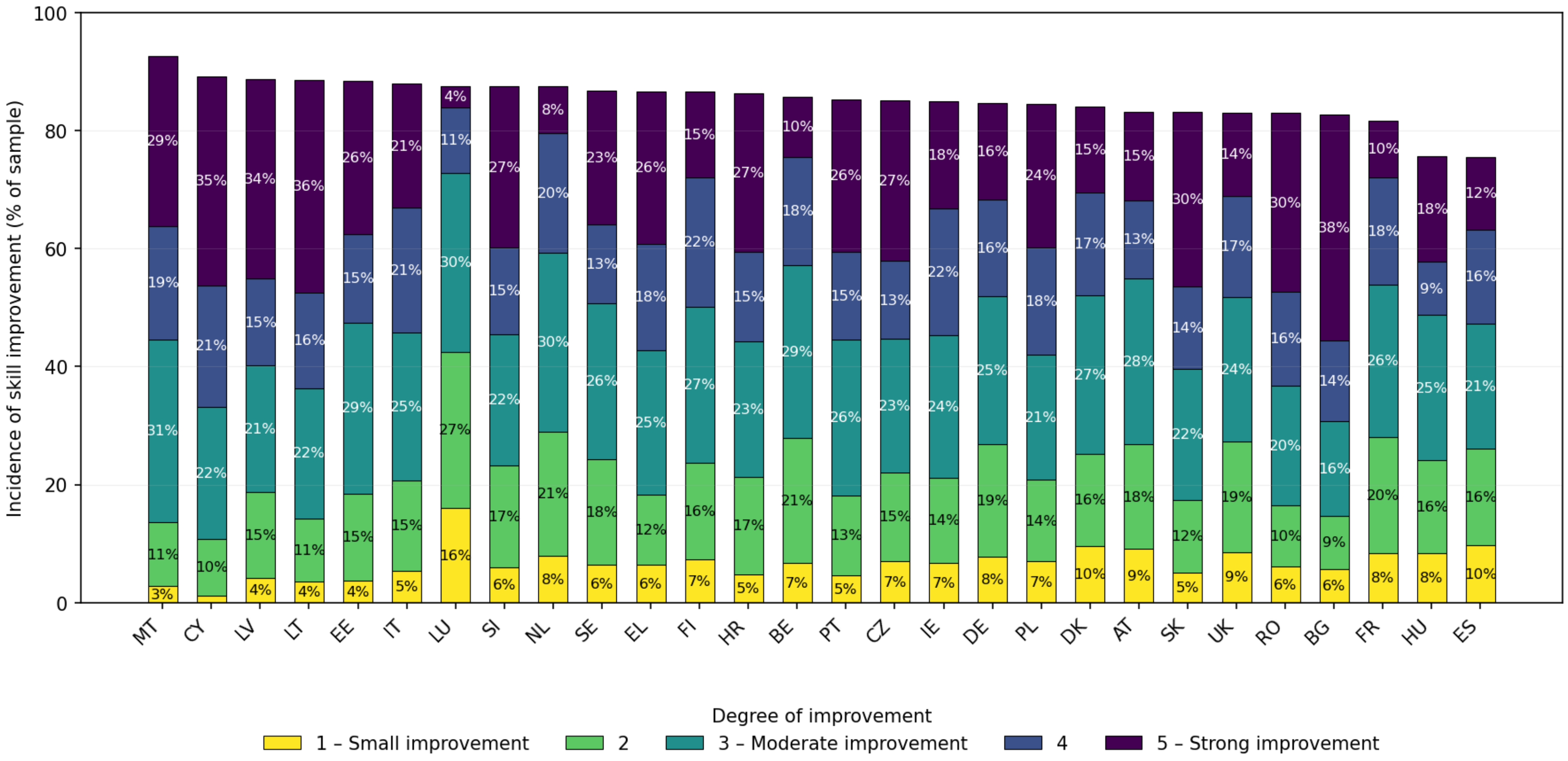
Table 2: Skill Change Categories (Incidence)

Skill change scale	All Employees	Tech-Change Employees	No Tech-Change Employees
0 (skills decreased or stayed same)	14%	8%	19%
1	7%	6%	9%
2	16%	16%	17%
3	25%	26%	24%
4	17%	20%	15%
5 (skills improved a lot)	20%	24%	17%

Source: ESJS1 (2014).
Note: Based on authors calculations.

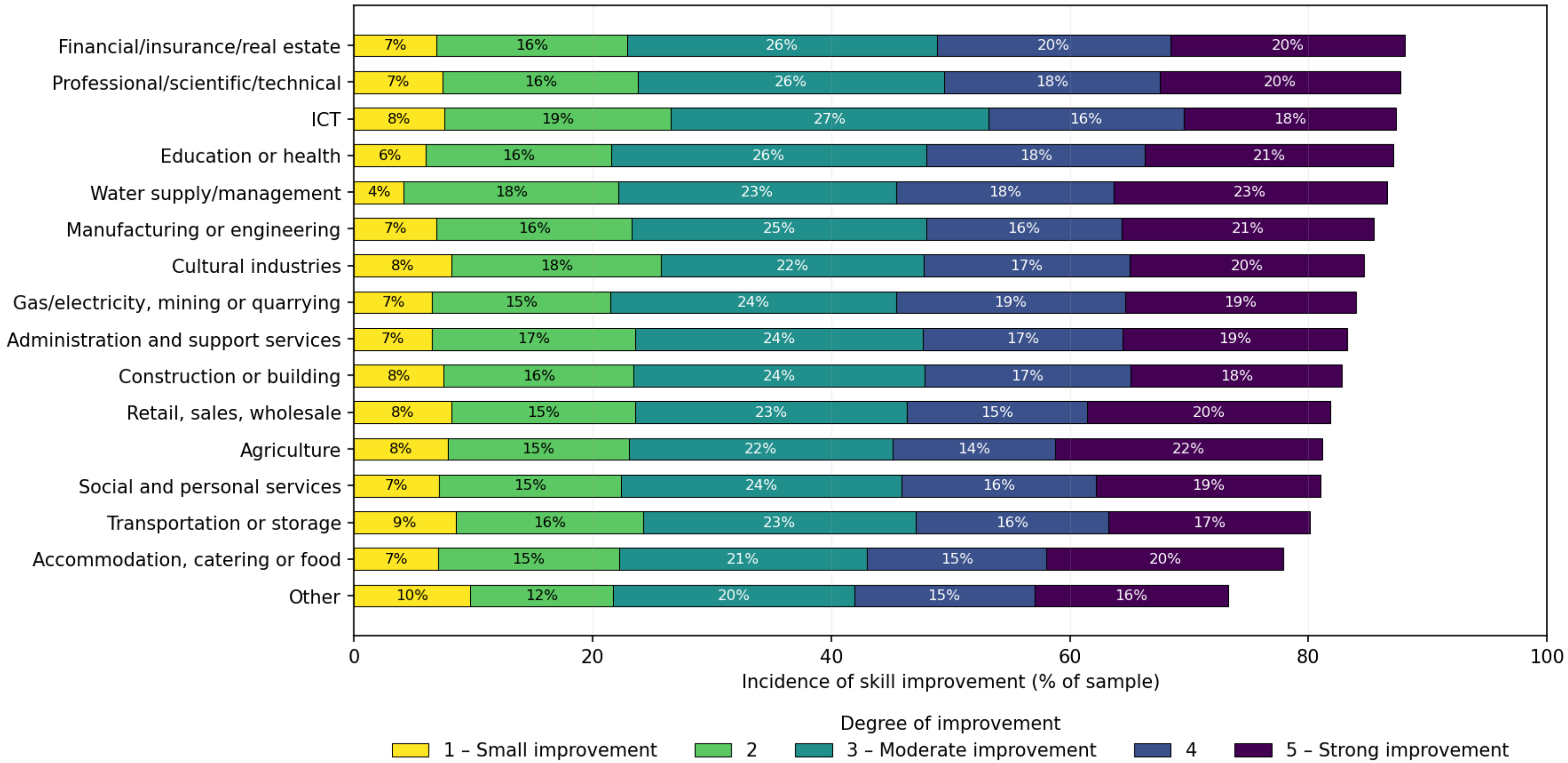
In Figure 4 we show the incidence of upskilling by country, as well as the distribution of upskilling intensity. We focus only on those that report some degree of upskilling (from 1 to 5 in Table 2). This allows us to visually show any differences in upskilling incidence (including the 0's would result in all bars summing to 100%). Heterogeneity in the overall incidence of upskilling across countries is modest, as the vast majority of employees in all countries report some degree of upskilling. However, heterogeneity on the intensive margin is larger. For example, Luxembourg has a higher incidence of skill improvement than Bulgaria, but Bulgaria has almost ten times the share of employees reporting the highest upskilling level.

Figure 4: Incidence of upskilling by country (1 – 5 scale)



Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

Figure 5: Incidence of upskilling by sector (1 – 5 scale)

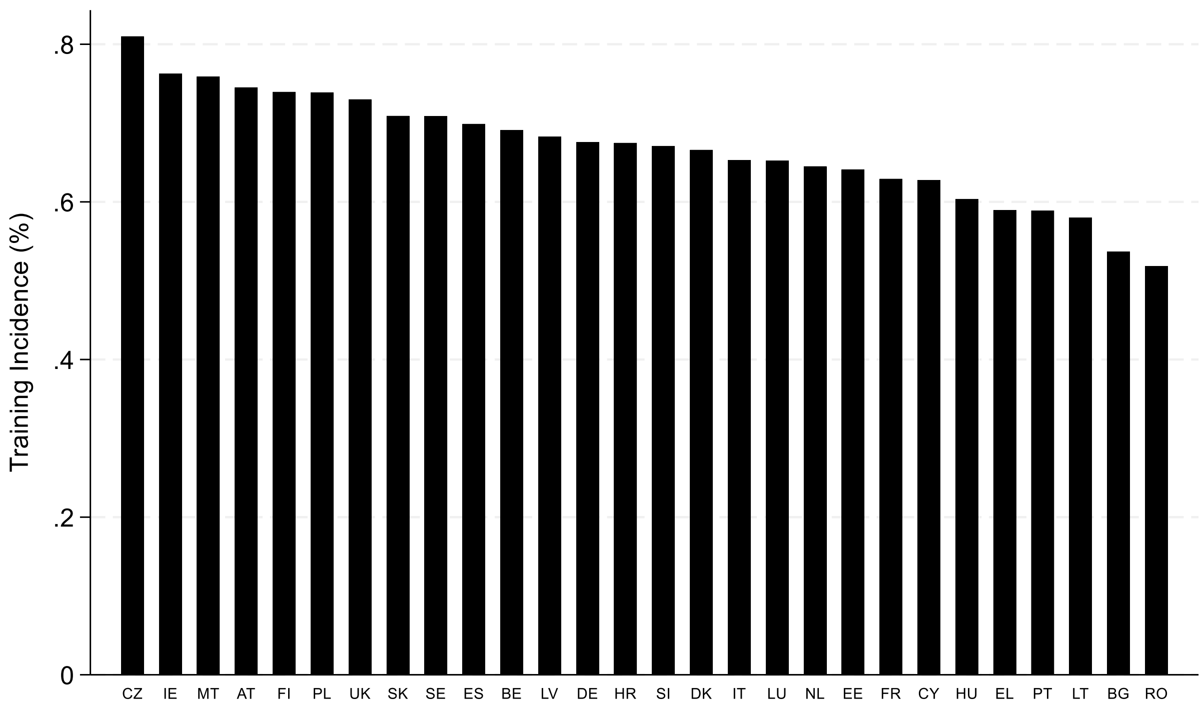


Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

In Figure 5 we show the incidence and intensity of upskilling across industries. Again, the majority of employees across all industries report some degree of upskilling. However, higher-skilled sectors such as Finance, ICT and Professional Services report higher overall upskilling, while sectors such as Accommodation and Food and Transportation have relatively low levels of upskilling incidence.

Employees in the ESJS data are asked whether, in the last 12 months or since they started their job, they underwent training. Two-thirds of employees report that they received training. However, there are notable differences across countries, as shown in Figure 6. Approximately 80 percent of employees in countries such as Czechia, Ireland and Malta report having received training. This compares to just 50 percent of employees in Romania and Bulgaria.

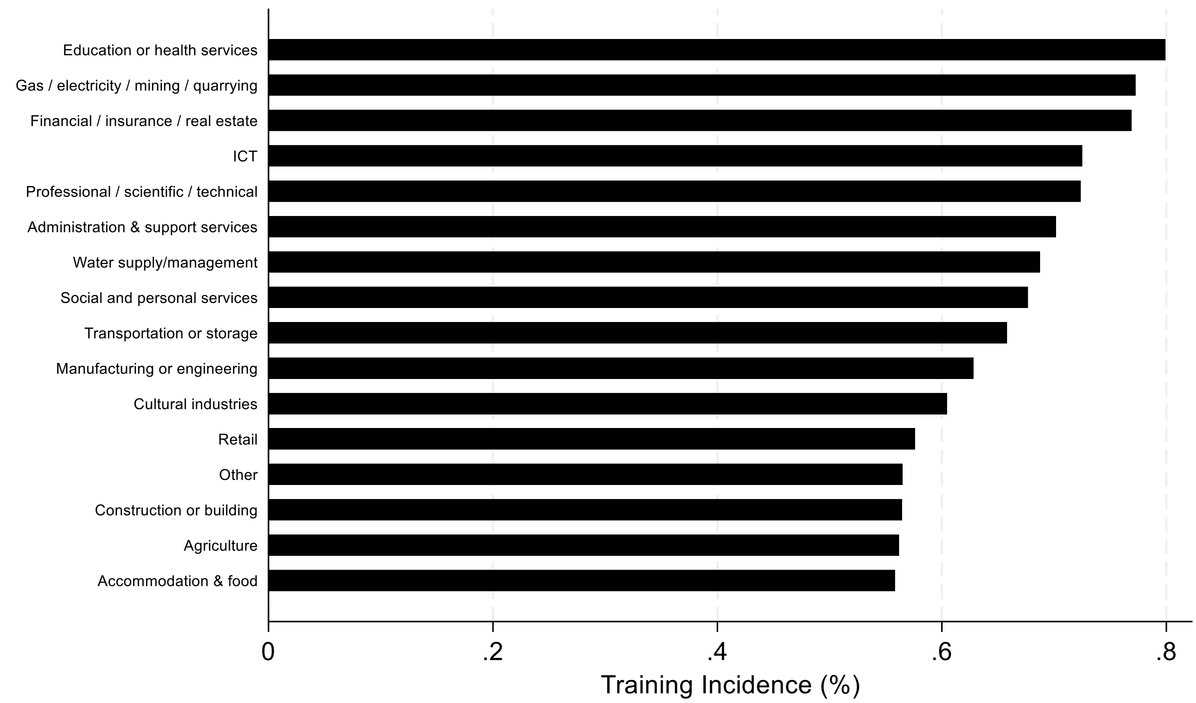
Figure 6: Incidence of training by country



Source: ESJS1 (2014).
Note: Based on authors calculations.

In Figure 7 we show the incidence of training by sector. The incidence of training tends to be higher in high-skilled sectors such as education, health, finance, ICT and professional services, where between 70 and 80 percent of employees report receiving training. The gas and electricity sector also has a high incidence of training, at just under 80 percent. Conversely, accommodation and food, agriculture and construction have the lowest training incidence, at just over 50 percent.

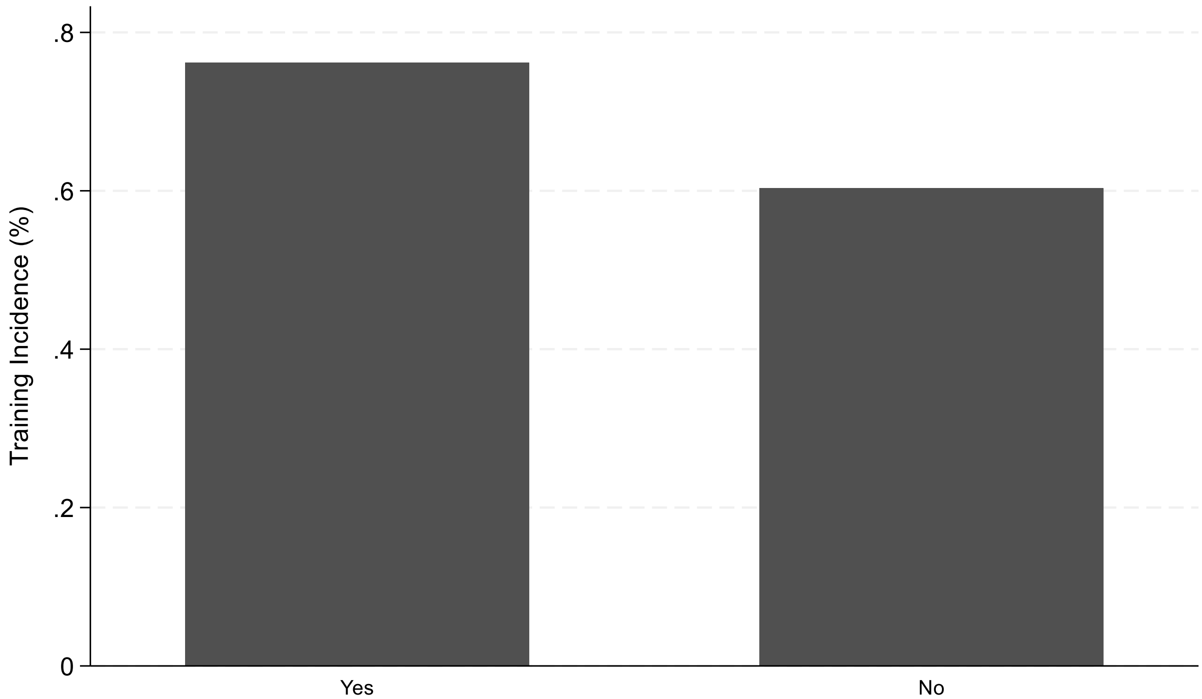
Figure 7: Incidence of training by sector



Source: ESJS1 (2014).
Note: Based on authors calculations.

Employees who experienced technological change are significantly more likely to have received training (see Figure 8). Just under 80 percent of employees that experienced technological change at work have received training, compared to just 60 percent of employees that were not exposed to technological change.

Figure 8: Incidence of training by whether employees experienced tech-change



Source: ESJS1 (2014).
Note: Based on authors calculations.

To examine specific upskilling channels, we use a follow-up question asked only to employees who reported skill improvement:

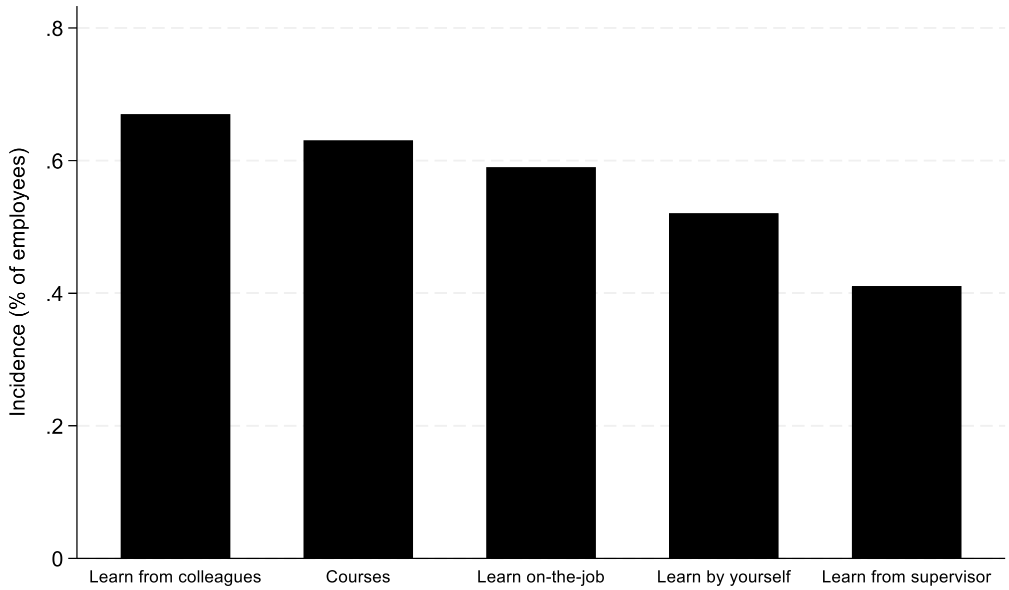
"Since you started your job with your current employer, have you done any of the following to improve or acquire new skills?

1. *You attended training courses (work-based, classroom based and online)*
2. *Your supervisor taught you on-the-job*
3. *You learned by interacting with colleagues at work*
4. *You learned at work through trial and error*
5. *You learned by yourself (e.g. with the aid of manuals, books, videos or on-line materials)"*

These items are not mutually exclusive, as employees can report training / learning methods. It is also possible that an employee answers no to all of the five categories. However, just 3 percent of employees do this. Figure 9 shows the incidence of each type of training method. The most common method is learning from colleagues – 67 percent of employees report doing this. Approximately 60 percent of employees report upskilling via a course or on-the-job learning. Just over half learn by themselves, while the least common upskilling method, at 41 percent, is learning from a supervisor.

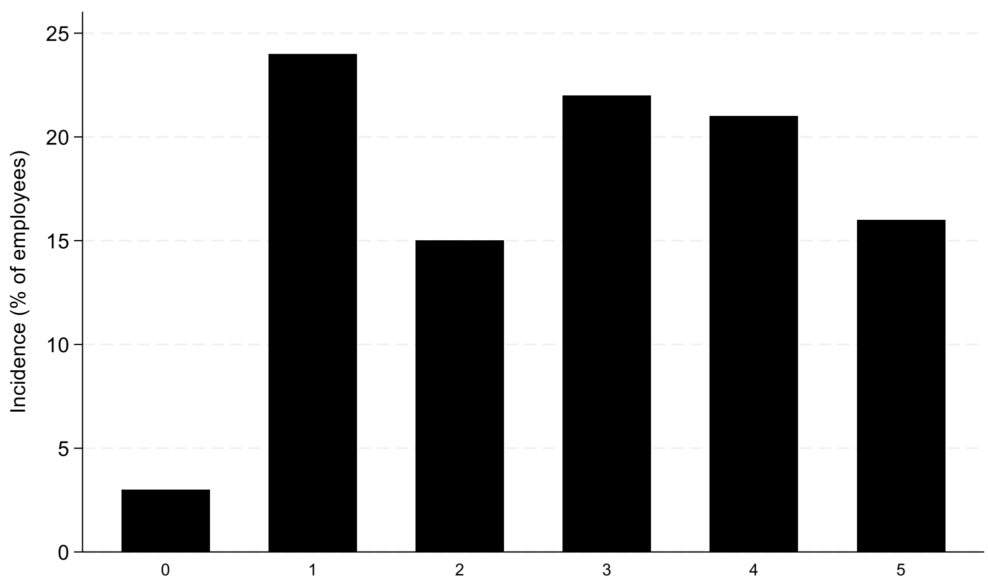
In Figure 10, we show the incidence of the number of training and learning methods used by employees. Just 3 percent report using none of the methods described above, while just under one quarter use just one method. This means that three quarters of all employees that report skill improvement have utilised multiple upskilling methods, with 16 percent using all five methods (learning from colleagues, attending courses, learning on-the-job, learning by yourself and learning from a supervisor).

Figure 9: Incidence of training & learning method (not mutually exclusive)



Source: ESJS1 (2014).
Note: Based on authors calculations

Figure 10: Distribution of number of training & learning methods used

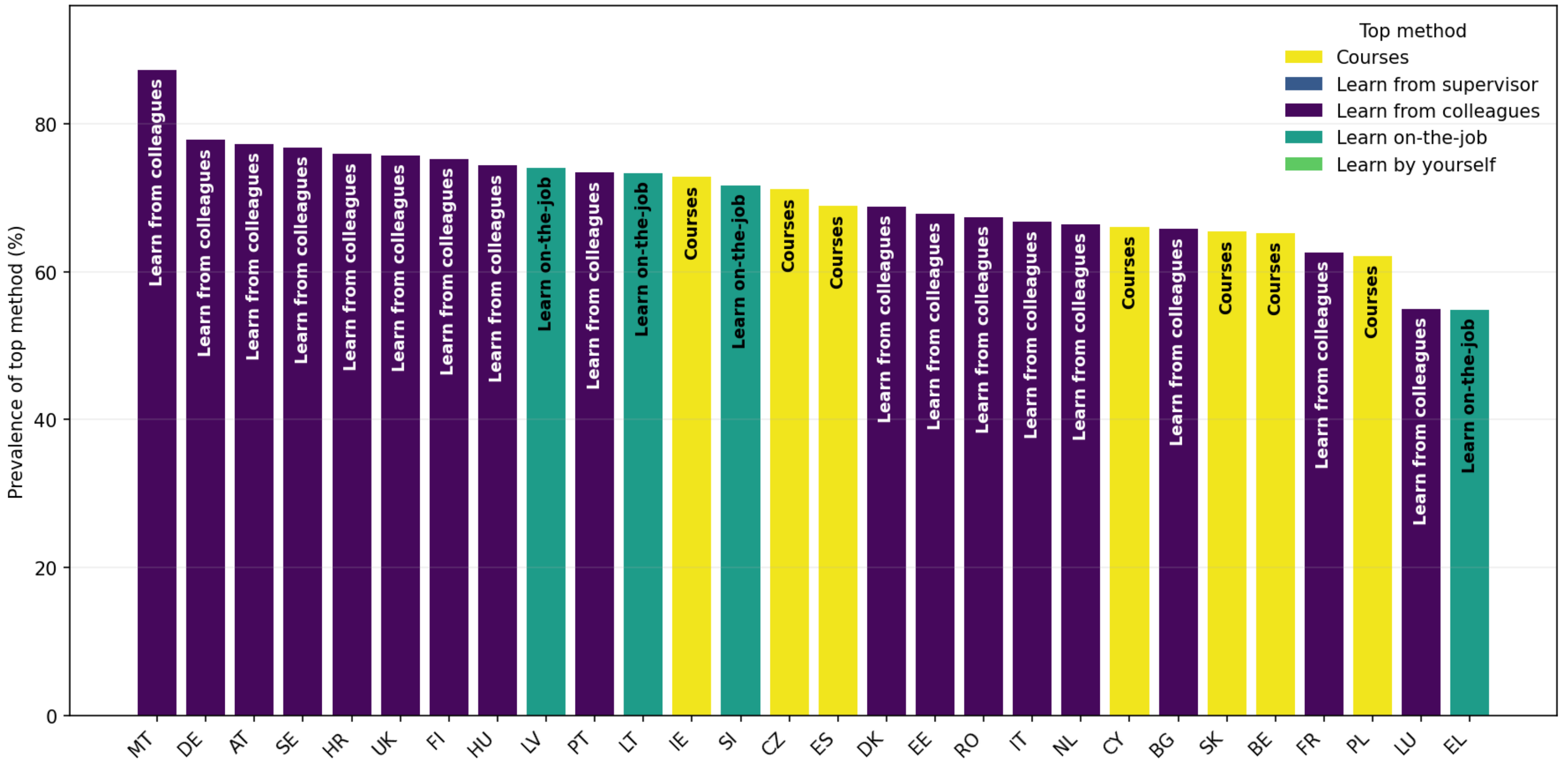


Source: ESJS1 (2014).

Note: Based on authors calculations

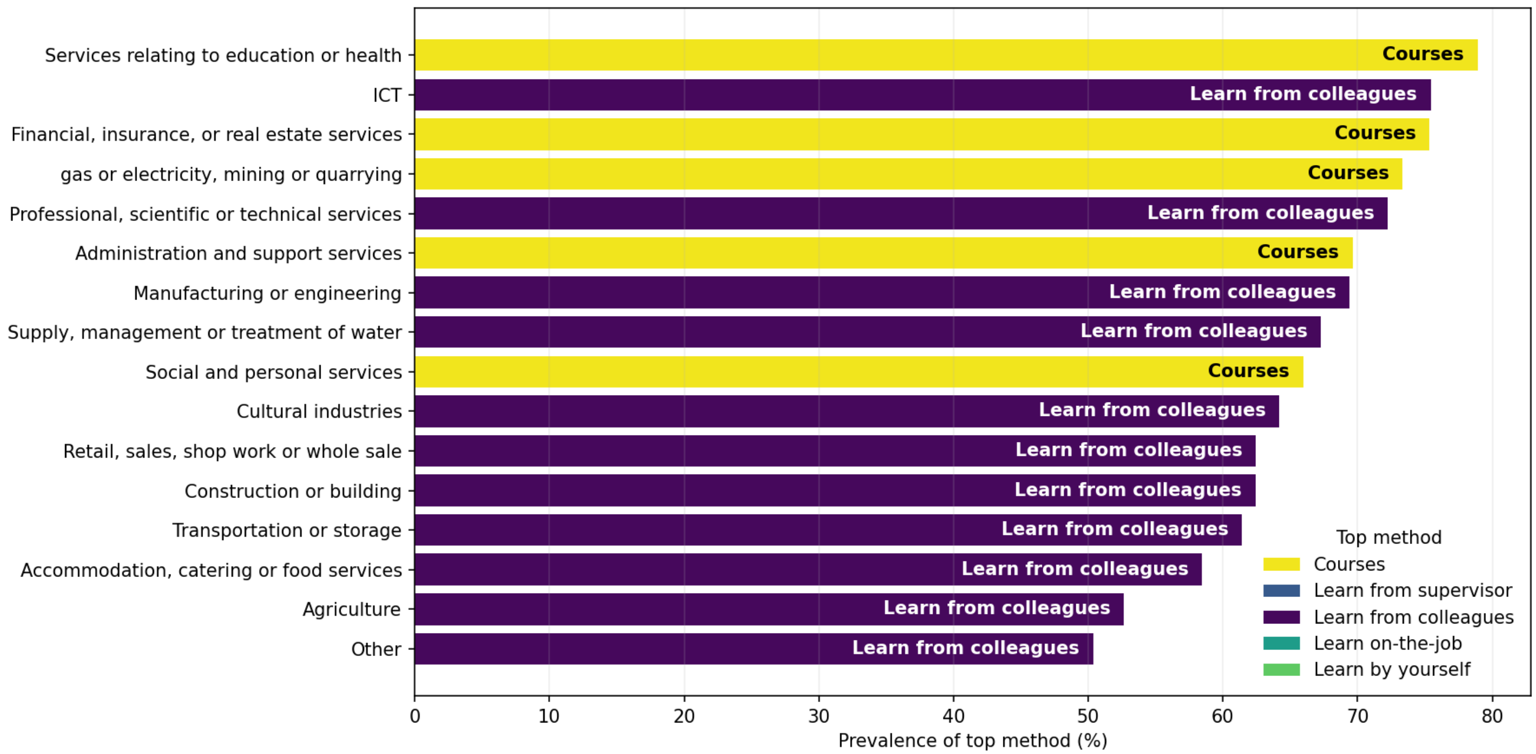
In Figure 11 we show the most common training and learning method by country, along with its incidence. Learning from colleagues is the most common method in 17 of the 28 countries. Learning by taking courses is the most common method in seven countries – Ireland, Czechia, Spain, Cyprus, Slovakia, Belgium, Poland. Learning on the job is the most common method in four countries – Latvia, Lithuania, Slovenia, Greece. Figure 12 shows the same type of graph, but by industry instead of country. Learning from colleagues is the most common method in 11 of the 16 categories, while taking courses is the most common method in Education and Health Services, Finance / Insurance / Real Estate, Gas / Electricity / Mining, Administration and Support Services, and Social and Personal Services. Finally, we show the most common methods across firm size. It is notable that learning from colleagues is the most common method among all firm size categories except for large firms with over 500 employees, in which training courses are the most common upskilling method reported by employees.

Figure 11: Most popular training and learning method and prevalence by country



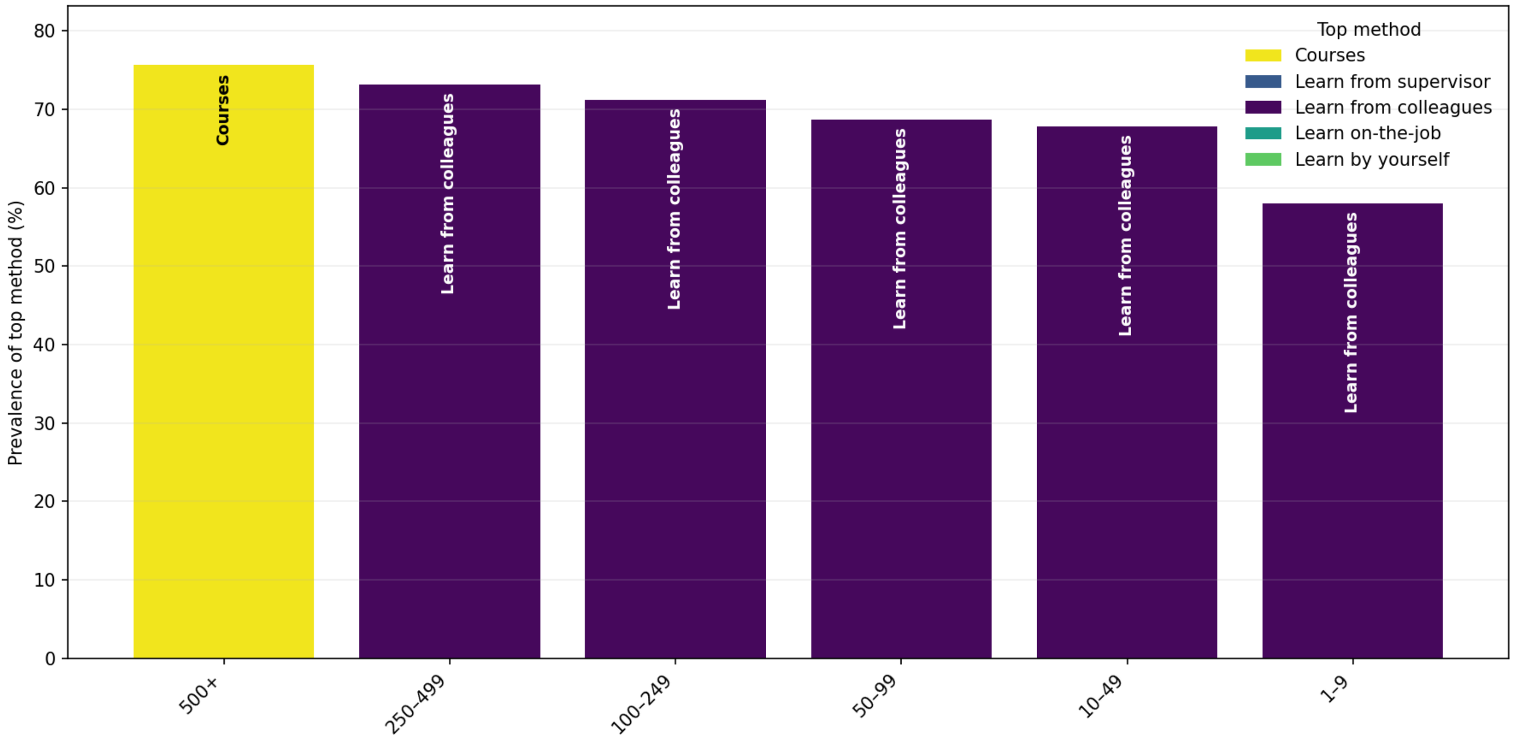
Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

Figure 12: Most popular training and learning method and prevalence by sector



Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

Figure 13: Most popular training and learning method and prevalence by Firm-size



Source: ESJS1 (2014).
Note: Weighted. Based on authors calculations.

1.4 Empirical Analyses

1.4.1 Technological Change and Upskilling

We assess the association between technological change and employees' upskilling using the following linear regression,

$$upskill - scale_i = \alpha + \beta Tech\text{-}change_i + X_i'\gamma + \sum_{\tau=2}^{28} \theta_\tau C_i^\tau + \epsilon_i, \tag{1}$$

where $Tech\text{-}change_i$ is a dummy variable equal to one if employee i reports a change in the technologies used at work and zero if not; X_i is a vector of employee characteristics including occupation, industry, age, gender, level of education, company tenure, firm-size, and whether the organisation that employee i works for has multiple locations/premises; C_i^τ are country fixed effects; and α is the intercept.

In addition to the continuous 0–5 upskilling scale, we estimate a set of probit models for the probability that employee i lies above each threshold of the upskill scale.

$$\Pr(\text{upskill-scale}_i \geq \delta) = \phi\left(\beta\text{Tech-change}_i + X_i'\gamma + \sum_{\tau=2}^{25} \theta_\tau C_i^\tau\right), \quad \delta \in \{1,2,3,4,5\} \tag{2}$$

where $\phi(\cdot)$is the standard normal CDF, and the other variables are the same as previously described. Equations (1) and (2) allow us to examine whether technological change is associated with any type of upskilling, as well as the links between technological change and upskilling intensity.

Table 3 summarises the results – column (1) shows the results from estimating equation (1), while columns (2) to (6) show the probit results corresponding to equation (2). Across all specifications, technological change is positively and significantly associated with upskilling. In the linear model, employees who experienced a change in workplace technologies report an upskilling score 0.42

points higher (on the 0–5 scale) than employees who did not, conditional on controls. The probit marginal effects are also uniformly positive and significant: experiencing tech-change increases the probability of being above each threshold by around 5–11 percentage points. The marginal effects are largest at intermediate and higher thresholds (at or above 3 on the upskilling scale), suggesting that technological change is especially associated with more substantial skill improvements rather than merely small adjustments. This pattern is consistent with the view that significant technological or organisational changes tend to require deeper skill upgrading (Autor et al., 2003; Acemoglu & Autor, 2011).

Table 3: Relationship between Tech-change and upskilling

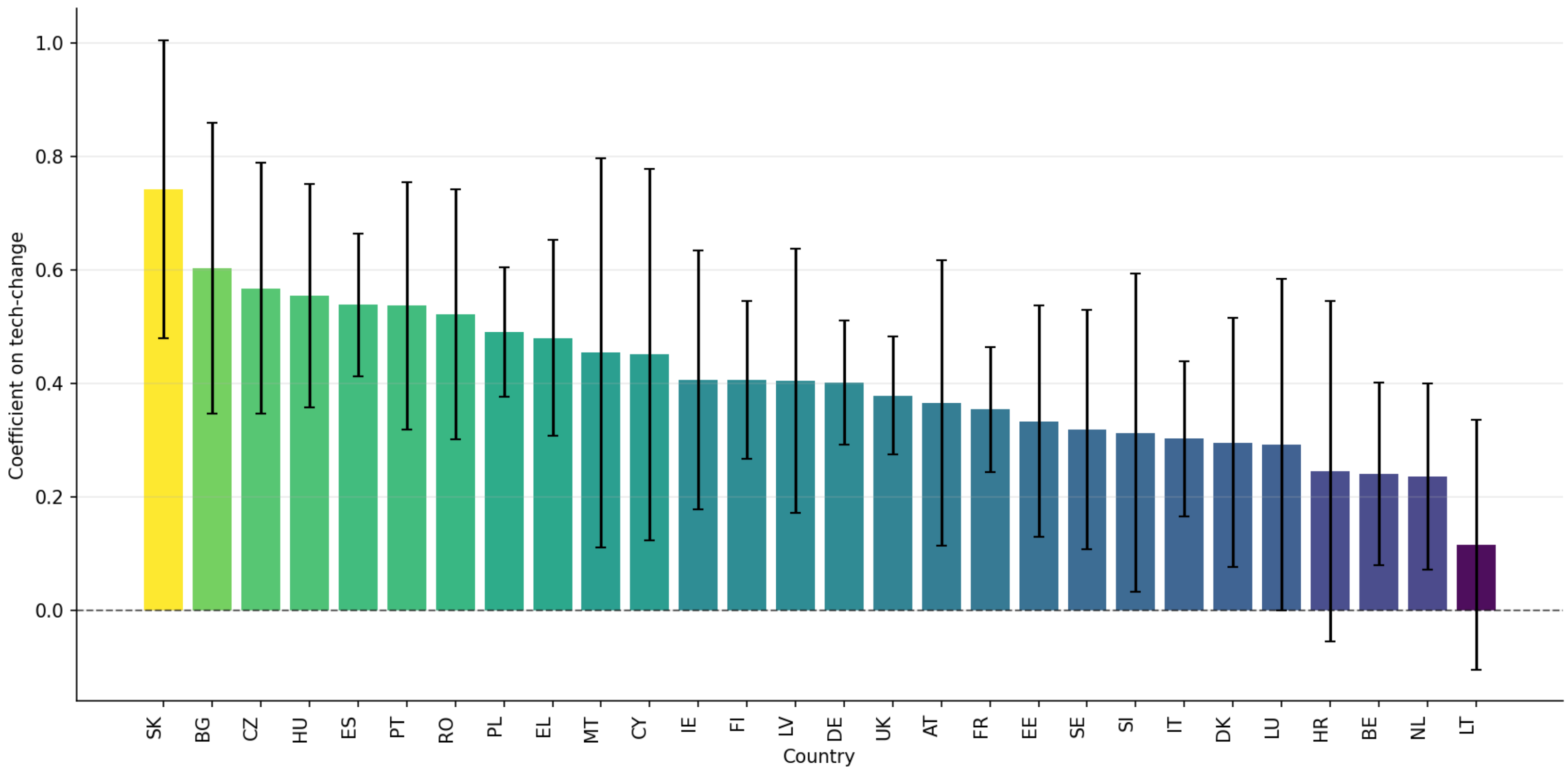
VARIABLES	(1) upskilling scale (0-5)	(2) Pr(upskilling scale≥1)	(3) Pr(upskilling scale≥2)	(4) Pr(upskilling scale≥3)	(5) Pr(upskilling scale≥4)	(6) Pr(upskilling scale=5)
Tech-change	0.41***	0.074***	0.094***	0.105***	0.087***	0.054***
	(0.02)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	46,139	46,139	47,114	47,114	47,114	46,139

Source: ESJS1 (2014).
Note: table shows regression coefficients for tech-change on upskilling level (1) and at upskilling level thresholds (2) – (6). Coefficients reported in (1) is from OLS and those presented in (2) to (6) are Probit marginal effects. Detailed controls outlined in Equation 1 are also accounted for. *=p<0.1, **=p<-.05, ***=p<0.01. Weighted.

We further estimate the linear model separately by country, industry, and firm-size category (see Figures 14 to 16). While the magnitude varies, the sign of the tech-change coefficient is positive and statistically significant in all countries. Country coefficients range from under 0.2 to over 0.7, with the strongest associations in Slovakia, Bulgaria, and Czechia and weaker ones in Croatia, Belgium, and Lithuania. A plausible interpretation is that in some countries technological change may be more tightly embedded in broader organisational restructuring and training strategies, generating larger skill gains. It is also possible that the types of technology vary across countries. For example, labour augmenting technology may be more prevalent in certain countries, whereas in other the introduction of technology may simply replace employees' tasks, leaving them with obsolete skills. This, in turn, is likely linked to cross-country differences in industry and occupational distributions.

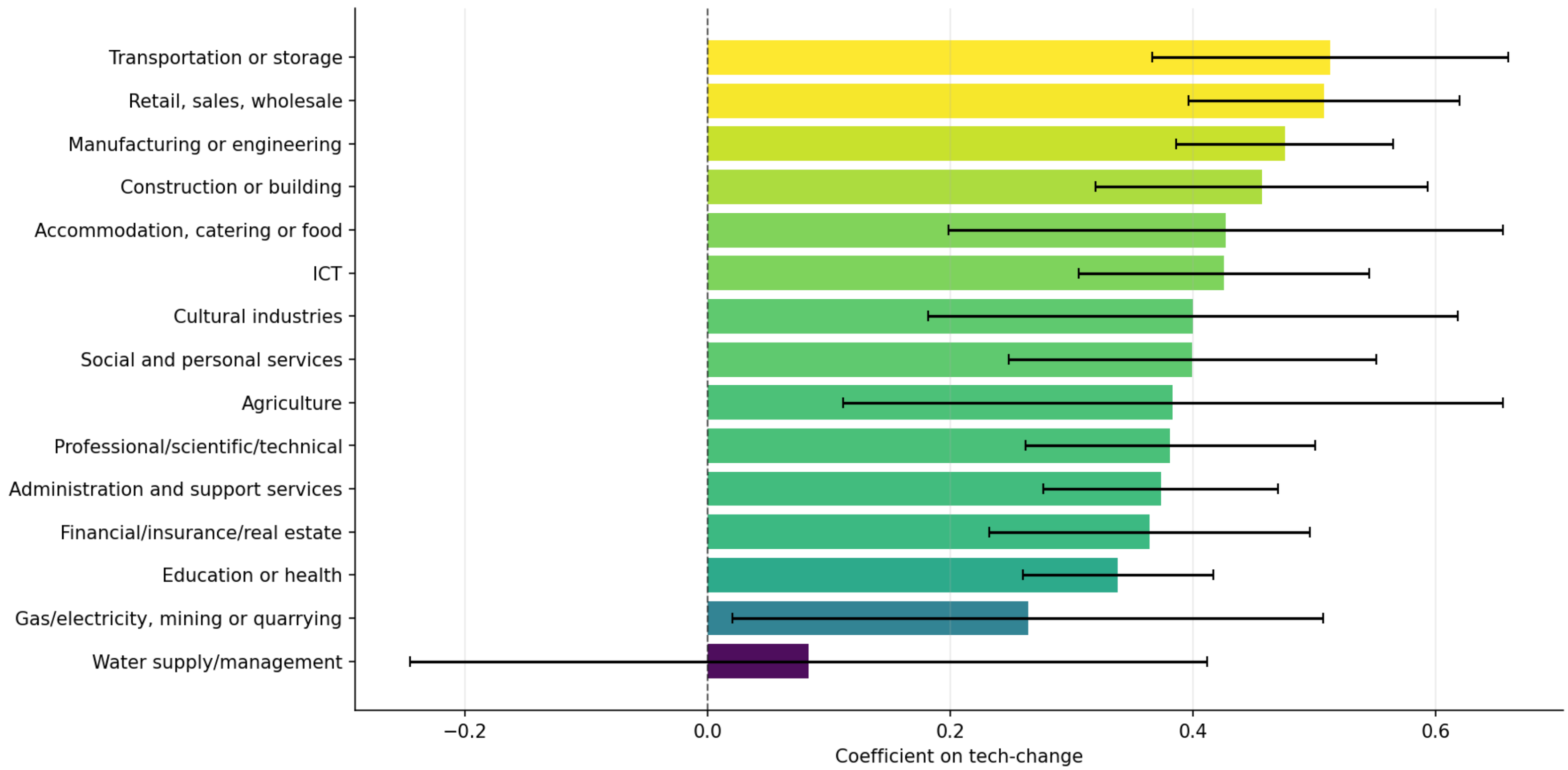
With regard to industries, there is a positive and statistically significant relationship between technological change and upskilling for most industries. The only two for which there is no statistically significant coefficient are Gas / Electricity / Mining and Water Supply / Management. The magnitude of the relationship varies across industries, and is largest in Transportation and Storage, Retail, Construction and Manufacturing / Engineering. Again, this may reflect differences the types of technologies that are being introduced. For example, the transport and storage sector have been significantly impacted by technology including GPS-managed fleets, route optimization algorithms, electric and hybrid vehicles, ride-hailing platforms, digital inventory systems. The introduction of these types of technologies would require upskilling of employees in order to utilize the new technology effectively. Note, however, that is also possible that some of these technologies could replace some employees. However, as this is an employee survey, we are focusing here on employees in employment. In Chapter 3 we examine the impact of new technology on employment. Finally, Figure 16 shows that the magnitude of the estimated relationship between technological change and upskilling is largest in small firms, with 0 to 9 employees. However, there is no clear or monotonic relationship between firm size and the estimated coefficients. Furthermore, the difference in the estimated impacts is quite small – ranging from a high of approximately 0.045 to a low of approximately 0.035. Ss such, we do not draw definitive conclusions.

Figure 14: Conditional effect of tech-change on upskilling scale (0 to 5) by country (from OLS)



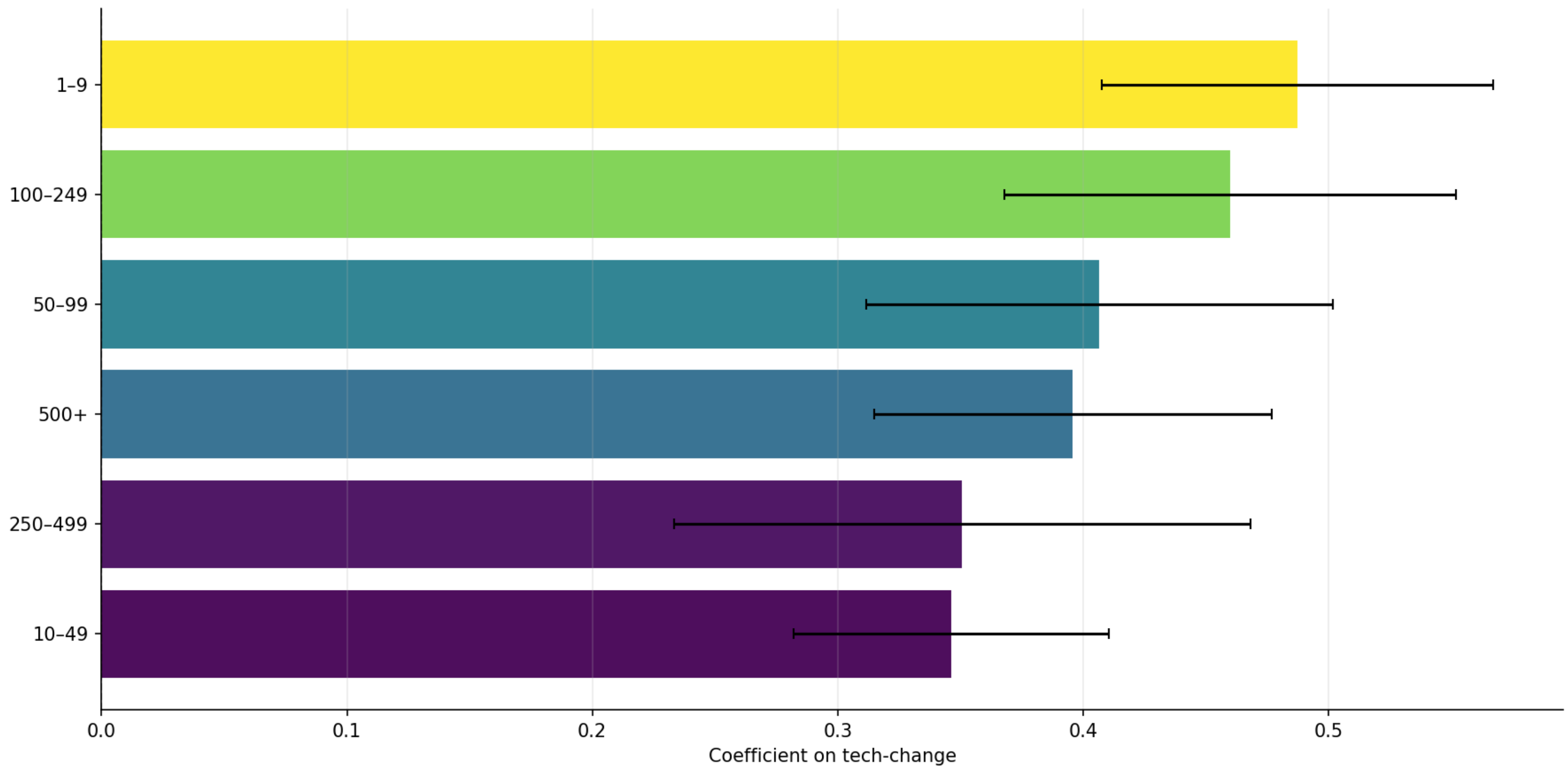
Source: ESJS1 (2014).
Note: Bars are OLS coefficients and whiskers represent 95% confidence interval. Detailed controls are included as per equation 1.

Figure 15: Conditional effect of tech-change on upskilling scale (0 to 5) by industry (from OLS)



Source: ESJS1 (2014).
Note: Bars are OLS coefficients and whiskers represent 95% confidence interval. Detailed controls are included as per equation 1.

Figure 16: Conditional effect of tech-change on upskilling scale (0 to 5) by Firm-size (from OLS)



Source: ESJS1 (2014).
Note: Bars are OLS coefficients and whiskers represent 95% confidence interval.

1.4.2 The Role of Training

We first investigate the relationship between training, in general, and upskilling, focusing solely on employees that experienced technological change. Similar to equations (1) and (2) in the previous section, we estimate the following OLS and probit regressions for those employees that experienced technological change,

$$(upskill - scale_i|\text{Tech- change}_i = 1) = \alpha + \beta Training_i + X_i'\gamma + \sum_{\tau=2}^{28} \theta_\tau C_i^\tau + \epsilon_i, \qquad (3)$$

$$\Pr(upskill\text{-}scale_i \geq \delta|\text{Tech- change}_i = 1) = \phi\left(\beta \text{Training}_i + X_i'\gamma + \sum_{\tau=2}^{25} \theta_\tau C_i^\tau\right), \delta \in \{1,2,3,4,5\} (4)$$

where *upskill-scale*, *X'* and C_i have the same definitions as previously defined. *Training* is a dummy variable capturing whether individual *i* experienced some form of training. As before, equation (3) shows the relationship between training and the upskilling scale, whereas the series of probit models from equation (4) shows more detail on the relationship between training and different levels of upskilling intensity. The results are shown in Table 4 overleaf. Column (1) of Table 4 indicates that employees that experience technological change report an upskilling value that is 0.36 units higher (on a 0-5 scale) than employees that did not experience technological change, after controlling for a range of employee and firm characteristics. The results in Columns (2) to (6) show the degree of upskilling can be significant. For example, tech-exposed employees are 10 percentage points more likely to report an upskilling value of 3 or more (on a 0-5 scale) than similar employees that have not experienced technological change.

Table 4: Relationship between training and upskilling among employees experiencing technological change

VARIABLES	(1) upskilling scale (0-5)	(2) Pr(upskilling scale≥1)	(3) Pr(upskilling scale≥2)	(4) Pr(upskilling scale≥3)	(5) Pr(upskilling scale≥4)	(6) Pr(upskilling scale=5)
Training	0.36***	0.065***	0.083***	0.100***	0.073***	0.038***
	(0.030)	(0.006)	(0.007)	(0.009)	(0.010)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,986	20,986	21,393	21,393	21,393	20,986

Source: ESJS1 (2014).
Note: table shows regression coefficients for training on upskilling level (1) and at upskilling level thresholds (2) – (6). Coefficients reported in (1) is from OLS and those presented in (2) to (6) are Probit marginal effects. Detailed controls outlined in are also included. *=p<0.1, **=p<-.05, ***=p<0.01

Next, we examine the incidence and potential effectiveness of specific types of training combinations. Recall that employees that report skill improvement are asked whether they underwent any of the following to improve their skills – attended training course; taught by supervisor on-the-job; learned by interacting with colleagues at work; learned through trial-and-error; learned by yourself (with the aid of manuals, books or online materials). As these are not mutually exclusive categories, employees can report multiple training and learning methods. There are a total of 32 unique combinations (2^5).

In Table 5, we show the incidence of each different training and learning combination among employees that experienced technological change. The first thing to note is that the most common training and learning approaches typically involving multiple methods. The most common consists of employees that have undergone all five approaches – 22 percent of all employees fall into this category. Among employees that report just one training method, the most common is courses – 7 percent of employees report learning via courses only, ranking this method as 3rd most common of the 32 different combinations. Courses also appear in all of the top 5 combinations. The least common methods involve learning from a supervisor in combination with either learning by yourself or learning at work through trial-and-error.

Table 5: Incidence of Training & Learning Combinations

Variable	Incidence (%)
Courses + Supervisor + Colleagues + Learn@Work + LearnBySelf	22.32
Courses + Colleagues + Learn@Work + LearnBySelf	14.44
Courses	7.37
Courses + Colleagues + Learn@Work	4.34
Courses + Supervisor + Colleagues + Lean@Work	4.31
Colleagues + Learn@Work + LearnBySelf	4.25
Courses + Colleagues + LearnBySelf	3.61
Supervisor + Colleagues + Learn@Work + LearnBySelf	3.60
Colleagues	3.28
Courses + Supervisor + Colleagues	2.93
Courses + Learn@Work + LearnBySelf	2.87
Courses + Supervisor + Colleagues + LearnBySelf	2.87
Courses + Colleagues	2.59
Supervisor + Colleagues + Learn@Work	2.11
Colleagues + Learn@Work	2.06
Supervisor	1.86
Courses + LearnBySelf	1.76
Learn@Work	1.57
LearnBySelf	1.40
Courses + Supervisor	1.25
Learn@Work + LearnBySelf	1.24
Courses + Supervisor + Learn@Work + LearnBySelf	1.09
Supervisor + Colleagues	1.05
Courses + Learn@Work	1.04
Courses + Supervisor + LearnBySelf	0.95
Colleagues + LearnBySelf	0.75
None	0.71
Supervisor + Colleagues + LearnBySelf	0.62
Supervisor + Learn@Work + LearnBySelf	0.55
Courses + Supervisor + Learn@Work	0.49
Supervisor + Learn@Work	0.46
Supervisor + LearnBySelf	0.26

Source: ESJS1 (2014).
Note: Based on authors calculations.

We examine, and rank, each mutually exclusive training and learning combination in terms of the magnitude of its association with upskilling. To do this, we estimate the following regression for employees that experienced technological change:

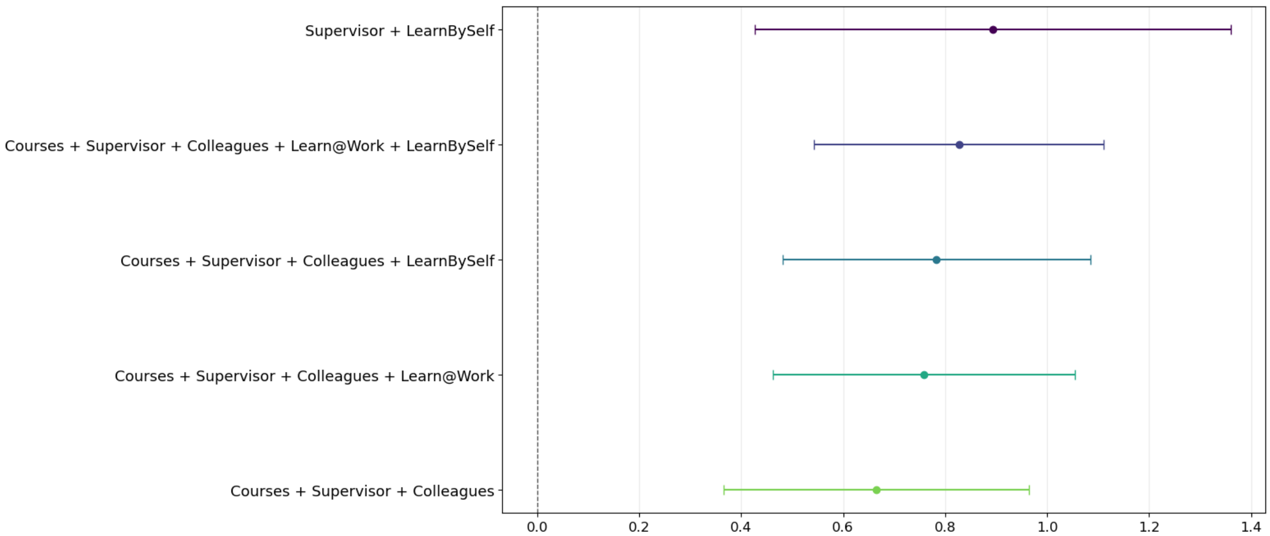
$$upskill\text{-}scale_i = \alpha + \sum_{\tau=2}^{32} \theta_\tau K_i + X_i'\gamma + \sum_{\tau=2}^{25} \theta_\tau C_i^\tau + \epsilon_i \qquad (5)$$

where $\sum_{\tau=2}^{32} \theta_\tau K_i$ denotes a series of dummy variables to capture each training combination, with the reference category being individuals that did not undertake any of the five training and learning categories. The other variables have been defined previously. For brevity, we rank the top five (and bottom five) combinations by the magnitude of their coefficients, thereby capturing which training combinations are most (least) associated with a high degree of upskilling (see Figures 17 and 18).

The training and learning methods that tend to have the strongest association with upskilling involve a combination of multiple training forms. This highlights that it is not only training incidence that matters, but also training intensity and the complementarity of different learning modes. Combining formal instruction with supervised practice, peer interaction, and self-directed learning may reinforce skill acquisition by supporting application, feedback, and transfer to job tasks. For example, the second largest coefficient in Figure 17 relates to employees that combine all five training and learning modes. Four of the top five involve combining at least three different training and learning modes. Courses feature prominently in the top five list. However, the combination with the largest estimated impact is learning from a supervisor combined with learning by yourself. However, note from Table 5 that this is the least commonly reported combination of training and learning, with just 0.26 precent of employees reporting this combination.

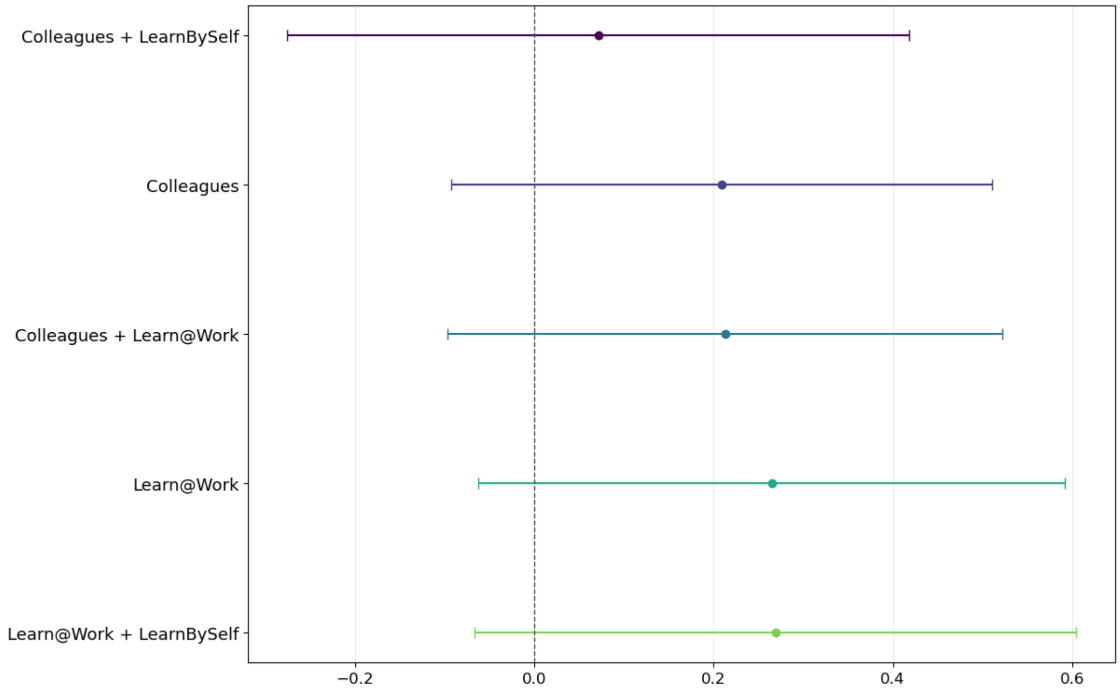
At the same time, these results should be interpreted as associations rather than causal effects. One plausible explanation for the strong relationship between multiple learning pathways and upskilling is selection: workers who are more skilled, motivated, or employed in more dynamic roles may be both more likely to engage in several forms of learning and more likely to upskill. While the analysis conditions on a rich set of worker, job, firm, and country characteristics, unobserved heterogeneity cannot be fully ruled out. The training and learning combinations with the weakest association with upskilling typically involve one or two modes and relate to more unstructured forms of learning—learning by yourself, learning from colleagues, and learning through trial and error at work (Figure 18).

Figure 17: Top 5 training & learning methods (relationship with upskilling)



Source: ESJS1 (2014).
Note: Based on authors calculations.

Figure 18: Bottom 5 training & learning methods (relationship with upskilling)



Source: ESJS1 (2014).
Note: Based on authors calculations.

1.5 Conclusion

Technological change is commonplace in the EU labour market. While it is possible that the introduction of new technologies can displace some tasks, or even jobs, new technologies also offer opportunities to complement the existing skillset of employees, leading to upskilling and increased productivity. In this chapter, using data from the first wave of the European Skills and Jobs Survey, we examined the incidence of technological change in the EU, its relationship with employee upskilling, and the types of training and learning methods that seem to be most effective in promoting upskilling among employees exposed to technological change.

Several important and policy relevant insights emerge from the analysis. First, a large number of employees are being impacted by technological change. Our analysis shows that just under half of all EU employees reported experiencing technological change in their workplace. Those that experience technological change are more likely to have completed training and technological change is positively associated with upskilling. For example, one quarter of employees that were exposed to technological change at work report that their skills have increased 'a lot'. This compares to just 17 percent among employees not exposed to technological change.

The importance of training in adapting to new technology is often highlighted by policymakers and academics. However, the discussion is typically silent on the type of training that may be effective. We are the first to provide a detailed ranking training and learning combinations, in terms of their association with upskilling among employees that experienced tech-change at work. Our analysis shows that employees that experience multiple forms of training and learning experience the greatest degree of upskilling. This emphasizes the importance of looking beyond a simple training incidence – it is not just the extensive margin, but also the intensive margin that matters when it comes to training. Furthermore, our analysis shows that combinations formal training and learning methods appear to be most effective. Structured courses, in particular, emerge as having a strong association with upskilling. Employees that avail of one or two methods of training and learning display a weaker association with upskilling, and more unstructured methods such as learning from colleagues and learning by yourself appear to be least effective.

From a policy perspective, our findings underpin the importance of strengthening adult learning and workplace learning systems in Europe - not just in terms of increasing participation, but in improving the quality and relevance of training provision. As technology continues to reshape labour demand, equipping employees with the capacity to adapt will be central to inclusive and productive labour markets. Policies should therefore prioritise access to well-designed, blended learning opportunities that combine formal instruction with workplace-based learning and supervisory support.

2. Chapter Two: Adapting to Technological Change – How EU Employees Learn to Use New Software and Computer Programmes

2.1 Introduction

A key area of interest for both researchers and EU policymakers is the role of training in facilitating employees to take advantage of new digital technologies at work. Chapter 1 highlighted the role of training courses, combined with other training and learning methods, in facilitating the upskilling of employees. Formal training courses are not the only avenue through which employees can adapt – they may learn via 'non-formal' or 'informal' learning methods as well, for example through interactions with family and friends or on their own initiative via books or online materials. Relatively little is known about these types of learning methods, largely because the phenomenon is difficult to quantify. As noted by De Grip (2024), the economic literature on informal learning is underdeveloped, despite it being more important for human capital development than formal training courses. In this paper, we attempt to address this gap in the literature by focusing on non-formal methods of adapting to new digital technologies at work. Using a survey of EU employees in 2021, we profile the non-formal support networks that employees draw on in order to learn new software or computer programmes. Furthermore, we explore whether specific non-formal learning patterns are conducive to employees' productivity.

At the outset, it is necessary to draw a distinction between 'informal' and 'non-formal' learning, as there can be inconsistencies in terminologies and definitions. De Grip (2024) defines informal learning as "*the acquisition of skills through learning by doing as well as by watching other employees, taking instructions, receiving supervision or feedback from supervisors or co-employees and self-study*". However, Cedefop makes a clear distinction between what they term 'informal' versus 'non-formal' learning.[3] Informal learning is defined as the *"acquisition of knowledge, know-how, information, values, skills and competences in the framework of daily activities – work, family or leisure – which are not explicitly designated as learning activities in terms of objectives, time or learning support*." Non-formal learning on the other hand relates to the "*acquisition of knowledge, know-how, information, values, skills and competences in the framework of planned activities – in terms of learning objectives, time or resources – where some form of learning support is present (e.g. student-teacher/trainer relationships)*." Non-formal learning, therefore, is viewed as 'intentional' from the learner's perspective, while informal learning is incidental learning that occurs during the course of daily activities. The types of learning methods that we study in this chapter – learning on your own; learning from a supervisor; learning from colleagues at work; learning from family or friends – is more consistent with Cedefop's non-formal learning definition. As such, from hereon we use the term non-formal learning.

Recent events underpin the importance of understanding how employees learn to use new technology at work. For example, the COVID-19 pandemic gave rise to the rapid adoption of digital communications technologies in many professional occupations. Furthermore, the diffusion of generative Artificial Intelligence (AI) technology and the growing use of software such as ChatGPT is changing the way people work. These phenomena are well documented in both the EU and international literature. We have already seen from Chapter 1 that almost half of EU employees report being impacted by the recent introduction of new technology. More specifically, Choi and Leigh (2024) provide evidence that the deployment of AI technologies in the US is strongly related to labour demand for employees with AI-related skills.

As a result of the diffusion of new digital technology, EU policy has begun prioritising the support of education and training provision in order to overcome potential digital skill gaps and advance its

[3] See https://www.cedefop.europa.eu/en/tools/vet-glossary/glossary?letter=I

productivity agenda. This is demonstrated by recent policy developments such as the establishment of the Union of Skills – the EU's flagship strategy to promote continued up- and re-skilling among EU employees, with a particular focus on digital skills (European Commission, 2025). This policy trend is also evident at the national level. Governments are deploying a suite of policies to support employers who invest in digital training. For example, a paper from the OECD (2024) shows that many OECD countries are providing fiscal incentives to employers who invest in AI skills. The school and university system is an important component to help equip future employees with the skills needed for a rapidly changing labour market. However, ensuring that employees can adapt to the introduction of new software and digital technologies throughout their working lives is important. Yashiro *et al.* (2022) show that older employees that are exposed to technological change in Finland exhibit an elevated likelihood of exiting the workforce early when compared to younger employees.

The existing evidence shows the employers have responded to recent waves of technological change by investing in training. Neirotti and Paolucci (2013) draw on data on Italian firms, showing that firms that invest in employee training are more likely to adapt to technological and organisational changes more smoothly. Battisti, Dustmann and Schönberg (2023) show a similar correlative trend among firms in Germany – firms that experience technological and organisational change are more likely to offer retraining opportunities to their employees. A review of the manufacturing and finance sectors by the OECD (2023) showed that most firms responded to AI skills needs by investing in training (as opposed to outsourcing or hiring/firing) in seven OECD countries. Muehlemann (2025) demonstrates that the adoption of AI technologies leads to firms in Germany targeting training resources toward more highly-skilled employees. McGuinness *et al.* (2025) illustrate that employees who experience changes to their tasks at work are substantially more likely to have received training than those who did not experience task disruption. Additionally, Redmond, Brosnan and Kelly (2025) demonstrate that EU employees in jobs where skill requirements have changed rapidly – as derived from large online job vacancy data – are simultaneously more likely to experience skills mismatch and receive training.

Less is known about non-formal learning. Due to the generalised nature of new digital technology, it is plausible that employees seek to improve their competencies through methods aside from formalised training at work. Specifically, employees may leverage their existing support networks – their colleagues, boss, family or friends – in a non-formal capacity to improve their capabilities with new software at work. The literature examining this phenomenon is constrained when compared to the literature on formal learning, partially because non-formal learning is less quantifiable than formal training programmes. Much of the literature on non-formal and informal learning at work is dedicated to profiling the characteristic determinants of employees who are more likely to engage in informal learning behaviours (see, for example, Berg and Chyung, 2008; Jeon and Kim, 2012; Uhunoma, Lim and Kim, 2021; Zia *et al.*, 2022) or evaluate the impacts of organisational policy changes on non-formal learning behaviour (e.g. Pankkonen, Moazami-Goodarzi and Vuori, 2025). Relatively few studies reconcile the relationship between technological change and non-formal learning.

Our paper seeks to fill this gap in the existing literature by profiling the non-formal support networks of EU employees when faced with the introduction of new software or computer programs at work. We find that 43 percent of surveyed employees in the EU learned to use new software or computer programs at work within the last 12 months. Self-guided learning emerges as an important component of an employee's learning process when it comes to new software and computer programmes. Approximately 1 in 20 EU employees learn new software and program on their own, without any formal training or additional support from colleagues or supervisors. Self-guided learning is also positively associated with perceptions that new technology is effective and useful. With the availability of resources that facilitate effective self-guided learning, employers and policymakers should be cognisant of this learning channel, and work to encourage it where applicable, particularly in conjunction with formal training and education. Learning new software and computer programs from family and friends is less common. However, it is substantially more likely to occur among those with low levels of education.

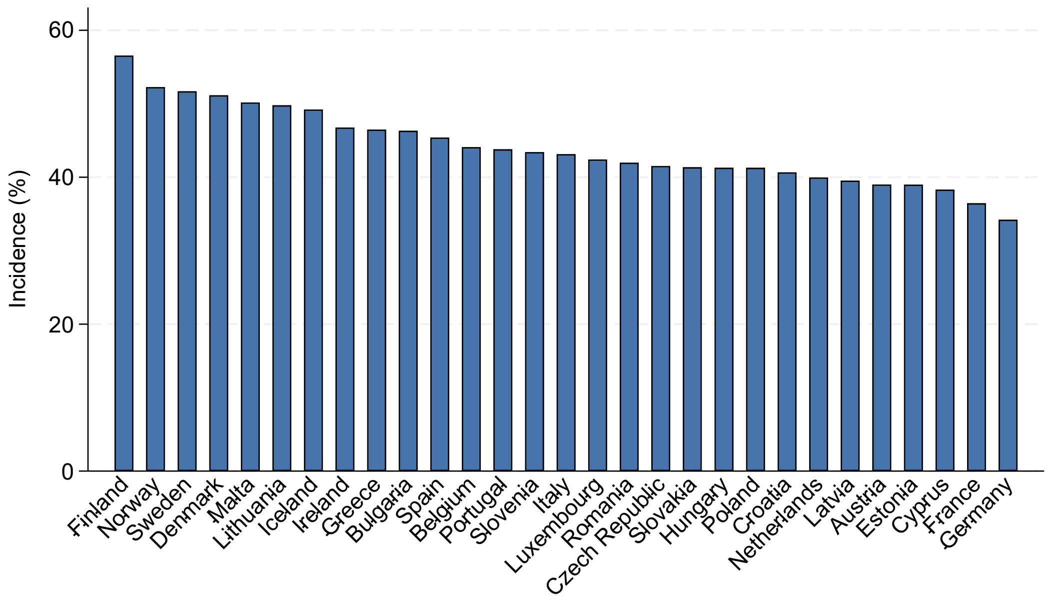
2.2 Learning to use New Software: Incidence and Employee Characteristics

We use the second wave of the European Skills and Jobs Survey (ESJS2). The ESJS2 is a survey of European employees (N ≈ 46,000), administered by CEDEFOP in 2021. Responses were collected via both telephone interview and online survey. The survey contains a range of demographic information, as well as a broad selection of detailed questions relating to the nature of respondents' work. To identify employees that recently experienced the introduction of new computer programs or software, we use the following question: *"In the last 12 months (or since you started your main job, whichever is shorter), did you learn to use any new computer programs or software to do your main job?*".[4]

Approximately 45 percent of surveyed employees reported learning to use new computer software or programs at work in the last 12 months. In Figure 19, we show how this varies across countries. Countries in Northern Europe – Finland, Norway, Sweden, Denmark – had the highest incidence of respondents learning new software at work, at over 50 percent. Estonia, Cyprus, France and Germany had the lowest incidence, at just over 35 percent. In Figure 20 we show the sector-level incidence. The ICT and Education sectors exhibited the highest incidence of employees learning new software, while Accommodation and Food Services exhibited the lowest incidence.

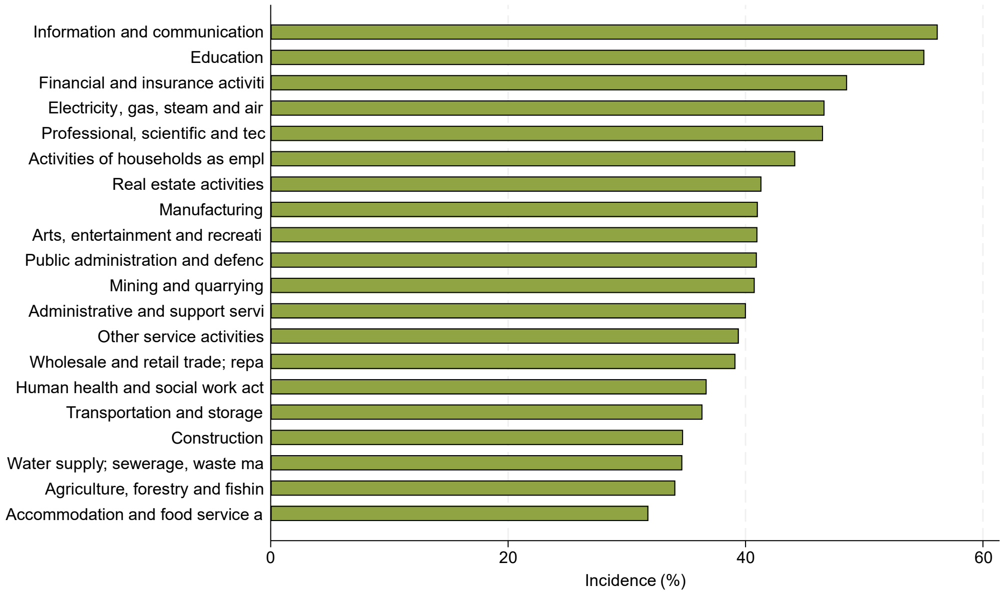
[4] The question specifies that respondents exclude minor or regular updates to software.

Figure 19: Country Incidence of Learning New Software (EU-27 Member States)



Source: ESJS1 (2014). Based on authors calculations.

Figure 20: Sectoral Incidence of Learning New Software (NACE Rev. 2 Industries)



Source: ESJS1 (2014). Based on authors calculations.

In Table 6, we show how the incidence of learning new software varies by gender, age and wage groups. While the incidence is relatively similar by gender, notable differences emerge by age and wage groups.[5] Younger employees are more likely to have learned new software or computer programs; for those aged 25-35, the incidence is 49 percent, compared to just 39 percent for employees aged 50-65. Similarly, 49 percent of high-paid employees recently learned new software or computer programs compared to 39 percent of low-paid employees.

[5] Low paid refers to the bottom three deciles of the wage distribution. Middle Paid refers to the middle four deciles of the wage distribution. High paid refers to the top three deciles of the wage distribution.

Table 6: Incidence of Learning New Software

Variable	Did not Learn Software	Learned Software
Gender		
Male	55.5%	44.5%
Female	57.9%	42.1%
Age Group		
25-35	51.3%	48.7%
36-49	56.9%	43.1%
50-65	61.5%	38.5%
Wage Group		
Low Paid	61.0%	39.0%
Middle Paid	57.8%	42.2%
High Paid	50.3%	49.7%
N	23,562	17,995

Source: ESJS1 (2014). Based on authors calculations.

2.3 Non-Formal Learning Methods

Respondents in the ESJS2 that learned to use new computer programs or software within the last 12 months are asked the following question about how they learned to use the new technology – *"And did you learn to use any of the new computer programs or software you started using in your job in any of the following ways?*

1. *On your own*
2. *From a supervisor/foreman*
3. *From your colleagues at work*
4. *From family or friends.*

Using this question, we can identify the specific learning modes through which respondents adapted to new digital technology at work. Note, however, that the question is only asked to the sub-sample of respondents who answered the survey online. As such, we have data on 11,577 of the 18,000 respondents that recently learned to use new software or computer programs. The responses to the question above are not mutually exclusive, meaning respondents could indicate that they learned using a combination of multiple non-formal learning methods. There are 16 possible combinations, including individuals that have learned new software but report "no" to all of the above four categories.[6]

We refer to the categories above as "non-formal learning" methods. Clearly, some methods are closer to informal learning than non-formal learning (e.g., learning on your own and from your family and friends). Nonetheless, we refer to them as non-formal both for ease of exposition, and because there is a separate question in the ESJS2 survey that specifically asks about formal training. As such, we can examine whether the non-formal training methods take place in conjunction with more formal training and education.[7] The formal training indicator is based on responses to a question that asks employees whether they undertook formal education or training to learn to use any new computer programs, software or computerised machinery that they started using in the last 12 months.

There are 9,401 employees for which we have data on non-formal training and learning methods alongside a formal training/education indicator. Of these 9,401 employees, approximately 95 percent (8,848 employees) undertook at least one of the four non-formal training and learning methods shown above.[8] Of the 8,848 employees that participated in some type of non-formal training and learning, 69 percent also participated in formal training. This indicates that approximately 30 percent of employees that learn new software or computer programs through non-formal channels, do so without the aid of more formal training and education.

[6] There are four possible methods, and 2^4 = 16.
[7] Either courses, workshops or on-the -job training with a dedicated trainer.
[8] Approximately five percent responded "no" to the four informal training and learning categories.

In Table 7, we show the incidence of each possible non-formal training and learning combination. We do this for the full sample of employees for which we have non-formal learning data, as well as separately for the group of employees that have undertaken formal training, and those that have not.[9] Column 1 shows the incidence for all employees for which we have non-formal learning data (irrespective of their formal training status). Learning on your own features in 4 of the top 5 categories. The most commonly used learning categories / combinations are: those who used all four methods of learning (15%); those who learned by themselves and from their colleagues (13%); those who only learned by themselves only (12%); those who learned by themselves, from their boss and their colleagues (11%); those who learned from their boss and colleagues (11%). The less frequent categories typically involve some type of combination that includes learning from your family and friends. Approximately one percent of employees learned from their family and friends only, 0.7 percent from family and boss, and 1.7% on their own, from their family and their boss.

When focusing on those that also participated in formal training (column 2 of Table 7), the pattern is broadly similar. However, the incidence of employees that participated in all types of non-formal training is higher, at 23%. The group that did not undertake formal training look different. These employees are far less likely to state that they participated in all non-formal learning methods (6%) and are more likely to indicate that they participated in no non-formal learning methods (11%).

[9] Note that the sample sizes in columns 2 and 3 of Table 7 sum to 9401 – which is the sample size of employees for which we have informal learning data and an indicator of formal training activity.

Table 7: Incidence of Non-Formal Training and Learning Combinations

Non-Formal Learning Group	All (N=11,577)	With Formal Training (N=6,284)	Without Formal Training (N=3,117)
All Methods	15.2%	23.4%	6.1%
Solo & Colleagues	12.9%	11.9%	14.9%
Solo Only	12.1%	8.4%	15.0%
Solo, Boss, Colleagues	11.0%	13.3%	9.8%
Boss & Colleagues	9.7%	10.2%	10.5%
None	8.9%	3.4%	10.9%
Colleagues Only	7.6%	5.3%	9.2%
Solo, Family, Colleagues	6.5%	7.1%	6.5%
Solo & Boss	3.5%	4.3%	2.6%
Boss Only	2.6%	2.7%	2.4%
Family, Boss, Colleagues	2.6%	3.0%	2.7%
Solo & Family	2.2%	1.8%	2.8%
Family & Colleagues	2.1%	1.8%	2.8%
Solo, Family, Boss	1.7%	2.2%	1.4%
Family Only	0.9%	0.6%	1.3%
Family & Boss	0.7%	0.6%	1.2%
Total	**100%**	**100%**	**100%**

One notable implication from the results shown in Table 7, is that approximately five percent of employees that recently learned to use new software or computer programs did so by themselves *only*, without the support of formal training or assistance from colleagues or a supervisor.[10] This highlights a feature of modern labour markets, in which technology is rapidly changing and advancing, and employees must use their own initiative to adapt to new programs and software. It may also reflect the quality and widespread availability of resources which allow self-directed learning. For example, it is possible to learn new software or programming languages, such as

[10] 15 percent of 3117 equals 468, which represents approximately five percent of the 9401 employees for which we have data on formal and informal training in response to learning new software and computer programs.

Python, using online and freely available video tutorials. It is also possible to utilise massive open online courses (MOOCs) in a flexible and cost-effective way to learn new digital and technology skills.

2.4 Determinants of Non-Formal Learning

We examine the type of employee characteristics that are associated with each of the four non-formal learning methods by estimating the following probit model,

$$\Pr(Nonformal_i = 1|X) = \Phi(X_1'\beta_1 + \epsilon_i) \tag{1}$$

where *Nonformal*$_i$ indicates the specific type of learning method that we are looking at. As there are four non-formal learning methods, we estimate four separate probit models in which the outcome variable is: 1) learn by themselves, 2) learn with their boss, 3) learn with their family and friends 4) learn with their colleagues. The vector X_i' includes control variables: gender, age, wage category (low, medium or high) and education level. We also include a binary variable indicating whether the respondent has received formal training in the past twelve months. In addition, include dummy variables for occupation (ISCO 2-Digit), country and sector (NACE level 1).

The marginal effects from estimating the probit model in equation (1) are shown in Table 8. We observe a gender difference in some learning methods. Women are 7 percentage points less likely to learn on their own than male respondents, while being approximately 3 percentage points more likely to use methods that involve learning form their boss or colleagues. Relative to older employees, younger employees are more likely to use all types of non-formal learning methods to learn new software or computer programs. Notably, those with low levels of education are substantially more likely to learn how to use new software or computer programs from family or friends. Employees with lower-secondary education (or below) are 18 percentage points more likely to report learning to use new software or computer programs from family or friends relative to those with a tertiary education.

Table 8: Determinants of Non-Formal Learning Patterns (ESJS2, 2021)

Variables	(1) Solo	(2) Boss	(3) Family/Friends	(4) Colleagues
Female	-0.071***	0.029**	-0.010	0.036***
	(0.012)	(0.013)	(0.012)	(0.012)
Age Group (ref: 50-64)				
25-35	0.034**	0.108***	0.118***	0.048***
	(0.015)	(0.016)	(0.015)	(0.015)
36-49	0.001	0.047***	0.048***	0.028**
	(0.014)	(0.015)	(0.014)	(0.014)
Wage Group (ref: High paid)				
Low Paid	-0.034	0.062***	0.025	0.015
	(0.022)	(0.023)	(0.022)	(0.021)
Middle Paid	-0.017	0.017	-0.014	0.018
	(0.016)	(0.018)	(0.017)	(0.016)
Education (ref: ISCED 5+)				
ISCED 1-2	-0.043*	0.068**	0.176***	0.034
	(0.026)	(0.028)	(0.029)	(0.025)
ISCED 3-4	-0.074***	0.029*	0.004	-0.005
	(0.014)	(0.015)	(0.014)	(0.013)
Formal Training	0.055***	0.193***	0.093***	0.078***
	(0.012)	(0.012)	(0.012)	(0.011)
Country/Occupation/Sector	YES	YES	YES	YES
Observations	6,440	6,457	6,458	6,455

Standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

2.5 Perceived Effectiveness of New Technology

ESJS respondents are asked about their attitude and perceptions regarding the effectiveness and ease-of-use of new digital technology. Specifically, they are asked the following question,

"To what extent do you agree with the following statements regarding the use of digital or computer technologies at work?

1. *They generally increase performance at work*
2. *They are useful for learning at work*
3. *They are easy to learn to use at work*
4. *They are enjoyable to use at work*

Respondents could respond to each statement using a 5-point scale, ranging from "*Strongly Agree*" to "*Strongly Disagree*". Using this question, we construct four binary outcome variables ($Attitudes_i$) that are equal to one if the respondent indicated that they strongly agreed or agreed with each statement and equal to zero otherwise. We then examine the relationship between perceived effectiveness of new technologies and informal learning methods using the following probit model,

$$\Pr(Attitudes_i = 1|X) = \Phi(NonformalMethod_i'\beta_1 + X_i'\beta_2 + \epsilon_i) \quad (2)$$

where *Attitudes*$_i$ can relate to either of the four categories listed above. For example, when focusing on the relationship between informal learning and performance at work, *Attitudesi* takes a value of 1 for those indicating that they strongly agree or agree that new technology increases performance, and zero otherwise. *NonformalMethod*$_i$ is a vector of dummy variables that captures each of the four non-formal learning methods. The vector X' contains control variables including education, age, occupation, wages, sector, country, gender, and a formal training indicator. The marginal effects from estimating equation (2) are shown in Table 9 overleaf.

Across all attitudinal indicators, the strongest associations relate to the use self-guided learning (learning on your own). Those that learn on their own are between 5 and 7 percentage points more likely to think that technology increases performance at work, is useful, is easy to learn, and is enjoyable to use, relative to those that do not learn on their own. Table 9 also indicates that learning from family and friends is associated with a lower likelihood of perceiving that technology is effective, relative to those who do not learn from family and friends. There is also some evidence that those who learn from colleagues are less likely to report that technology is enjoyable to use at work, relative to those who do not learn from colleagues.

Note that we are examining associations and are not making strong causal claims. It is possible that reverse causality may apply to some of our estimates. It could be the case that, for example, more useful technologies cause people to be more likely to take the initiative to learn by themselves, as opposed to self-guided learning changing attitudes and perceptions. Furthermore, other unobservable characteristics may play a role. For instance, some respondents may simply have stronger baseline ability with technology, which means that they are both more likely to learn by themselves, as well as find new technology easy to learn. Similarly, respondents who have lower baseline technological ability may simultaneously rely more on their friends and family and be less likely to see new technology as useful at work. While we do control for respondent-specific factors (i.e. such as age or educational attainment), we cannot rule out a potential role for these types of unobservable factors.

Table 9: Non-Formal Learning Patterns and Individual Attitudes Toward Technology

Variables	(1) Increase Performance	(2) Useful	(3) Easy to Learn	(4) Enjoyable
Non-Formal Learning Method				
Learn on your own	0.051***	0.059***	0.058***	0.072***
	(0.009)	(0.009)	(0.012)	(0.011)
Learn from supervisor	0.024***	0.037***	0.057***	0.062***
	(0.009)	(0.008)	(0.011)	(0.010)
Learn from colleagues	-0.008	0.029***	-0.006	-0.021*
	(0.010)	(0.009)	(0.012)	(0.012)
Learn from family & friends	0.002	-0.049***	0.023*	0.053***
	(0.010)	(0.009)	(0.012)	(0.011)
Controls	Yes	Yes	Yes	Yes
Country/sector/occupation	Yes	Yes	Yes	Yes
Observations	6,449	6,444	6,458	6,456

Standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

2.6 Conclusions

Given the rapid transformation of the EU labour market as a result of digitisation, it is important to understand how EU employees are adapting to such changes. While formal training clearly plays a role in smoothing digital transitions for employees, a less-explored area relates to non-formal learning – in which employees engage in upskilling via more unstructured learning approaches.

In this chapter, we have shown that almost half (45 percent) of employees in the EU learned to use new computer programs or software in the previous 12 months. Non-formal and unstructured learning appears to play an important role when it comes to employees adapting to this type of new technology. Approximately 30 percent of employees that learn new software or computer programs through informal channels, do so without the aid of more formal training and education, relying entirely on some combination of self-guided learning, learning from colleagues, learning from family or friends, or learning from their supervisor. A notable finding is that approximately five percent of employees that recently learned to use new software or computer programs did so through self-guided learning *only*, without the support of formal training or assistance from colleagues or a supervisor.

We also show that there are differences in the characteristics of employees by learning method. Women are less likely than men to use self-guided learning to learn new software or computer programs, but more likely to learn from colleagues or their supervisor. Notably, those with a low level of education are substantially more likely to use family and friends to help them learn new software and programs relative to those with a higher level of education. This is important, as this type of non-formal learning is typically associated with more negative perceptions of technology at work, in terms of its ability to increase performance and its usefulness and ease-of-use.

The reliance and apparent effectiveness of self-guided learning has important policy implications. In modern labour markets, technology is rapidly changing and advancing. Formal education and training may struggle to keep pace with these changes, meaning employees must use their own initiative to learn new programs and software. The quality and availability of self-guided resources continues to grow, enabling this type of autonomous learning. For example, it is possible to learn new software or programming languages, such as Python, using online and freely available video tutorials. It is also possible to utilise massive open online courses (MOOCs) in a flexible and cost-effective way to learn new digital and technology skills. Employers and policymakers should be cognisant of this type of learning, and facilitate and encourage this where possible, ideally in combination with formal training and education opportunities.

3. Chapter Three: Organisational Technological Change and Employment Growth in EU Firms

3.1 Introduction

As new technologies are introduced to the labour market, it is important to understand the impact on employees. How, and to what extent, will new technologies affect the labour market outcomes of employees, and how will overall employment be impacted? While it is possible that some technologies may replace employees and lead to job losses, it is also possible that new technologies can enhance productivity and complement the skills of existing employees, potentially leading to job creation and increased employment (see, e.g., Bessen, 2019; Goos, 2018; Acemoglu and Restrepo, 2020; Akerman et al., 2015).

In this chapter, we examine the impact of organisational technological change on employment growth within firms, using a survey of EU employees (the European Skills and Jobs Survey – ESJS). We show that employment growth is more likely to occur in firms that recently introduced new organisation-level technologies, compared to firms that did not. However, despite the positive relationship between technology adoption and employment growth, organisation-level technological change often leaves incumbent employees fearing job loss, even those employed in firms that have seen their workforce grow over time. This highlights the uncertainty that exists among employees around technological change, and the potential multidimensional impacts that technological change can have on the labour force. The balance between the substitutability and complementarity of new technologies with employees is critical in determining whether outcomes for employees are positive or negative, and this balance may shift over time as technologies continue to evolve. Even if employees are benefitting from technology today, uncertainty may remain about the impact that technology will have on jobs in the future.

The importance of understanding the impact of technological change on employees and jobs is reflected in a substantial increase in the academic literature on this topic in recent years. A highly influential paper by Frey and Osborne (2017) predicted that up to half of all jobs could be automated within a decade or two. However, subsequent work suggested that this was likely a substantial overestimate, as focusing on tasks instead of jobs reduces automation risk to just 9 percent of jobs (Arntz et al., 2017). McGuinness et al. (2023) warn against focusing on "technological alarmism", especially when unsupported by empirical evidence, and it is worth noting that, almost ten years after the predictions of Frey and Osborne (2017), unemployment rates remain low across the EU, US and UK.

Several studies highlight the potential for technological change to affect different types of employees in different ways, leading to labour market polarisation (see, e.g., Autor et al., 2006; Goos et al., 2009; Maarek and Moiteaux, 2021). This is a process which sees a growth in jobs at the top and bottom of the wage distribution at the expense of jobs in the middle. This relates to the task content of jobs. Mid-skilled jobs in the middle of the wage distribution are more likely to contain tasks that are automatable. For example, mid-skilled clerical and administrative functions. Technology, on the other hand, is more likely to complement the skills of high-skilled / high-paid employees, while low-skilled jobs often contain tasks that are more difficult to automate (e.g., cleaners and fast-food production). Bachmann et al. (2019) study the longer-run implications of labour market polarization, by following affected employees over time. They show a shift away from middle-skilled, routine occupations, which has gained pace in recent years. However, impacted employees generally find a new job relatively quickly, as opposed to entering long-term unemployment.

Automation and new technology can also create new tasks for which labour has a comparative advantage, potentially leading to new tasks within existing occupations or even to new types of occupations (see, e.g., Acemoglu and Restrepo, 2019 & 2018). Others have found that new technologies have been associated with net job creation (Koch et al., 2019), or at least delivered improved productivity without leading to substantial job loss (Graetz and Michaels, 2018).

Despite a large body of existing empirical work, gaps in the evidence base still exist. These gaps are highlighted in a systematic review of the literature on automation and employment by Filippi et al. (2023). The authors highlight that a comparison of observed (*ex post*) automation and employment effects across European countries is largely absent from the literature; most studies focus on individual countries, regions or within-country sectors. While the authors state that research relating to the automatability of tasks and occupations in Europe exists (e.g., Foster-McGregor et al., 2021), they pose that relatively little has been found with regard to observed employment effects. By examining the link between changes in employment and realised technological change at an organisational level, our study attempts to, in some way, fill this gap.

3.2 Data & Descriptive Statistics

To examine the impact of technological change on employment in Europe, we leverage the second wave of the European Skills and Jobs Survey (ESJS2), administered by Cedefop in 2021. The ESJS2 is a cross-sectional representative survey of EU employees (N = 46,000), and contains a wide variety of questions relating to the nature of work.

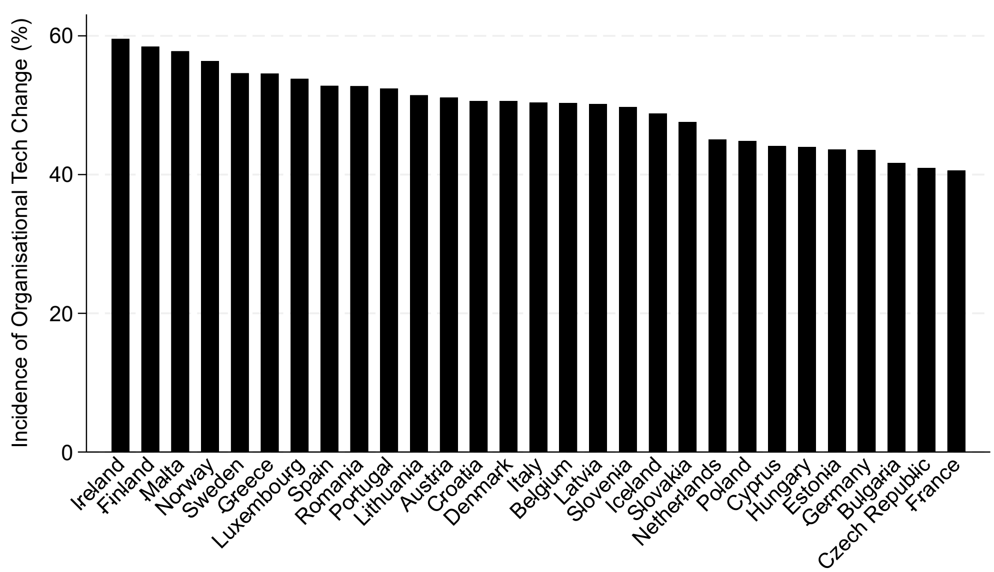
Two questions in the ESJS2 are central to our study. The first question relates to whether or not employees have experienced recent technological change at work. Specifically, the question asks "*In the last twelve months (or since you started your main job, whichever is shorter), did any of the following changes take place in your workplace? – New digital technologies i.e. new computer systems/computer devices/computer programs.*" Using this question, we identify respondents who worked in firms where new technology was recently introduced. The second question captures changes in firm-level employment over the same recent time period – "*Overall, did the number of* *people who work at your workplace increase, stay about the same or decrease in the last twelve months (or since you started working in your main job whichever is shorter)?"*. As such, we can identify whether respondents have experienced recent organisational technological change, as well as capturing whether employment in their firm has changed over the same time period (i.e. in the last twelve months or since the respondent began their employment). As such, it is possible to compare employment changes between firms that incorporated new technology and firms that did not over the same period.

Note that we are using survey data at an employee level to capture changes in firm-level employment within the employing firm. As such, our data are self-reported by the employee, meaning our estimates may be liable to measurement error. We are relying on employees providing an accurate depiction of changes to employment within their firm. While this may be difficult for some employees, the specific nature of the question should make it easier for employees to report accurate information – they are asked about employment changes (increased or decreased), but they do not need to know the exact number of employees. While other studies that use administrative firm-level data may have advantages in terms of improved precision relating to firm-level information, the ESJS has the advantage of including novel questions relating to technological change and firm-level employment growth across the EU that are not available elsewhere.

Just under half (49 percent) of all employees report experiencing recent (in the last 12 months) technological change within their organisation. There is significant variation across countries (Figure 21). Ireland, Finland, Malta, Norway and Sweden exhibited the highest rates of organisational technological change, estimated at 55-60 percent of respondents. In contrast, Estonia, Germany, Bulgaria, Czechia and France exhibited comparatively lower rates of organisational technological change, with all countries having rates below 45 percent. We also examine the sectoral incidence (at NACE Level 2) of organisational technological change (Figure 22). The sectors with the highest incidence included, Financial and Insurance Activities, Education, Information and Communication, while Accommodation and Food saw the lowest.

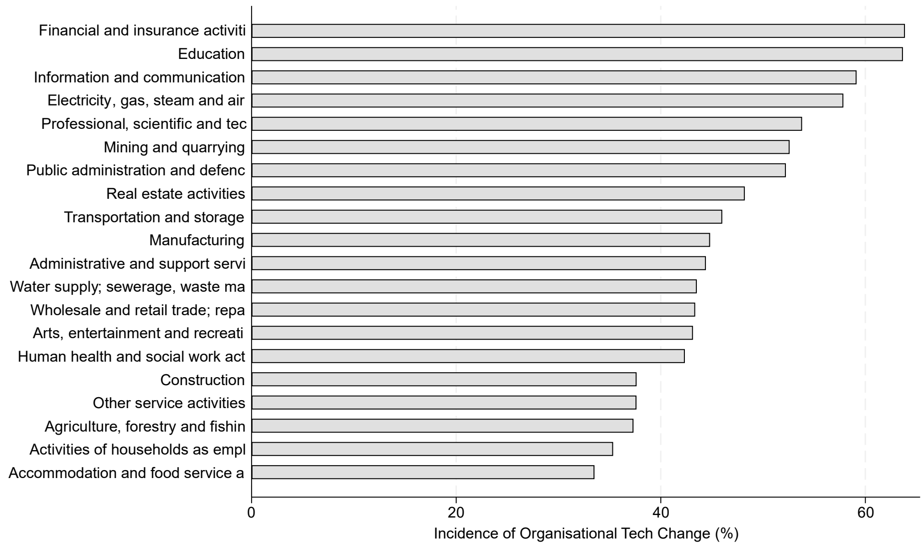
In Table 10 we show the incidence of organisational technological change by employee characteristics. Men are slightly more likely to work in firms where technological change has taken place in the last twelve months than women respondents (51 versus 47 percent). Younger employees, those in higher paid jobs and those with a high level of educational attainment are also more likely to work in organisations that saw recent technological change. Additionally, respondents employed in larger firms are substantially more likely to observe changes in the technology used in their workplace; 58 percent employees in large (250+ employees) firms report technological change compared to just 35 percent of employees in small firms (1-10 employees).

Figure 21: **Incidence of Organisational Technological Change (EU-27 Member States, ESJS2)**



Source: ESJS1 (2021). Authors' calculations.

Figure 22: Incidence of Organisational Technological Change (NACE Sectors, ESJS2)



Source: ESJS1 (2021). Authors' calculations.

Table 10: Incidence of Organisational Technological Change by Subgroups

Variable	% Organisational Tech Change
All	49.1%
Gender	
Males	51.0%
Females	47.2%
Age Group	
25-35	52.6%
36-49	49.4%
50-64	45.5%
Wage Group	
Low Paid	40.9%
Middle Paid	48.5%
High Paid	58.2%
Education	
Low Educated	37.1%
Middle Educated	41.2%
High Educated	56.4%
Company Size	
1-10	35.4%
11-49	46.7%
50-249	54.3%
250+	57.6%

Source: ESJS1 (2021). Authors' calculations.

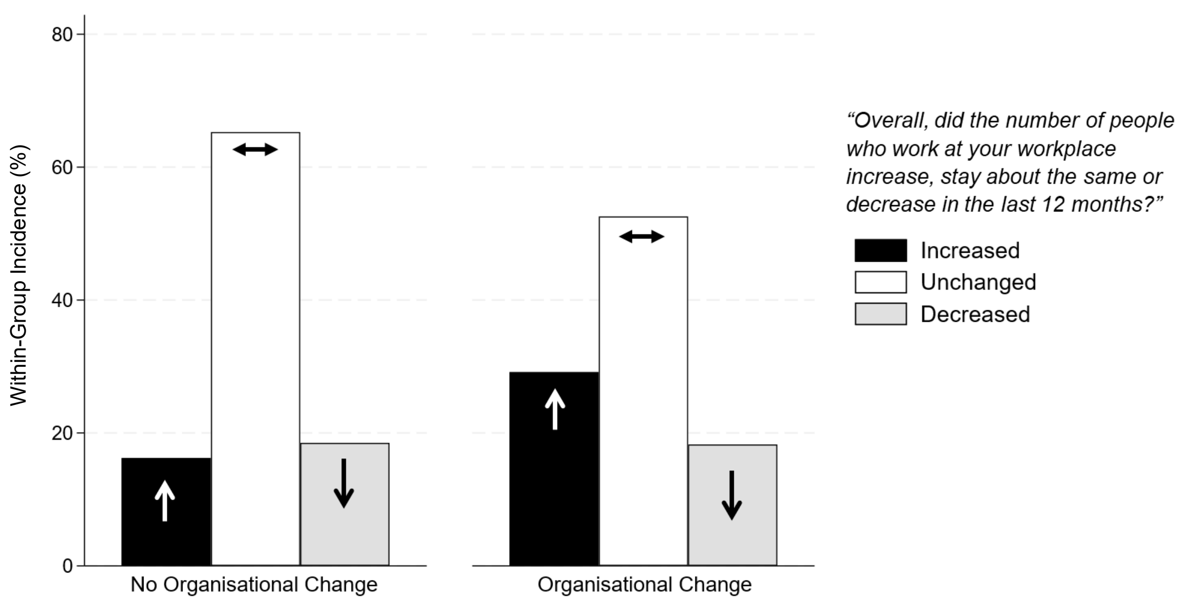
In Table 11 we report the composition of the ESJS2 sample with regard to organisational technological change and firm-level employment changes. The largest groups in the sample are those who reported no aggregate change in employment in their firm throughout the recent reporting period, accounting for 59 percent of all employees. Approximately 14 percent of the sample reported that their organisation had recently adopted new technology *and* that there was an increase in the number of employees over the same period. The equivalent figure was 8.7 percent for those who reported that their firm had adopted new technology but employment decreased. Therefore, descriptively, we observe a positive correlation between the adoption of new technology and firm employment growth. We illustrate this further by reporting the within-group incidence of firm-level employment changes by technological change group (Figure 23). In the group that observed organisational technological change, approximately 30 percent of respondents reported an increase in employment within their firm, compared to just 16 percent among employees that reported organisational technological change.

Table 11: Organisational Tech Change and Employment Changes

	Organisational Tech Change	
Employment Changes	*No*	*Yes*
Increased	8.5%	13.9%
Unchanged	34.2%	25.0%
Decreased	9.7%	8.7%
N		**30,645**

Source: ESJS1 (2021). Authors' calculations.

Figure 23: Incidence of Employment Changes by Technological Change Group



Source: ESJS1 (2021). Authors' calculations.

3.3 Methodology

We examine the relationship between firm-level organisational technological change and firm-level employment changes by estimating the following probit model,

$$\Pr(Increased_i = 1 | X) = \Phi(\beta_1 OrgTech_i + \beta_2 X_i' + \epsilon_i) \quad (1)$$

where $Increased_i$ is a binary variable equal to one if the respondent reported that the number of employees in their firm increased, and zero if employment remained unchanged or decreased. $OrgTech_i$ is a binary variable equal to one if respondent i reports that their firm had adopted new technology at work or not. X_{ij}' represents a vector of control variables including age, gender, occupation (ISCO 2-Digit level), sector (NACE 2), highest level of attained education, years of tenure and company size. ϵ_{ij} is the error term. We estimate the model for all employees, as well as separately by country, firm size and sector.

Note that identification comes from changes within firms over time, albeit from employee-reported changes that are based on retrospective questions. Nonetheless, this offers advantages over simple cross-sectional estimates that rely only on variation across firms. For example, comparing employment numbers across firms depending on whether or not they recently implemented new technology may give estimates that simply reflect the fact that high-tech firms tend to be larger than low-tech firms. However, the fact that we are using employment changes within a firm, coupled with technology changes in the same firm over the same time period, can, to some extent, overcome this issue. Furthermore, we control for the size of the firm in all regressions.

We also examine whether employees in firms that experience differing trends in technological change and employment changes experience systematically different views about future job loss. For instance, take the group of respondents that work in firms where new technology is introduced, and the employment level of the firm has declined over time. It is plausible that these respondents may worry about losing their job, given that such employees may be exposed to potential task displacement and consequent automating dynamics. On the other hand, employees in firms that experienced both technological change and employment growth may be more optimistic, and both groups may differ to employees in firms that did not experience recent technological change.

We define six mutually exclusive groups depending on whether the respondent has 1) reported that new technology has / hasn't been introduced in their workplace and 2) reported that employment levels at their workplace have increased / stayed the same / decreased over time. We then examine how employees' views about the likelihood of future job loss varies across different groups. To do this, we estimate the following probit model,

$$\Pr(JobLoss_i = 1|X) = \Phi(\theta_1 EmploymentTech_i + \theta_2 X_i' + \epsilon_i) \quad (2)$$

Where $JobLoss_i$ captures an employee's fear of job loss. It is based on the question – "*Do you think there is any chance at all of you losing your main job in the next twelve months?*". Respondents who responded "*Yes, a very high chance*" or "*Yes, some chance*" are assigned a value of one, while respondents who did not are assigned a value of zero.[11] The variable $EmploymentTech_i$ is a categorical variable denoting which technological change/employment group respondent i is assigned to. X_i' correspondents to the same set of covariates as defined earlier.

[11] The zeros include respondents that answered "no chance at all", as well as those who answered "Don't' know". However, the vast majority (99%) of the zeros answered "no chance at all".

3.4 Results

In Table 12, we report the results (marginal effects) from estimating equation (1). Employees in firms that recently implemented organisational technological change are 10 percentage points more likely to report that the number of employees within their firm has grown over the same period, relative to employees that reported no technological change. This is after controlling for age, gender, firm size, education, tenure, occupation (at the 2-digit ISCO level) and NACE sector. This is consistent with our descriptive evidence presented earlier, that organisational tech-change is positively associated with employment growth. This is consistent with some of the existing empirical evidence which suggests that technological change often coincides with net job creation.

The other results in Table 12 suggest that younger employees, men, and those in large firms are more likely to report firm-level job growth. Employees with shorter job tenure are also more likely to report that the number of employees has recently increased in their firm. This makes sense, as the fact that an employee was recently hired is consistent with recent increases in employment numbers. Those with higher levels of education are slightly less likely to report increases in employment relative to those with low levels of education. However, the effects are of a relatively small magnitude.

Table 12: Organisational Technological Change and Employment Changes (Marginal Effects)

	(1)
VARIABLES	Increased Employment
Organisational Tech Change	0.104***
	(0.005)
Age	-0.003***
	(0.000)
Female	-0.023***
	(0.005)
Education (ref: Low Education)	
Medium Education	-0.020**
	(0.009)
High Education	-0.021**
	(0.009)
Tenure (ref: less than 1 year)	
1-5 years	-0.059***
	(0.009)
More than 5 years	-0.096***
	(0.009)
Company Size (ref: 1-10 employees)	
11-49 employees	0.069***
	(0.006)
50-249 employees	0.092***
	(0.007)
250+ employees	0.114***
	(0.007)
Observations	29,537
Country Dummies	YES
Occupation Dummies (2 Digit ISCO)	YES
Sector Dummies	YES

Notes: Source – ESJS2 (2021). Low education includes none, primary and lower secondary. Medium education includes upper secondary and post-secondary (non-tertiary). High education includes tertiary education. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In Table 13 we examine whether our estimates differ depending on the size of the firm that the respondent is employed in. There is very little difference. Across all subsamples, the marginal effect of organisational technological change is positive and statistically significant, with estimates ranging from approximately 9 to 12 percentage points. Next, we examine whether our estimates vary substantially across countries (Figure 24). The marginal effect of organisational technological change is positive for all countries, and statistically significant for the vast majority of countries. The largest estimates are found in Denmark, Netherlands and Norway. Estimated impacts are not statistically significant in Iceland, Austria, Luxembourg and Lithuania.

In Figure 25, we show the estimated impacts of organisational technological change on employment across sectors. In almost all sectors, the adoption of new technology is positively associated with employment increases over time. However, the magnitude of the estimated impacts varies. It is notable that sectors such as Water Supply, Agriculture, Mining and Quarrying and Manufacturing are show some of the largest estimated impacts. This has implications for a highly policy relevant topic – that of the 'twin transtion'. This relates to the green and digital transitions which are taking place across EU economies and which have potentially significant implications for labour markets. The green and digital transitions can reinforce each other, as new technology facilitates a move towards reduced carbon emissions and greener jobs, and it has been estimated that the green transition could create 884,000 more jobs in the EU by 2030 (Muench et al., 2022). Our results are consistent with this, showing that the strongest positive association between technological change and job growth occur in sectors that are at the forefront of the green transition.

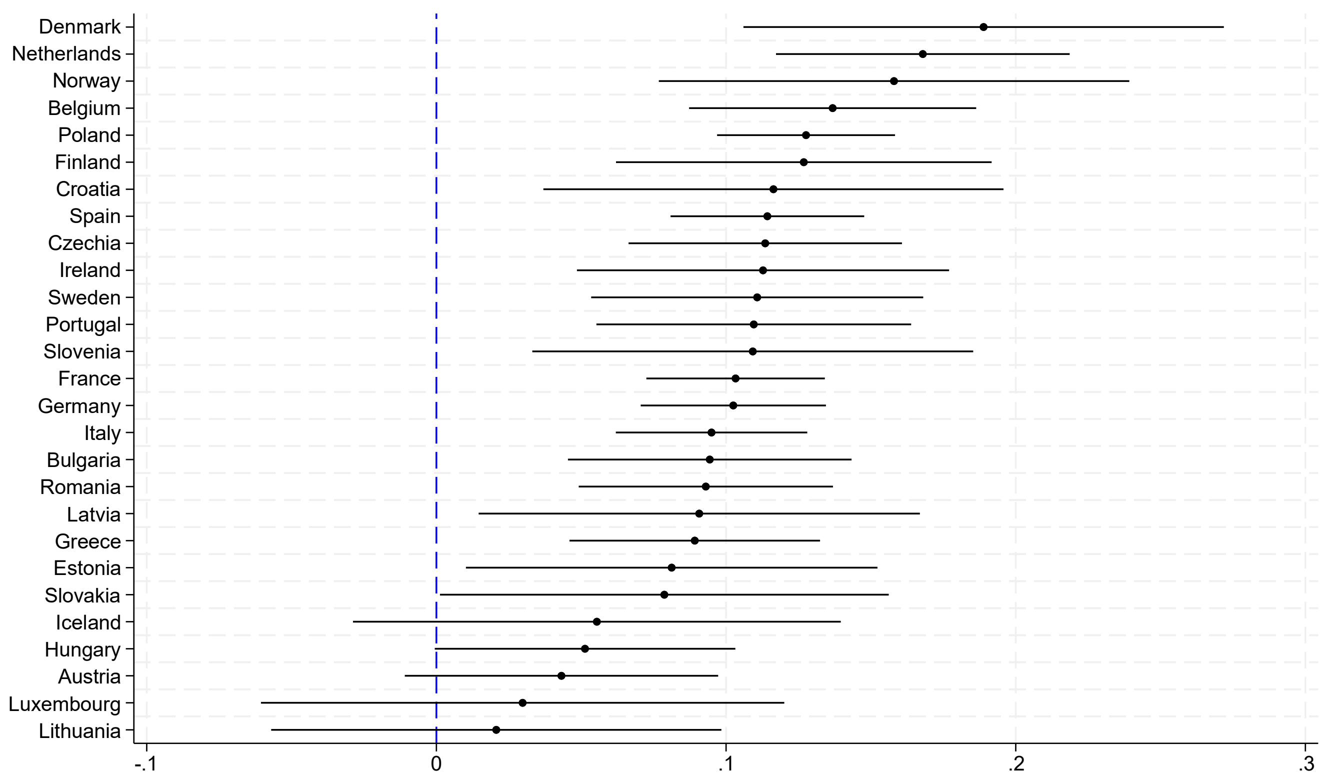
Table 13: Organisational Technological Change and Employment Changes by Firm Size

Variables	(2) 1-10	(3) 11-49	(4) 50-249	(5) 250+
Organisational Tech Change	**0.086*** (0.009)**	**0.115*** (0.009)**	**0.096*** (0.010)**	**0.110*** (0.010)**
Observations	5,758	8,194	7,664	7,896

Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1*

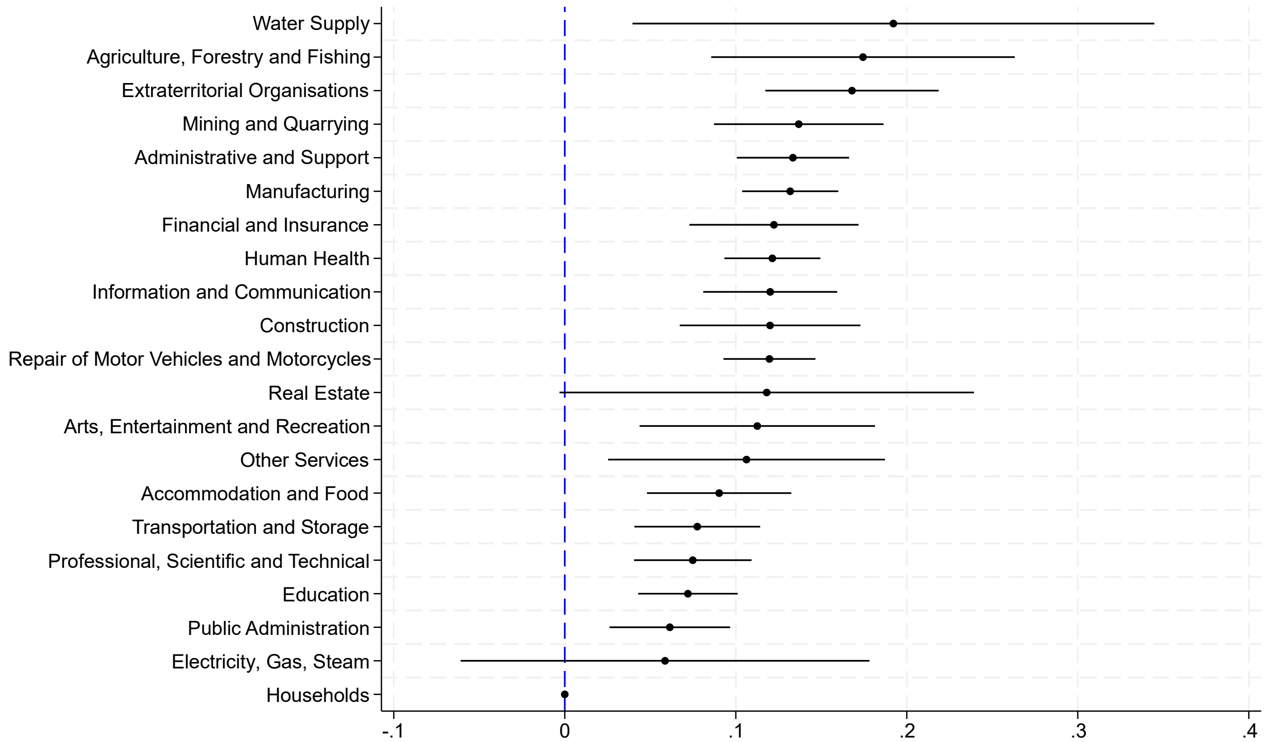
Source: ESJS1 (2021). Authors' calculations.

Figure 24: Marginal Effect of Technological Change on Employment Increases (EU-27 Member States)



Source: ESJS1 (2021). Authors' calculations.

Figure 25: Marginal Effect of Technological Change on Employment Increases (NACE 2 Sector)



Source: ESJS1 (2021). Authors' calculations.

Turning to the relationship between the perceived likelihood of job loss and technological and employment changes, we report the results of equation (2) in Table 14. It is clear that employees in firms that are shrinking in employment are substantially more likely to fear losing their job than employees in firms that are unchanged or increasing in size, regardless of whether technological change has occurred or not. The marginal effect is slightly larger for the cohort in firms with no new technology (approximately 15 percentage points) than for the tech-exposed group (approximately 13 percentage points). Employees in tech-exposed firms where employment either stayed the same or increased were also more likely to fear losing their job than the corresponding non-tech-exposed groups. Relative to the reference group (no technological change, unchanged employment), the group that experienced organisational technological change and no employment change (employment increases) were 3.5 (4.1) percentage points more likely to fear losing their job. This suggests that the introduction of new technology is associated with a heightened fear of job loss among employees, even if they are employed in a firm with growing numbers of employees.

Table 14: Technological Change, Employment Changes and Employee Outcomes

Variables	2) Fear of Job Loss
No Tech Change, Unchanged	*Ref.*
No Tech Change, Increased	-0.017
	(0.011)
No Tech Change, Decreased	0.153***
	(0.010)
Tech Change, Unchanged	0.035***
	(0.007)
Tech Change, Increased	0.041***
	(0.009)
Tech Change, Decreased	0.133***
	(0.011)
Constant	--
	--
Controls	YES
Country/Occupation/Sector	YES
Observations	29,551
R-Squared/Pseudo R-Squared	

Standard errors in parentheses.
Estimates in Column 1 are coefficients. Estimates in Columns 2-5 are marginal effects.
*** p<0.01, ** p<0.05, * p<0.1*

3.5 Conclusions

A significant concern for EU policymakers relates to the potential automating effects of new technology in the EU labour market. As a result, a considerable amount of research has been dedicated to evaluating the extent to which tasks and jobs have been disrupted by technology. While the focus is often on the potential for new technology to automate and replace existing jobs, comparatively less evidence exists which examines the realised impacts of technology on employment of EU employees. We provide evidence on this issue by examining the relationship between firm-level technological change and employment in the EU.

We show that organisational technological change is widespread across Europe. On average, 49.1 percent of EU employees reported that their workplace had integrated new technology within the last twelve months. There was notable variation between member states, ranging from 60 percent in Ireland to 40 percent in France. Our results show that the introduction of new technology within an organisation is positively associated with employment growth; respondents that work in firms where new technology was recently introduced are approximately 10 percentage points more likely to report workplace employment increases over the same period. While this pattern is observed across member states, the magnitude varies. The estimated impact is highest in countries including Denmark, Netherlands and Norway.

Our findings have implications for the policy discussion relating to the twin transitions. Much has been said about the interaction of the digital and green transitions, and whether the outlook for employment is positive or negative. Some recent studies have predicted that the green transition can lead to net job creation, supported by innovative technologies to help reduce emissions. Our analysis shows that sectors that are likely to be heavily impacted the green transition, such as agriculture, water supply and manufacturing, show the strongest employment gains that coincide with technological change.

Despite the positive association between organisational technological change and employment, employees that are in firms where new technologies are being introduced are more likely to fear losing their jobs. This is the case even among employees in firms where actual employment has recently increased. This underscores the uncertainty that exists among employees about the role that technology will play in the future.

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