TRAILS

Enabling Data Analytics for Actions
Tackling Skills Shortages & Mismatch

Project Title:	**TRAILS - Enabling data analytics for actions tackling skills shortages & mismatch**
Contract No:	101132673
Instrument:	Research and Innovation Action
Thematic Priority:	HORIZON-CL2-2023-TRANSFORMATIONS-01
Start of project:	1 January 2024
Duration:	36 months

Deliverable No: D5.1

PORTFOLIO I: Training for Labour Market Inclusiveness and Resilience

Document Control Page

Deliverable Name	PORTFOLIO I: Training for Labour Market Inclusiveness and Resilience
Deliverable Number	D5.1
Work Package	Work Package 5
Associated Task	T5.1
Covered Period	M04-M18
Due Date	30/06/2025
Completion Date	30/06/2025
Submission Date	30/06/2025
Deliverable Lead Partner	ESRI
Deliverable Author(s)	Paul Redmond, Lorcan Kelly, Luke Brosnan, Georgios Panos, Stamatia Ftergioti, Ioannis Pragidis, Vasiliki Kotsirou
Version	1.0

Dissemination Level		
PU	Public	**X**
CO	Confidential to a group specified by the consortium (including the Commission Services)	

Document History

Version	Date	Change History	Author(s)	Organisation
0.1	Month 6, 2025	Version before revisions	Paul Redmond, Lorcan Kelly, Luke Brosnan, Georgios Panos, Stamatia Ftergioti, Ioannis Pragidis, Vasiliki Kotsirou	ESRI, AUTH, DUTH
0.2	Month 6, 2025	Version after revisions	Paul Redmond, Lorcan Kelly, Luke Brosnan, Georgios Panos, Stamatia Ftergioti, Ioannis Pragidis, Vasiliki Kotsirou	ESRI, AUTH, DUTH
1.0	Month 6, 2025	Final submission	Paul Redmond, Lorcan Kelly, Luke Brosnan, Georgios Panos, Stamatia Ftergioti, Ioannis Pragidis, Vasiliki Kotsirou	ESRI, AUTH, DUTH

Internal Review History

Name	Institution	Date
Lorenzo Incoronato Marco Pagano	UNINA	Month 6, 2025
Anna van Cauwenberge	IPSOS	Month 6, 2025

Quality Manager Revision

Name	Institution	Date
Lorenzo Incoronato, Marco Pagano	UNINA	Month 6, 2025
Anna van Cauwenberge	IPSOS	Month 6, 2025

Table of Contents

LIST OF FIGURES

LIST OF TABLES

ACRONYMS

Acronym	Explanation
CATI	Computer Assisted Telephone Interview
CAWI	Computer Assisted Web Interview
CEDEFOP	European Centre for Development of Vocational Training
ESJS2	European Skills and Job Survey (2021)
EU	European Union
ISCO	International Standard Classification of Occupations
NACE	*Nomenclature générale des Activités économiques dans les Communautés Européennes*

EXECUTIVE SUMMARY

The introduction of new technologies continues to impact the labour market in the EU. While there may be fears of job losses in some occupations or industries, there are also opportunities for achieving greater productivity provided the technological innovations can be utilised effectively. This is a major area of policy focus within the EU. We are currently in the middle of *Europe's Digital Decade,* in which the EU sets out a vison and goals for the digital future of Europe out to 2030. Part of this is to develop digital and high-tech skills with the aim of creating 20 million ICT specialists in the EU by 2030, as well as ensuring that at least 80% of the population are equipped with basic digital skills. There is also a focus on innovation and promoting the adoption of new technologies within EU companies.

Given the policy focus on improving digital skills, it is important that we first understand the extent to which new technologies are impacting workers across the EU, and how this varies by sector. Our analysis shows that 42 percent of employees across the EU experienced recent changes to the technology that they use in their jobs. Employees in the ICT sector experienced the highest incidence of technological change, at 57 percent. Our findings also show that technological change is having a significant impact on how employees do their jobs. Of those that experienced technological change at work, approximately 80 percent indicated that the new technology changed some of their tasks.

Skills mismatches will arise if employees cannot keep pace with technological change. Our findings show that 67 percent of EU employees have a technological skills deficit, which we call *tech-underskilling*. The highest incidence of tech-underskilling occurs in sectors such as ICT, professional and technical services, and education. The incidence of tech-underskilling is also positively correlated with technological change – that is, the sectors where large numbers of employees experience technological change tend to be the same sectors in which large numbers of employees experience tech-underskilling. This is a key issue, as tech-underskilling, and underskilling more generally, can lead to negative outcomes for employees and households. For example, our findings show that tech-underskilled employees are four percentage points more likely to fear losing their job in the near future, compared to employees that are not tech-underskilled. Furthermore, our household-level analysis shows that skills mismatch, in general, is associated with higher risks of relative poverty, diminished financial resilience in coping with unexpected expenses, and lower positions within national income distributions for European households, again underscoring the importance of this as a policy issue.

The provision of training is key to enable workers to adapt to new technologies in the workplace and thereby avoid skills mismatch. It is reassuring to note that most tech-underskilled workers in the EU indicated that they recently participated in some type of training. For employees that experienced technological change at work, the incidence of training is approximately 84 percent for those who are tech-underskilled. However, it is not just the incidence of training that is important. The type of training and its effectiveness are also key considerations. Our findings indicate that training, on average, yields positive outcomes on measures of worker performance. Trained employees are more likely to report that they perform their tasks faster and that technology is generally beneficial for improving their performance at work. Furthermore, the intensity and type of training matters. Our results show that, in general, employees that are exposed to multiple training types (seminars, courses and on-the-job training) experience the greatest benefits in terms of task performance.

Given the policy focus on improving digital skills in the EU, our findings are highly policy relevant. The high incidence of technological change and the corresponding high rates of technological skill deficits highlights the importance of upskilling and training in this area. This is particularly relevant in sectors that have high exposure to technological change. If employees cannot keep pace with technological change, this will lead to skills mismatches, which in turn can lead to negative outcomes for employees, households and businesses. Through initiatives like, *Europe's Digital Decade,* EU policy can support employers to upskill and re-train employees to adapt to technological change. Our research shows that increasing training intensity by facilitating multiple types of training methods is the best way to improve employee performance.

Purpose of the Deliverable

The purpose of this deliverable (D 5.1) is to (i) measure the incidence of technological change across sectors in the EU, (ii) examine the extent to which technological change is associated with skills mismatch across sectors, (iii) explore the relationship between skills mismatch key labour market outcomes at the individual and household level (iv) assess the incidence of training among those that experience technology-based skill deficits, and (iv) examine the effectiveness of training in enabling EU workers to keep pace with the requirements of new technologies in the workplace.

Relation with Other Deliverables and Tasks

This paper builds upon several other deliverables from the TRAILS project that have been produced as part of Work Packages 1, 2 and 3. In particular, D(1.1) provides a comprehensive review of the literature on skills mismatch, both in terms of theoretical and empirical work. This was important for framing the research questions and motivating the topics covered in the current deliverable. This deliverable also draws heavily from D(2.1), which conducted analyses of core secondary datasets, one of which was the European Skills and Jobs Survey which is used in this deliverable. It also builds on D(3.1) which provided a comprehensive assessment of the current state of skills mismatch in the EU. The findings from this deliverable will also feed into future output from Work Package 5, including D(5.2), D(5.3) and D(5.4), which will further examine skills portfolios, resilience and labour market mobility. This deliverable will also inform D(3.2) which will further examine the role of training in the EU labour market.

Structure of the Document

This document is structured into two distinct, but closely related, chapter. The first chapter, entitled 'Technological Change, Skills Mismatch and Training in the European Labour Market', examines the incidence and consequences of technological skills deficits among EU employees. It then investigates the role played by training in enabling workers to adapt to new technologies in the workplace as well as analysing the effectiveness of different training combinations.

Chapter 2, entitled, 'Skills Mismatch and Household Well-being Across Europe' builds on the work of Chapter 1 by exploring the consequences of skills mismatch for households. The majority of the existing work on skills mismatch, including that of Chapter 1, focuses on employee level outcomes, such as job satisfaction and fear of job loss. Chapter 2 develops an innovative approach which allows us to examine the impact of skills mismatch on household level outcomes, such as poverty risk, financial resilience. Taken together, both chapters underscore the policy importance of skills mismatch in the EU.

Chapter One: Technological Change, Skills Mismatch and Training in the European Labour Market

1. Introduction

Digital skills have risen to the fore of European economic policy.[1] As new digital technologies continue to reorient production processes, alter task content and disrupt the European labour market, digital skills have grown increasingly important for workers and the European Union (EU) economy. As such, ensuring the adequate supply of digital skills to limit skill shortages is important. To do this, policymakers must first understand where digital training needs are most acute. It is therefore critical to identify the sectors that are most affected by technological change and digital skill deficits (otherwise known as "digital underskilling"). Furthermore, it is important to understand the extent to which affected workers are receiving adequate digital training in response to technological developments so that digital training policy may be appropriately targeted. In other words, are European workers being affected by digital skill deficits? If so, are those workers being supported through effective training programmes?

The existing literature in this area highlights the important impacts that technological change can have on the labour market and underpins the importance of targeted policy to allow workers to adapt to technological change through training and education. Rapid technological change can lead to skills mismatch and, in turn, productivity losses. Acemoglu and Restrepo (2019) highlight this dynamic through the lens of task destruction – in which the introduction of technology at work leads to the obsolescence of tasks previously performed by labour – and task creation – such that new, labour-dependent tasks are introduced as a result of new technology at work. Such 'task churn' can give rise to skills mismatch, which, if not addressed adequately by education or training, can lead to productivity losses. Goldin and Katz (2008) characterise these dynamics as a "race between technology and education", such that education and training systems should rapidly respond to changes in production processes (i.e. due to technological change) in order to protect workers against skills mismatch, unemployment and productivity losses.

[1] See here: https://digital-strategy.ec.europa.eu/en/policies/digital-skills

In this chapter, we provide valuable empirical insight into this policy issue. To do this, we structure the chapter around four key research questions. First, which sectors of the European economy are most affected by technological change and digital skill deficits? Using the second wave of the European Skills and Jobs Survey (ESJS2), we identify employees that have been affected by meaningful technological change in the workplace, such that their day-to-day tasks have been altered by the recent introduction of new technology. Furthermore, we exploit information from the ESJS2 to assess the extent to which employees exhibit a digital skill deficit (i.e. their digital skills require improvement to do their job well). Using this measurement approach, we compare the incidence of both technological change and digital underskilling across sectors in order to identify areas where digital training policy needs may be most acute.

Our second research question relates to the outcomes of European workers that experience digital skill deficits. The existing empirical literature suggests that underskilling – in which workers' skills are not at a sufficient level to meet the demands of their job – is both widespread and is associated with harmful impacts on workers and the economy. Studies from Kampelmann and Rycx (2012), Mahy et al. (2015) and Kampelmann et al. (2020) show that an underskilled workforce is associated with reduced firm-level productivity and profitability. In addition, 27% of underskilled workers believe that their skills will become obsolete in the future, leading to fear of job loss and negative perceptions of job security (Cedefop, 2018). Furthermore, digital underskilling – a variant of underskilling in which employees' digital skills are not sufficient for the needs of their job – has been shown to be widespread across the EU (Pouliakas and Souto-Otero, 2022). While some of the existing literature examines the outcomes of underskilled workers (for example, see Sánchez-Sánchez and McGuinness, 2015), to our knowledge, no papers focus explicitly on digital underskilling. In our study, we examine how digital underskilling is related to employee wellbeing, specifically focusing on job satisfaction, perceptions of job security, work-life balance and fear of job loss.

Training is the primary method through which digital skill gaps may be overcome. As such, a key concern for policy is whether the training needs of digitally-underskilled workers are being sufficiently addressed. Our third research question centres on this; are workers that exhibit digital skill deficits receiving adequate training? The importance of training is outlined by Acemoglu and Restrepo (2021), who pose that training investments should serve to support workers in up-/re-skilling in tandem with task-altering technological change. However, evidence from the OECD (2019) and ILO (2021) suggests that this has not manifested in most cases, showing that many adult learning systems are not adequate to support workers in light of rapid digitalisation. As such, training provision in Europe remains an urgent priority for both researchers and policymakers.

Few studies have examined the explicit relationship between skills mismatch and training. One exception comes from McGuinness and Ortiz (2016), who use employer-employee linked data to evaluate the role of mismatch in determining firm training costs in Ireland. The authors demonstrate that firms with more mismatched (or less well-matched) workers experience higher training costs.

That said, given the study's limited geographical scope, a gap in the evidence base remains. Using information from the ESJS2, we formally model the associative relationship between digital underskilling and training receipt among EU workers that have been affected by recent technological developments in the workplace. By comparing training outcomes between workers that are digitally underskilled and not digitally underskilled, we gain further insight into whether training programmes are being accurately targeted toward workers that are underskilled, in turn assessing targeting quality among existing training programmes at work.

Our final research question concerns the efficacy of training; does training improve worker performance, and if so, which types of training are most effective at doing so? While understanding whether underskilled workers are receiving training is important, it is equally important for training programmes to meaningfully improve the outcomes of workers. To assess this, we evaluate the extent to which 1) self-reported worker performance and 2) workers' propensity to work well with new technology differs between workers that received training and workers that did not. From a policy perspective, it is also important to understand which types of training are the most effective at improving worker performance so that training investments are efficient. As such, we allow our analysis to vary depending on the combinations of training types –courses, seminars and on-the-job training – that workers received in order to understand which training types are associated with the largest productivity benefits. We also examine whether our estimates systematically vary across three dimensions – sector, gender, and age – to evaluate differences between groups.

2. Data & Measurement

2.1 Technological Change

We utilise the 2021 wave of the European Skills and Jobs Survey (ESJS2) to evaluate the training needs of workers who experience technological change. The ESJS2 is a representative survey of employees in the EU-27 (plus Norway and Iceland)[2], containing approximately 46,000 respondents. The survey contains a range of detailed demographic information (e.g. age, gender), as well as a wide variety of highly specific questions relating to the nature of respondents' work. The survey was administered by Cedefop in 2021, with responses being provided via both computer-assisted

[2] Herein, we refer to the full sample of countries (EU-27, Norway and Iceland) as 'EU-27+'.

telephone interview (CATI) and computer-assisted web interview (CAWI). The aim of our measurement approach is to 1) identify European workers who have been affected by technological change and 2) compare within-group differences in training receipt and training-related outcomes. We identify workers who have been affected by meaningful technological change at work using Question 38 in the ESJS2: "*In the last 12 months (or since you started your main job), did you learn to use any new computer programs or software to do your main job?*" and Question 44: "*In the last 12 months (or since you started your main job), did you learn to use any new computerised machinery to do your main job?"* We consider respondents to have experienced technological change if they responded "Yes" to either question.

It's important to acknowledge the limitations of this measurement approach. One limitation is that our technological change measure does not account for employee choice when experiencing changes in technology at work. Due to the phrasing of the questions used, it's plausible that the group that experience technological change consists of both 1) employees who were compelled to learn new technology due to changing job tasks at work, and 2) employees who chose to learn new technology at work, independent of their task requirements. In other words, our measure does not distinguish whether employees learned new technologies due to changes in job tasks or by personal initiative. Some may have adopted new technologies voluntarily, while others may have done so out of necessity. Moreover, our measure may omit workers whose jobs changed but who failed to acquire the required digital skills. Nevertheless, the targeted and specific nature of the questions in this survey presents an opportunity to capture a very salient measure of self-reported technological change in the workplace.

Across the entire sample, 42 percent of respondents experienced recent technological change. In Figure 1, we examine the incidence of technological change across different sectors of the EU economy.

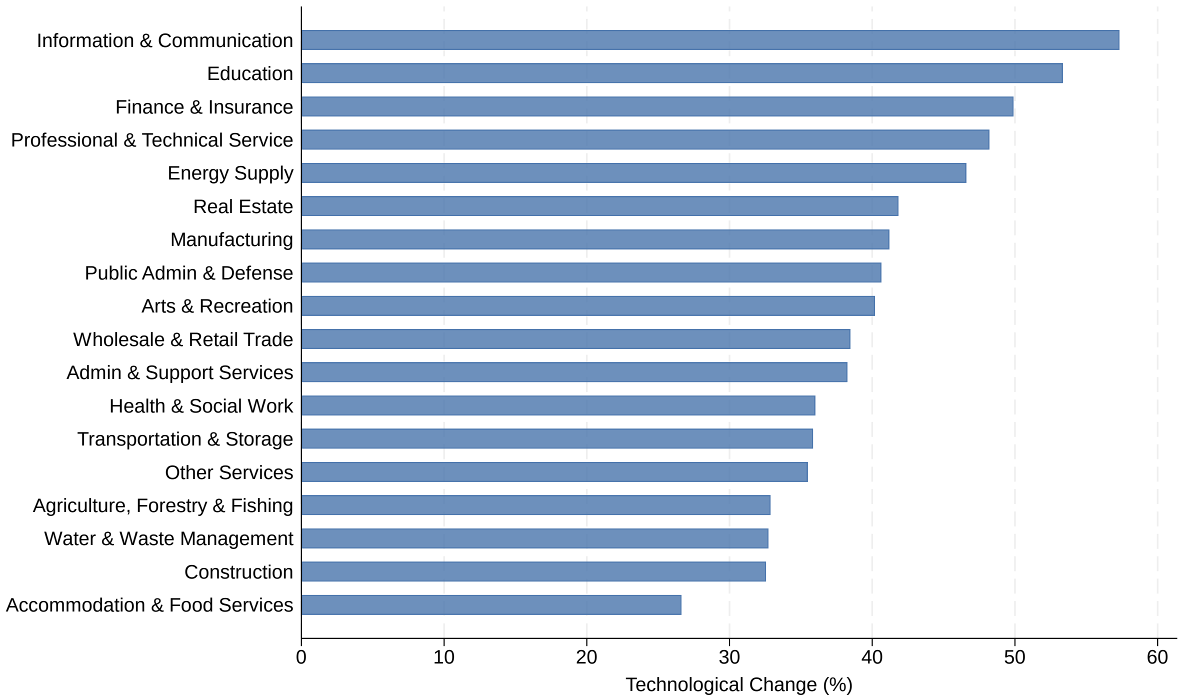

Figure 1: Incidence of Technological Change by NACE Sector

Source: ESJS2, Author's elaboration
Note: Sectors with less than 200 observations are omitted from this analysis. 'Technological Change' refers to respondents who indicated that they had learned new computerised machinery, computer programmes or software at work in the previous twelve months or since they began their current tenure (whichever is shorter).

Technological change has manifested across sectors with varying degrees of magnitude. The Information and Communication sector exhibits the highest incidence; 57 percent of respondents in the Information and Communication sector reported that they had recently learned to use new technology at work. The lowest estimate is attributed to the Accommodation and Food Sector (27 percent). Broadly, the sectors that were most affected by technological change are typically characterised as higher-skilled jobs (e.g. Information and Communication, Education, Finance and Insurance, Professional Services), whereas the sectors that were least affected are generally characterised by manual tasks (e.g. Transportation and Storage, Agriculture, Water and Waste Management, Construction). Some of the sectoral features could be partially attributed to the time at which the survey was administered. Given that the ESJS2 was collected in 2021, and the questions relating to technological change refer to the previous twelve months (or whenever the respondent began their tenure, whichever was shorter), it is likely that some of the technological change captured in the data could be attributed to the advent of widespread remote working because of the

COVID-19 pandemic. For example, the education sector largely transitioned from in-person activities to remote learning via online classrooms facilitated by communications software that was not previously utilised for these purposes (e.g. Zoom, Microsoft Teams).

In Figure 2 below, we report the incidence of technological change by country. The highest country-level incidences of technological change are attributed to the Northern European / Scandinavian countries (i.e. Finland, Norway, Denmark and Sweden), while the lowest values are attributed to Latvia, Cyprus, France and Germany.

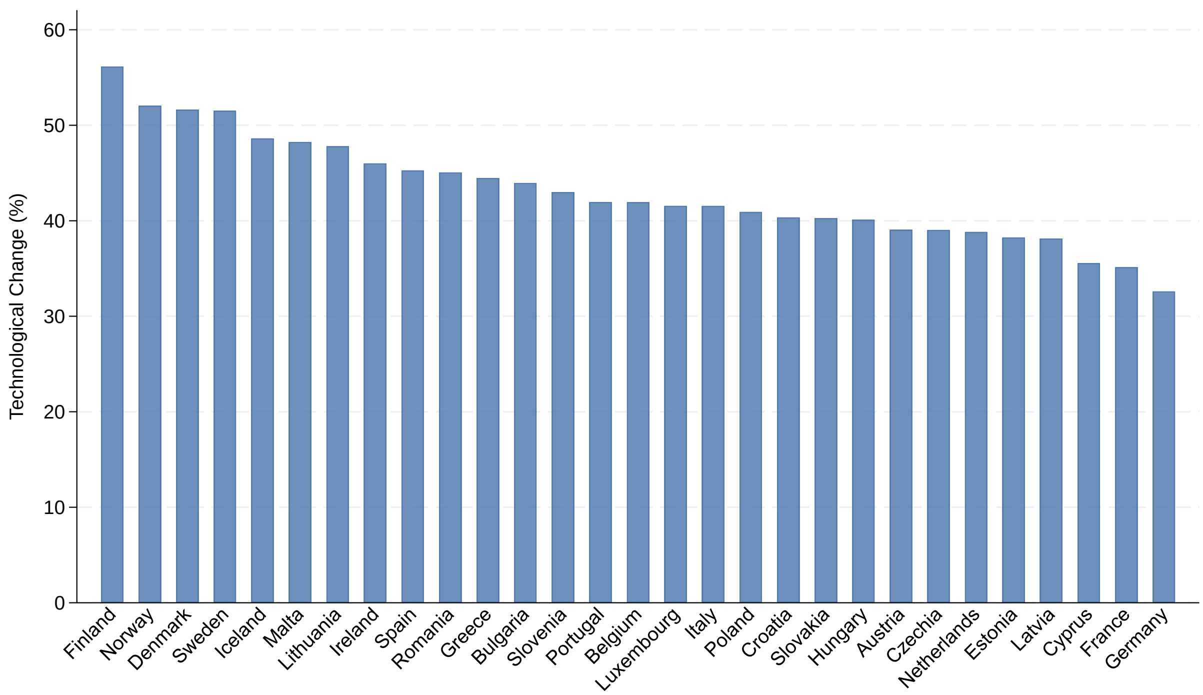

Figure 2: Incidence of Technological Change by EU-27+ Country

Source: ESJS2, Author's elaboration

Note: Countries with less than 200 observations are omitted from this analysis. 'Technological Change' refers to respondents who indicated that they had learned new computerised machinery, computer programmes or software at work in the previous twelve months or since they began their current tenure (whichever is shorter).

While technological change may be widespread, it is also important to assess whether technological change has resulted in substantial changes in task content at work. To do this, we draw on responses to Question 45 of the ESJS ("*As a result of the new computer programs or software, or new computerised machinery you learnt for your main job, did your job tasks change in any of the* *following ways?*”). Respondents could indicate that their tasks had changed in the following ways: 1) “*You now do some different or new tasks*”, 2) “*You now do some of your tasks at a faster pace than before*” and/or 3) “*You now do not do some tasks you did before*”. Of the 19,546 respondents that had reported technological change, 15,487 (or 79.2 percent) reported that their tasks had changed in at least one of the three listed ways. That is, where technological change occurred, substantial changes to occupational task content followed. We refer to this as *meaningful* (task-altering) technological change. In Figure 3 below, we show the incidence of *meaningful* (i.e. task-altering) technological change across NACE Level 1 sectors. The incidence of meaningful technological change closely reflects the incidence of technological change across sectors, with minor variation in the ordering.

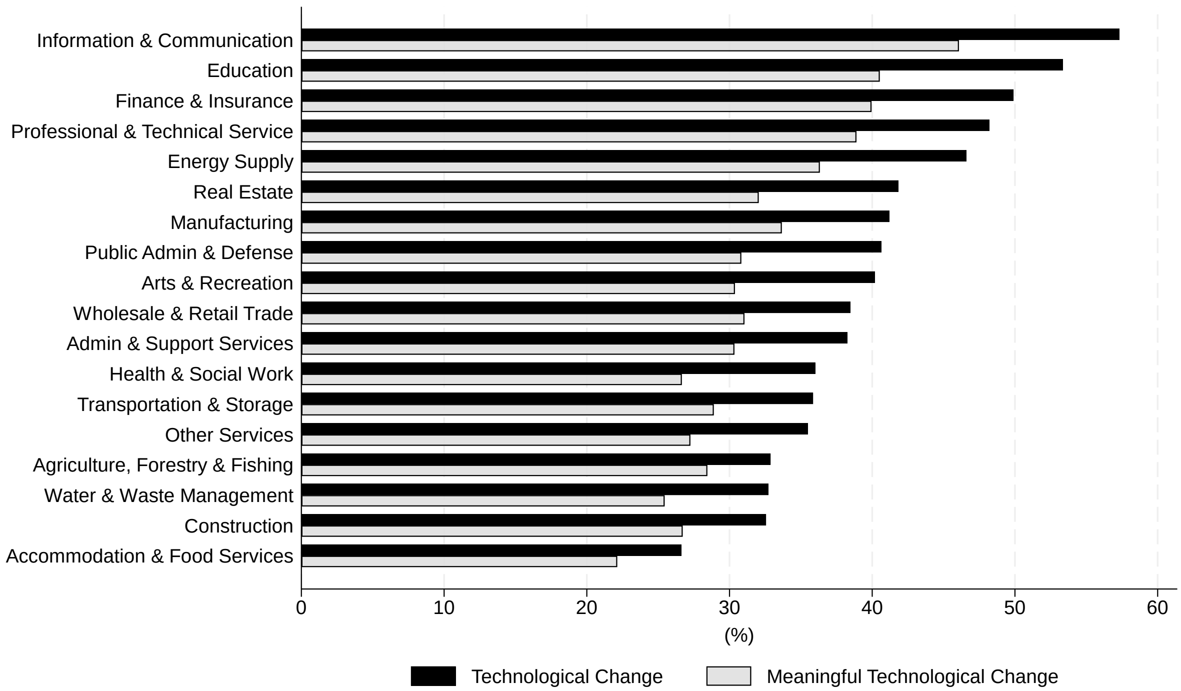

Figure 3: Incidence of Meaningful Technological Change by EU-27+ Country

Source: ESJS2, Author's elaboration

Note: Sectors with less than 200 observations are omitted from this analysis. 'Technological Change' refers to respondents who indicated that they had learned new computerised machinery, computer programmes or software at work in the previous twelve months or since they began their current tenure (whichever is shorter). 'Meaningful Technological Change' refers to refers to respondents who indicated that they had experience technological change, as well as changed in the task content of their work as a result of the introduction of new technology (task displacement and/ task creation and/or improved task efficiency).

2.2 Tech-Underskilling

As outlined in the introduction, we intend to identify respondents that exhibit a digital skill gap (or be "tech-underskilled"). To do this, we draw on responses to Question 61 in the ESJS2: "*To what extent do you need to further develop your computer/IT skills to do your main job even better?*" We consider a respondent to be tech-underskilled if they responded "Great Extent" or "Moderate Extent" to Question 61.[3] Among the entire sample, approximately 67 percent of respondents reported that they were tech-underskilled. However, there is a noticeable difference when disaggregating the incidence by whether or not respondents had experienced recent technological change. Approximately 60 percent of respondents that had not experienced technological change reported that they were tech-underskilled, compared to 77 percent of respondents that had been affected by recent technological change.

We report the incidence of tech-underskilling by NACE Level 1 sector in Figure 4. The highest rates of tech-underskilling are largely among sectors that are typically characterised by highly skilled tasks (e.g. Information and Communication, Professional and Technical Services, Education), while the lowest rates of tech-underskilling are attributed to sectors that are more manually focused (e.g. Accommodation and Food Services, Transportation and Storage, Water and Waste management). At a sectoral level, the incidence of tech-underskilling is shown to be positively correlated with the incidence of technological change (see Figure 5). That is, sectors in which employees report the greatest incidence of technological change are typically the same sectors with a high incidence of tech-underskilling.

[3] Given that this measure is self-reported, it is possible for measurement error to occur. For example, respondents might believe that they do not possess adequate digital skills to perform at work, but their employer could deem their skills adequate. That said, it's plausible that most workers' conceptions of their digital skill levels are broadly in line with employers' perceptions, given their shared professional experience.

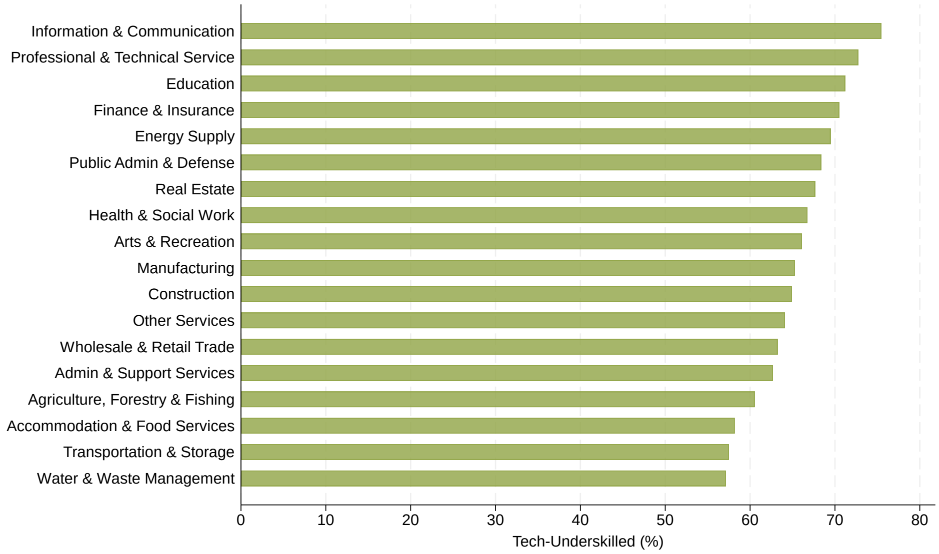

Figure 4: Incidence of Tech-Underskilling by NACE 1 Sector

Source: ESJS2, Author's Calculations. Note: Sectors with less than 200 observations are omitted from this analysis. 'Tech-Underskilling' refers to respondents who reported that they needed to improve their digital skills to do their main job better.

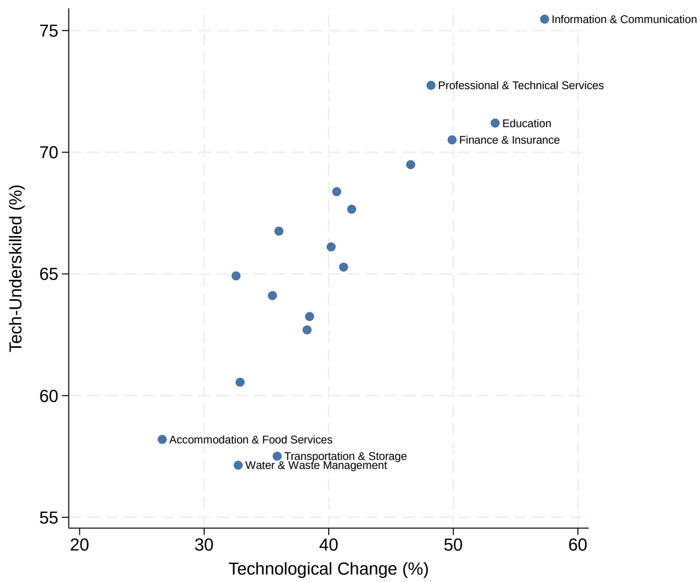

Figure 5: Scatterplot of Technological Change and Tech-Underskilling Incidence (NACE 1 Sector)

Source: ESJS2, Authors' Elaboration Note: Sectors with less than 200 observations omitted from analysis. 'Technological Change' refers to respondents who indicated that they had learned new computerised machinery, computer programmes or software at work in the previous twelve months or since they began their current tenure (whichever is shorter). 'Tech-Underskilling' refers to respondents who reported that they needed to improve their digital skills to do their main job better.

Some sectors with the high rates of tech underskilling are sectors that we would typically associate with greater digital task content (e.g., information and communication), while other sectors with lower rates of digital underskilling may have lower digital task content (e.g., water and waste management). Higher digital skill requirements may partially explain higher rates of digital underskilling among workers in these sectors; where the necessity for digital skills is higher, digital skill deficits may be more salient. Similarly, where digital skills are less important, workers are less likely to report having digital skill deficits.

We illustrate the relationship between tech-underskilling and the digital content of jobs by exploiting information on the digital tasks that respondents reported performing at work in the ESJS2. We calculate an index variable to capture the digital components of work (weighted by task complexity), similar to McGuinness et al. (2025). We use responses to Question 37 ("*Did you use any of the computing devices from the previous question to do the following activities as part of your main job in the last month?*"), in which respondents are asked if they did any of eight digital tasks of varying complexity. The eight tasks were 1) web browsing, 2) word processing, 3) making presentations, 4) using spreadsheets, 5) using advanced formulae in spreadsheets, 6) working with occupation-specific software, 7) managing databases and 8) writing code or programmes. We weight individual tasks based on their complexity, assigning higher weights to tasks with higher complexity and lower weights to tasks with lower complexity. We outline the specific calculation in the equation below.

$$DigitalIntensity_i = \frac{\sum \left[\begin{array}{c} (web_i + word_i + presentations_i) + \\ 2(spreadsheets_i + formulae_i + occsoftware_i) + \\ 3(databases_i + coding_i) \end{array} \right]}{15}$$

For the first three tasks (web browsing, word processing and presentations), we assign a weight of one. For the second three tasks (using spreadsheets, using advanced formulae in spreadsheets and working with occupation-specific software),we assign a weight of two. For the last two, most complex tasks (managing databases and writing code or programmes), we assign a weight of three. For each respondent, we aggregate the values for each task based on their responses, and index the sum total (i.e. divide by the maximum possible value, fifteen), giving us an indexed value of digital task intensity for each respondent.

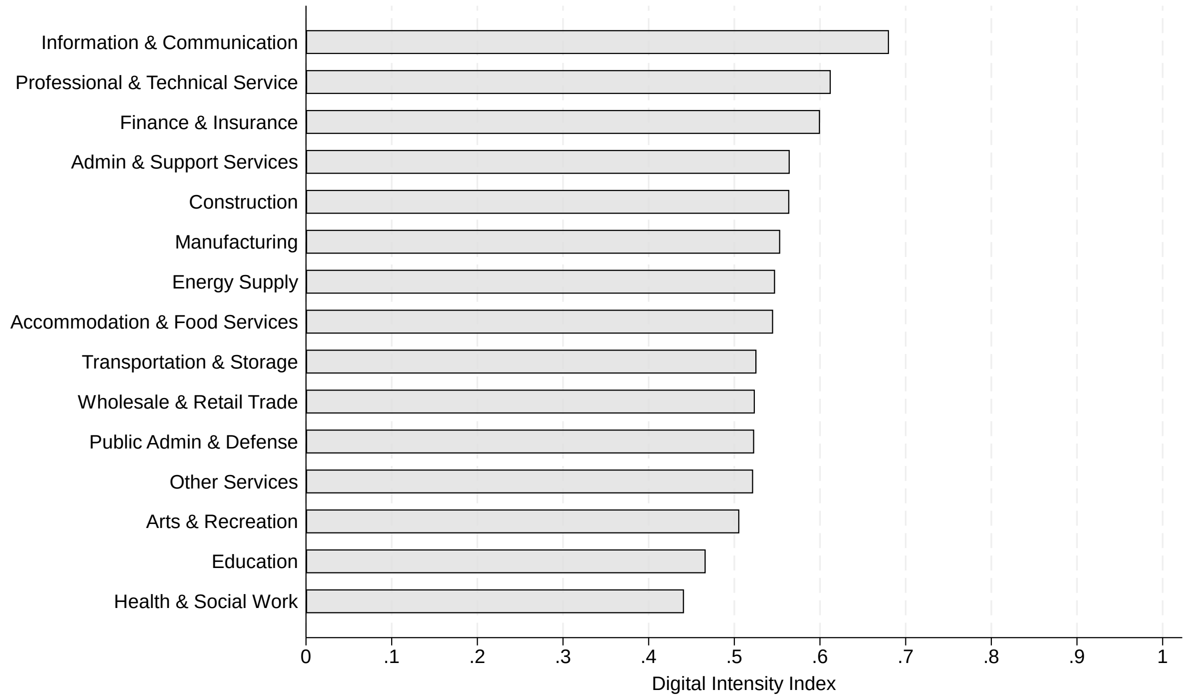

Figure 6: Average Digital Intensity Index by NACE 1 Sector

Source: ESJS2, Authors' Elaboration

Note: Sectors with less than 200 observations omitted from analysis. The Digital Intensity Index is derived from questions in the ESJS relating to whether respondents performed eight digital tasks at work, with more complex tasks being weighted more heavily.

We report the average value of our digital intensity index for each sector in Figure 6. The sector with the highest average digital skill intensity is the Information and Communication sector (0.68), while the lowest average is attributed to the Health and Social Work sector (0.44). At the sectoral level, these figures are positively correlated with the incidence rates of technological change and digital underskilling (see Figures 7 and 8).[4] This suggests that 1) the sectors that are most affected by technological developments are typically those where the digital skill requirements at work are highest, and 2) that digital skill deficits are more likely to occur in jobs with high digital skill requirements.

[4] At NACE 1, the digital intensity index is strongly correlated with the technological change rates (ρ = 0.81) and digital underskilling rates (ρ = 0.73). Similarly, at NACE 2, the correlation coefficients are 0.87 for technological change rates and 0.77 for the digital underskilling rates.

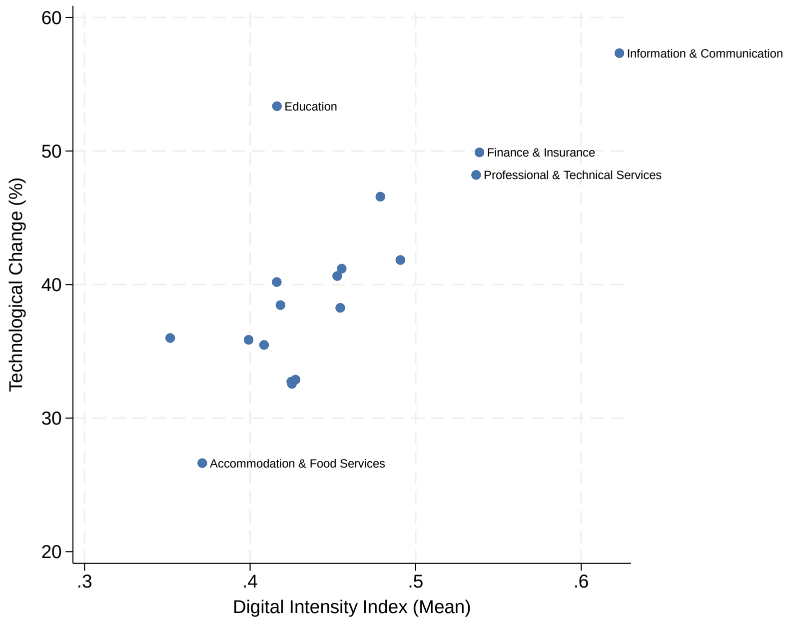

Figure 7: Scatterplot of Technological Change Incidence and Digital Intensity Index (NACE 1 Sector)

Source: ESJS2, Authors' Elaboration

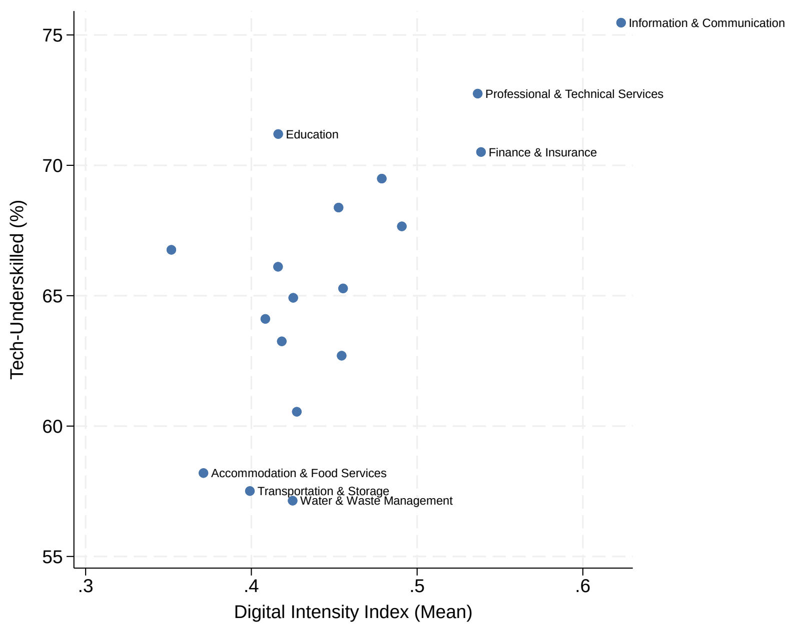

Figure 8: Scatterplot of Tech-Underskilling Incidence and Digital Intensity Index (NACE 1 Sector)

Source: ESJS2, Authors' Elaboration

Note: Sectors with less than 200 observations omitted from analysis.

2.3 Training

As outlined previously, we examine the training needs of workers who experience technological change and tech-underskilling. As such, it is necessary to evaluate the nature and degree of training received by workers in these groups. We identify respondents as having undergone training using their responses to Question 52 in the ESJS2: "*In the last 12 months, have you participated in any of the following education or training activities to learn new job-related skills? – Courses / Seminars / On-the-Job Training*". We consider a respondent to have been trained if they responded "*Yes*" to any of the three training modes listed, and to not have received training if they responded "*No*" to all three.[5]

We report the incidence of training receipt by both technological change group and whether or not respondents are tech-underskilled in Figure 9 below. There is a noticeable disparity in training receipt by whether or not respondents have experienced recent technological change, as well as whether they are tech-underskilled or not. First, training is far more common among the group that experienced recent technological change than the group that were unaffected by technological change. This disparity may, in part, be driven by task changes at work as a result of the introduction of new technology and the consequent need for training in order to adapt to the new task composition of labour. In addition, when comparing within technological change groups, tech-underskilled workers were more likely to have received training than workers that were not tech-underskilled. For respondents that were affected by technological change, the incidence of training is approximately 84 percent for tech-underskilled workers (N = 14,920), compared to 77 percent for workers that were not tech-underskilled (N = 4,589).

[5] As with our other self-reported measures, this measure is not without limitations. For example, the question does not specify whether workers were required to receive training by their employer, or whether they elected to undergo training independently. As such, it's possible that the trained group consists of workers who selected into training, which may be driven by other factors that we do not observe. We do not have the data at hand to address this concern comprehensively.

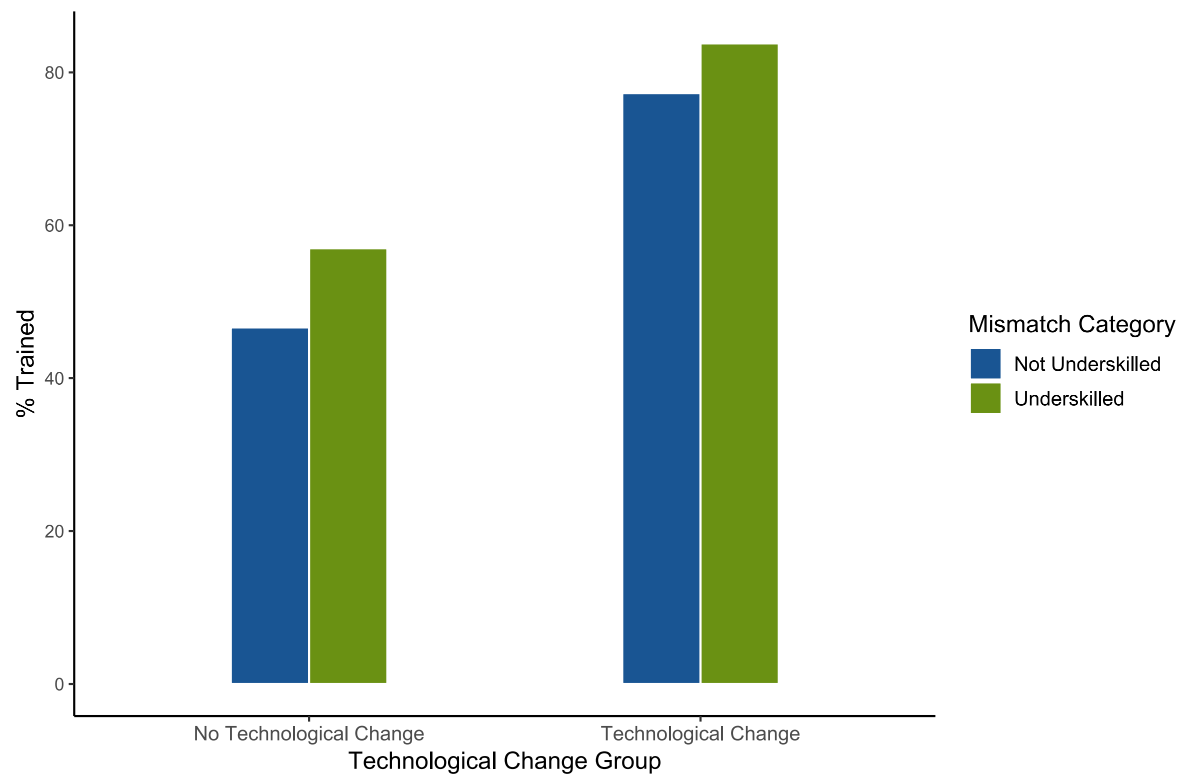

Figure 9: Incidence of Training by Technological Change and Tech-Underskilled Status

Source: ESJS2, Authors' Calculations

We report the incidence of training across NACE sectors for the group that were affected by technological change in Figure 10 below. Among employees who have experienced recent technological change in the workplace, the incidence of training is uniformly high, with all NACE 1 sectors exhibiting training rates in excess of 75 percent. The Education sector exhibits the highest training rate (89 percent), while the lowest training incidence is attributed to the Wholesale and Retail Trade sector (76 percent). The high training rate for the Education sector may reflect changes to the way classes were delivered during the COVID-19 pandemic. As new technologies were used to deliver lectures remotely, universities would have been required to provide appropriate staff training.

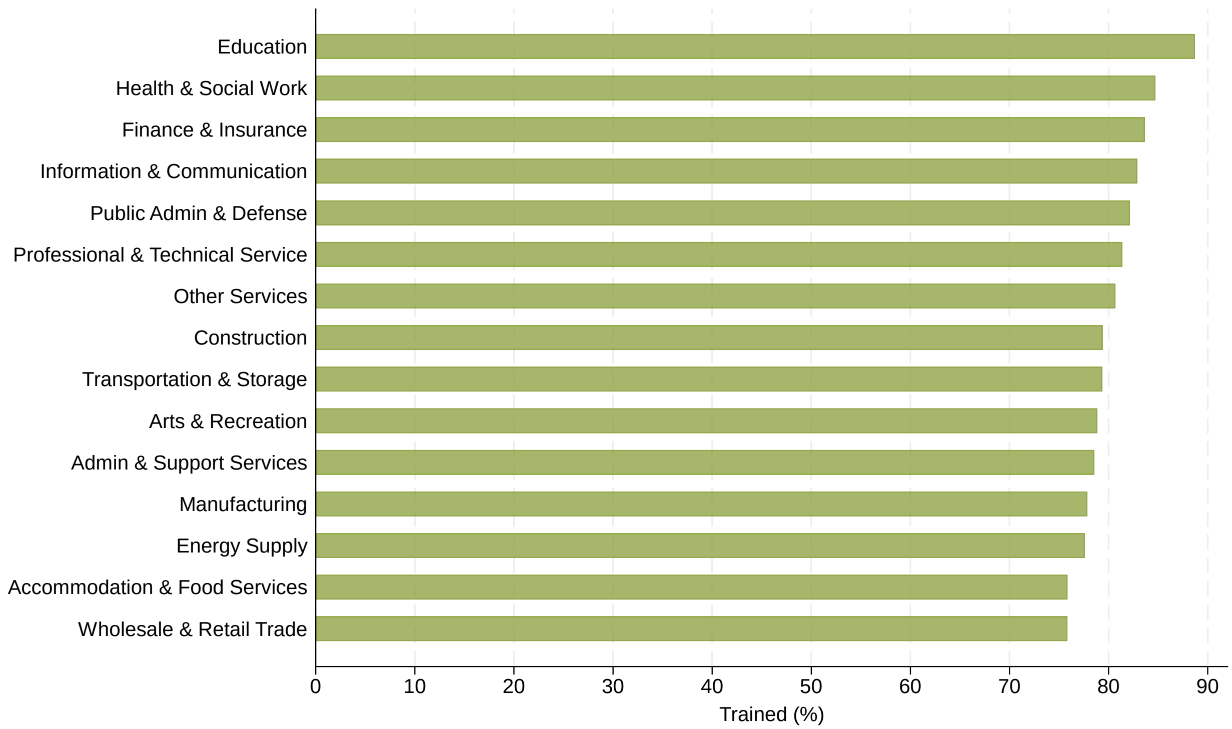

Figure 10: Incidence of Training by NACE Sector (Technological Change Group)

Source: ESJS2, Authors' Calculations

3. Empirical Strategy

We first examine the relationship between tech-underskilling and employee outcomes. To do this, we focus on the sample of respondents who have experienced technological change, as per our measure outlined in the previous section (approximately 19,500 respondents). We focus on four employee-level outcomes: 1) fear of job loss, 2) job satisfaction, 3) perceptions of job security and 4) work-life balance. It is possible that tech-underskilling could impact workers negatively through any of these channels. Workers who do not possess the necessary digital skills to do their job may fear losing their job or perceive their job to be insecure, given that their reduced productivity may be viewed unfavourably by their employers. Furthermore, the worker's job satisfaction may be harmed in a similar way. It is plausible that a worker would be more satisfied with their job if they felt their digital skills, and therefore their work performance, was at a higher standard. In addition, tech-underskilled workers may feel compelled to compensate for their lack of digital skills by working harder, which may inadvertently impact their perception of work-life balance in their job.

We construct binary variables for all outcomes. Job satisfaction ($Satisfied$) is derived from question 65 in the ESJS2: "*On a scale from 0 to 10, where 0 is completely dissatisfied, 5 moderately satisfied and 10 is completely satisfied, how satisfied are you, overall, with your job?*". We consider respondents to be satisfied with their job ($Satisfied = 1$) if they report a value of six or higher, and unsatisfied ($Satisfied = 0$) if they report a value below six. Similarly, for perceptions of job security ($Secure$) and work-life balance ($Balanced$), we derive a binary variable equal to one if respondents gave a response of six or higher to the corresponding answer to Question 64 (*"On a scale from 0 to 10, where 0 is completely dissatisfied, 5 moderately satisfied and 10 is completely satisfied, how satisfied are you with the following aspects of your job? – Job Security / Work-Life Balance"*), and zero if they gave a response of lower than six to the corresponding answer. For fear of job loss ($Fear$), we consider respondents to fear losing their job (i.e. $Fear = 1$) if they gave the response "*Yes, a very high chance*" or "*Yes, some chance*" to Question 66 ("*Do you think there is any chance at all of you losing your main job in the next twelve months?*").

We estimate the following probit model to evaluate the relationship between digital underskilling and the four outcomes discussed above:

$$\boldsymbol{Pr(Outcomes_i \,|\, X_i = 1) = \Phi(\alpha + \beta Underskilled_i + Z_i'\theta + \epsilon_i)} \tag{1}$$

In which $Outcomes$ relates to one of the four outcome variables we describe above. $Underskilled$ refers to whether or not respondent i exhibits a digital skill gap. Z' is a vector of control variables, including gender, tenure (years), wages, hours worked (i.e. part-time/full-time), contract type, highest education level achieved, area type (i.e. urban/rural), company size, sector (i.e. public/private), occupation (ISCO 2-Digit occupational category), country and industry (NACE 1). It is also important to specifically control for the nature of the technological change that is taking place in the workplace, as well as the digital components of the occupation in which respondents are working. To account for this, we include 1) dummy variables indicating whether the technological change that took place was the introduction of computerised machinery, new programmes/software, or both, and 2) our digital intensity index variable discussed in the previous section. Finally, α_i denotes the intercept and ϵ_i denotes the idiosyncratic error term.

We also assess whether digital underskilling is a predictor of training. That is, we aim to establish whether tech-underskilled workers are more likely to receive training than those who are not tech-underskilled, conditional on having experienced technological change. To do this, we estimate the following probit model:

$$\boldsymbol{Pr(Trained_i \,|\, X_i = 1) = \Phi(\alpha + \beta Underskilled_i + Z_i'\theta + \epsilon_i)} \tag{2}$$

In this model, $Trained$ denotes a binary variable indicating whether respondent i has undergone training in the past twelve months (as discussed in the previous section). $Underskilled$ denotes a binary variable indicating whether the worker feels that their skills need to be improved to do their job better. For comparison, we estimate this model separately for general underskilling and tech-underskilling.[6]

It is possible that the relationship between underskilling and training is endogenous. On the one hand, workers that are underskilled may be systematically more likely to receive training, if their employers (or the workers themselves) identify the underskilling problem and respond with training investment. However, workers who have undergone training may be less likely to be underskilled than those who do not receive training, given that the fundamental purpose of undergoing training is to improve the skills of workers. As such, there is a plausible case for reverse causality. Nevertheless, for the purposes of our research, we are primarily interested in the associative relationship (i.e. "Are underskilled workers more likely to receive training?"), rather than inferring strong causality (i.e. "Does underskilling *cause* training receipt?" or "Does training alleviate underskilling?").

As the ESJS2 contains a wide range of information on the nature of work, it is possible to explore avenues through which training may influence worker productivity and mitigate potential digital skills gaps. We specifically focus on two channels through which training may reduce the likelihood of digital skills gaps. First, we examine the potential for training to facilitate more efficient task completion in light of the introduction of new technology. To do this, we draw on responses to Question 45 ("*As a result of the new computer programs, software, or new computerised machinery you learnt for your main job, did your job tasks change in any of the following ways? – You now do some of your tasks at a faster pace than before*") in the ESJS2. We identify respondents as experiencing more efficient task completion if they responded "Yes" to Question 45 and construct a binary variable ($Fast$) to capture this. The underlying assumption is that training is key in facilitating workers to take advantage of the productive capabilities of new technology, thereby enabling them to conduct tasks at a faster pace than was the case prior to the technology's introduction. The second channel that we examine is the role of training in determining workers' attitudes toward the productive potential of technology more broadly. To do this, we use responses to Question 46: "*To what extent do you agree with the following statements regarding the use of digital or computer technologies at work? - They generally increase performance at work*". As with $Fast$, we construct a binary variable ($IncreasePerformance$) that is equal to one if respondents answered "Yes" to this question. This broadly follows the same logic as the model examining $Fast$; training may allow respondents to take advantage of new technology at work, meaning they may look more favourably on technology's productive potential. We formalise these models in Equations 3 and 4 below.

[6] The general underskilling indicator is derived from Q63: "*And to what extent do you need to further develop your overall level of knowledge and skills to do your main job even better?*"

$$Pr(Fast_i \mid X_i = 1) = \Phi(\alpha + \beta Trained_i + Z_i'\theta + \epsilon_i) \quad (3)$$

$$Pr(IncreasePerformance_i \mid X_i = 1) = \Phi(\alpha + \beta Trained_i + Z_i'\theta + \epsilon_i) \quad (4)$$

Where $Fast$, $IncreasePerformance$ and $Trained$ are binary variables as previously defined, Z' is the same vector of control variables used in Equation 1, and α and ϵ_i refer to the intercepts and idiosyncratic error terms respectively.[7] Note that the question relating to improving performance at work is only asked to those who responded to the ESJS2 via online survey (i.e. the Computer Assisted Web Interview (CAWI)) group). To ensure comparability across outcome variables, we also estimate a specification predicting $Fast$, excluding responded who did not answer via CAWI (Column 2).

3.1 Training Type & Intensity

It is likely that the type of training that workers receive will affect the extent to which underskilling is offset and the productivity gains of technology are realised. Furthermore, the intensity (or volume) of training is likely to play a role in determining worker outcomes. To examine both of these factors, we estimate an adapted version of the models outlined in Equations 3 and 4, replacing the $Trained$ binary variable with a series of binary variables that capture the type(s) of training that workers received in the previous twelve months. Recall that Question 52 asks workers whether they undertook courses, seminars or on-the-job training in the previous twelve months. Using responses to Question 52, we define seven mutually exclusive groups[8] depending on the type(s) of training undertaken by each respondent. This approach allows us to examine potential compositional and intensity effects, such that we can observe both the type(s) and number of training modes that

[7] Similar to the relationship between tech-underskilling and training, it is plausible that the relationships between training and the outcome variables discussed are endogenous. While unlikely, it could be the case that employers may invest in training workers that are not well positioned to take advantage of the new technology, or broadly do not believe that technology improves worker performance. However, as was the case with tech-underskilling and training, we are interested in the associative relationship, rather than inferring causality.

[8] These groups are 1) those who undertook courses only, 2) those who undertook seminars only, 3) those who undertook on-the-job training only, 4) those who undertook courses and seminars, but not on-the-job-training, 5) those who undertook courses and on-the-job training, but not seminars, 6) those who undertook seminars and on-the-job-training, but not courses and 7) those who undertook all forms of training.

workers received.[9] As we are interested in the effectiveness of different types of training among those who were trained, we focus on respondents who indicated that they received training in the previous twelve months.

In addition to the outcome variables $Fast$ and $IncreasePerformance$, we are also interested in the extent to which workers that are affected by technological change are satisfied with the training they receive. Although self-reported satisfaction is an imperfect proxy, it offers insight into perceived training quality relative to workers' needs.[10] To do this, we use Question 64 in the ESJS2: "*On a scale from 0 to 10, where 0 is completely dissatisfied, 5 moderately satisfied and 10 is completely satisfied, how satisfied are you with the following aspects of your job? – Training Provided*." We construct a binary variable $Satisfied$ that is equal to one if the respondent provided a score of greater than or equal to six, and zero if they provided a score lower than six. We formalise our estimation in equation (5) below,

$$\boldsymbol{Pr(Outcome_i \,|\, X_i = 1) = \Phi(\alpha + \beta TrainingType_i + Z_i'\theta + \epsilon_i)} \qquad (5)$$

Where $Outcome$ is the binary variable $Fast$, $IncreasePerformance$ or $Satisfied$, depending on the specification, $TrainingType$ is the categorical variable defined above and Z' is the vector of control variables defined previously.

[9] The underlying assumption here is that workers who undertake more diverse training modes (i.e. two or three types of training) are likely to be subject to higher training intensity. This may not always be the case – the cumulative time spent on a short course and seminar can be lower than the cumulative time taken on a longer, harder course. Nevertheless, it is plausible that training diversity is likely correlated with training intensity.

[10] We accept that this measure fails to fully account for worker engagement with training. For example, a worker may receive (objectively) high-quality training but may simply refuse to engage meaningfully with it. In turn, workers may not reap the benefits of training, leaving them unsatisfied.

4. Results

We first examine the association between tech-underskilling and employee outcomes (job satisfaction, job security, work-life balance and fear of job loss). We report the marginal effects associated with the model outlined in Equation 1 in Table 1 below. Our results in Column (1) indicate that tech-underskilled workers were approximately 3 percentage points more likely to fear losing their job in the near future than those who were not tech-underskilled, all else being equal. In addition, workers who performed more digital tasks at work were substantially more likely to fear losing their job than workers in less digitally focused occupations. We also observe a positive and statistically significant association between being tech-underskilled and reporting high job satisfaction (Column 2). On average, tech-underskilled workers were 2.6 percentage points more likely to report being satisfied with their job than those who were not tech-underskilled. In addition, higher paid workers and workers in jobs with high digital task content were more likely to report high job satisfaction. We do not find evidence of a difference between employees who experienced tech-underskilling and those who did not in terms of their perceptions of job security (Column 3) and good work-life balance (Column 4).

The positive relationship between tech-underskilling and job satisfaction appears counterintuitive. However, note that our measure of tech-underskilling is a binary variable that codes those who are tech-underskilled as one, and those who are not tech-underskilled (i.e. either well-matched or overskilled in their technical skills) as zero. This means that, when comparing tech-underskilled workers, the reference category includes both matched employees as well as tech-overskilled employees. Therefore, it is possible that the relationship between tech-underskilling and job satisfaction could be driven by tech-overskilled respondents being more likely to be *unsatisfied*, as opposed to strong job satisfaction among tech-underskilled workers. While the ESJS2 does not contain information on whether respondents are tech-overskilled, it does contain information on whether employees are generally overskilled. As we would expect general overskilling and tech-overskilling to be correlated, we can perform an (albeit imperfect) robustness check on our estimates by excluding overskilled workers from our estimates, assessing whether this relationship is driven by overskilled workers. We report the results in Table 2 below. When overskilled workers are excluded, the relationship between tech-underskilling and job satisfaction is no longer statistically significant. The relationship between tech-underskilling and fear of job loss remains statistically significantly and increases slightly in magnitude.[11] Furthermore, when overskilled

[11] We also estimate a set of specifications that includes workers that are generally overskilled, but report that they are tech-underskilled (see Table A1 in the appendix). The results of this specification are broadly in line with the findings reported in Table 2. Notably, the statistical significance of the marginal effect on tech-underskilling predicting good work-life balance increases and remains negative, supporting the consideration that tech-underskilling is associated with poor work-life balance.

employees are excluded from the reference group, our results also show weak evidence that tech-underskilling is associated with lower satisfaction with work-life balance (Column 4 of Table 2).

Table 1: Tech-Underskilling and Job Satisfaction, Job Security, Work-Life Balance and Fear of Job Loss (Marginal Effects)

Variables	(1) Fear Job Loss	(2) Job Satisfaction	(3) Job Security	(4) Work-Life Balance
Tech-Underskilled	**0.030****	**0.026*****	**0.004**	**-0.012**
	(0.013)	**(0.009)**	**(0.015)**	**(0.013)**
Female	-0.041***	0.009	-0.011	-0.023
	(0.010)	(0.012)	(0.012)	(0.016)
Tenure	-0.002***	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Wages)	-0.041**	0.035***	0.040***	0.034***
	(0.017)	(0.013)	(0.013)	(0.012)
Part-time	0.055***	-0.017	-0.025	0.008
	(0.014)	(0.012)	(0.022)	(0.023)
Digital Intensity	0.156***	0.078***	-0.029	0.009
	(0.027)	(0.019)	(0.025)	(0.032)
<u>Tech Change Type</u>				
Computer Programmes	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Computerised Machinery	0.045***	-0.006	-0.066***	-0.062***
	(0.017)	(0.017)	(0.021)	(0.022)
Both	0.061***	0.010	-0.059***	-0.030*
	(0.013)	(0.011)	(0.015)	(0.016)
<u>Contract Type</u>				
Permanent	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Temporary	0.280***	-0.007	-0.116***	-0.023
	(0.022)	(0.012)	(0.024)	(0.018)
No Contract	0.050	-0.025	-0.166***	-0.105
	(0.044)	(0.033)	(0.061)	(0.067)
<u>Education</u>				
Lower Secondary	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Post-Secondary	-0.051**	0.025	0.102**	0.036
	(0.025)	(0.019)	(0.044)	(0.040)
Tertiary	-0.056**	0.020	0.144***	0.097***
	(0.022)	(0.015)	(0.038)	(0.034)
Country/Occupation/Industry	YES	YES	YES	YES
Pseudo R-Squared	0.113	0.063	0.064	0.047
Observations	13,748	13,809	8,788	8,788

Country-clustered standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1*

Table 2: Tech-Underskilling and Job Satisfaction, Job Security, Work-Life Balance and Fear of Job Loss (Marginal Effects, Overskilled Workers Excluded)

Variables	(1) Fear Job Loss	(2) Job Satisfaction	(3) Job Security	(4) Work-Life Balance
Tech-Underskilled	**0.041*** **	**0.012**	**-0.015**	**-0.021***
	(0.013)	**(0.008)**	**(0.015)**	**(0.011)**
Female	-0.039***	0.007	-0.012	-0.024
	(0.011)	(0.011)	(0.011)	(0.015)
Tenure	-0.002***	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Wages)	-0.038**	0.035***	0.042***	0.037***
	(0.017)	(0.013)	(0.013)	(0.011)
Part-time	0.046***	-0.009	-0.021	0.005
	(0.015)	(0.013)	(0.023)	(0.025)
Digital Intensity	0.166***	0.064***	-0.038	0.006
	(0.028)	(0.018)	(0.026)	(0.034)
Tech Change Type				
Computer Programmes	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Computerised Machinery	0.047**	-0.011	-0.067***	-0.059**
	(0.018)	(0.017)	(0.025)	(0.027)
Both	0.063***	0.015	-0.055***	-0.024
	(0.013)	(0.010)	(0.016)	(0.015)
Contract Type				
Permanent	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Temporary	0.278***	0.000	-0.106***	-0.017
	(0.023)	(0.013)	(0.023)	(0.019)
No Contract	0.052	-0.021	-0.175***	-0.096
	(0.044)	(0.032)	(0.066)	(0.068)
Education				
Lower Secondary	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Post-Secondary	-0.049*	0.018	0.094**	0.035
	(0.027)	(0.021)	(0.043)	(0.043)
Tertiary	-0.055**	0.015	0.139***	0.097***
	(0.025)	(0.017)	(0.038)	(0.035)
Country/Occupation/Industry	YES	YES	YES	YES
Pseudo R-Squared	0.114	0.064	0.066	0.050
Observations	13,248	13,309	8,288	8,288

Country-clustered standard errors in parentheses. Overskilled workers excluded.
**** p<0.01, ** p<0.05, * p<0.1*

Next, we examine whether tech-underskilling predicts training receipt. We report the marginal effects associated with Equation 2 in Table 3 below. The results indicate that underskilled workers are more likely to receive training than those who are not underskilled. In our first specification (Column 1), we examine the role of general underskilling in predicting training receipt. Underskilling is associated with a 3.2 percentage point increase in the likelihood of receiving training, relative to not being underskilled (i.e. either being well-matched or overskilled). Our second specification focuses on tech-underskilling, where we observe a 5 percentage point gap between tech-underskilled and non-tech-underskilled employees. Across both specifications, female respondents, higher-paid respondents, those in jobs with a high digital component and respondents who experienced changes in both computer programmes and computerised machinery at work were more likely to receive training.

Next, we examine the effectiveness of training in facilitating employees to perform their tasks faster and improve their performance. We report the marginal effects associated with Equations 3 and 4 in Table 4 below. The marginal effects on $Trained$ across all of the models indicate that trained respondents are more likely to report that they perform their tasks faster and that technology is generally beneficial for improving their performance at work. Specifically, training (of any kind or combination) is associated with a 10.7 percentage point increase in the likelihood of reporting that tasks are done faster than before technology was introduced at work, all else equal. For meaningful comparison with our third specification (i.e. in which the likelihood of reporting that technology generally increases performance at work), we also restrict the sample to respondents who gave responses to the ESJS2 via web interview (CAWI) only. We find that the estimated marginal effect of training is larger in this subgroup; trained respondents are 13.2 percentage points more likely to report doing their tasks faster than before among the CAWI subgroup. While the outcome variable is self-reported, these estimates are indicative of a productivity effect of training in light of technological change; trained workers are more prepared to take advantage of new technology at work to perform their tasks more efficiently. This is consistent with the estimates in Column 3, in which training is associated with a 6 percentage point increase in the probability of reporting that technology is generally good for improving worker performance.

Table 5 compares the effectiveness of different types and combinations of training, by showing the marginal effects associated with estimating Equation 5. The first thing to note is that training intensity matters. Employees that receive all three types of training (courses, seminars and on-the-job training) are more likely to be satisfied with their training and to report quicker and improved task performance when compared to employees that experience just one or two training types. The estimates also provide insights into the relative effectiveness of the different training combinations. Of all possible combinations, the combination of seminars and on-the-job training appears to be the most effective training strategy.

Table 3: Underskilling, Tech-Underskilling and Training (Marginal Effects)

Variables	(1) Training	(2) Training
Underskilling	**0.032******	
	(0.009)	
Tech-Underskilling		**0.050******
		(0.009)
Female	0.026***	0.026***
	(0.007)	(0.007)
Tenure	-0.002***	-0.002***
	(0.000)	(0.000)
ln(Wages)	0.027***	0.027***
	(0.006)	(0.006)
Part-time	-0.014	-0.012
	(0.011)	(0.011)
Digital Intensity	0.153***	0.154***
	(0.020)	(0.020)
<u>Tech Change Type</u>		
Computer Programmes	*Ref.*	*Ref.*
Computerised Machinery	-0.005	-0.009
	(0.017)	(0.018)
Both	0.093***	0.094***
	(0.011)	(0.011)
<u>Contract Type</u>		
Permanent	*Ref.*	*Ref.*
Temporary	-0.012	-0.014
	(0.016)	(0.016)
No Contract	-0.052	-0.052
	(0.037)	(0.037)
<u>Education</u>		
Lower Secondary	*Ref.*	*Ref.*
Post-Secondary	-0.015	-0.015
	(0.016)	(0.016)
Tertiary	0.011	0.010
	(0.017)	(0.017)
Country/Occupation/Industry	YES	YES
Pseudo R-Squared	0.085	0.088
Observations	13,780	13,784

Country-clustered standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Table 4: Training, Faster Tasks and Improved Performance (Marginal Effects)

Variables	(1) Faster Tasks	(2) Faster Tasks (CAWI Only)	(3) Improve Performance
Trained	**0.107*** **	**0.132*** **	**0.060*** **
	(0.013)	**(0.016)**	**(0.010)**
Female	-0.003	0.003	0.013
	(0.010)	(0.011)	(0.010)
Tenure	-0.004***	-0.003***	-0.000
	(0.001)	(0.001)	(0.001)
ln(Wages)	-0.016**	-0.016*	0.011
	(0.008)	(0.010)	(0.008)
Part-time	-0.044***	-0.038***	-0.011
	(0.010)	(0.012)	(0.012)
Digital Intensity	0.212***	0.213***	0.064***
	(0.026)	(0.032)	(0.021)
<u>Tech Change Type</u>			
Computer Programmes	*Ref.*	*Ref.*	*Ref.*
Computerised Machinery	0.081***	0.113***	0.010
	(0.023)	(0.025)	(0.024)
Both	0.165***	0.178***	0.066***
	(0.011)	(0.015)	(0.013)
<u>Contract Type</u>			
Permanent	*Ref.*	*Ref.*	*Ref.*
Temporary	0.017	0.024	-0.014
	(0.016)	(0.019)	(0.024)
No Contract	-0.088**	-0.089**	-0.042
	(0.036)	(0.035)	(0.034)
<u>Education</u>			
Lower Secondary	*Ref.*	*Ref.*	*Ref.*
Post-Secondary	0.017	0.031	0.012
	(0.026)	(0.033)	(0.018)
Tertiary	-0.022	-0.008	0.023
	(0.026)	(0.030)	(0.018)
Country/Occupation/Industry	YES	YES	YES
Pseudo R-Squared	0.084	0.099	0.088
Observations	13,746	8,788	8,779

Country-clustered standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

Table 5: Training Types and Satisfaction, Faster Tasks and Improved Performance (Marginal Effects)

Variables	(1) Satisfied Training	(2) Faster Tasks	(3) Faster Tasks (CAWI Only)	(4) Improve Performance
Courses	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Seminars	-0.050**	0.035*	0.039*	0.024
	(0.023)	(0.019)	(0.023)	(0.022)
On-the-Job Training	0.007	0.059***	0.064***	0.009
	(0.029)	(0.019)	(0.022)	(0.016)
Courses & Seminars	0.043*	0.056***	0.064***	0.028
	(0.024)	(0.019)	(0.022)	(0.022)
Courses & On-the-Job Training	0.063**	0.076***	0.064***	0.012
	(0.027)	(0.019)	(0.019)	(0.022)
Seminars & On-the-Job Training	0.073**	0.079***	0.102***	0.004
	(0.033)	(0.020)	(0.026)	(0.022)
All	**0.111*** **	**0.116*** **	**0.123*** **	**0.045** **
	(0.017)	**(0.015)**	**(0.017)**	**(0.019)**
Country/Occupation/Industry	YES	YES	YES	YES
Pseudo R-Squared	0.038	0.077	0.085	0.079
Observations	7,122	11,256	7,119	7,114

Country-clustered standard errors in parentheses.
**** p<0.01, ** p<0.05, * p<0.1*

B1: Supplementary Analysis using Adult Education Survey Data

We supplement our analysis on the relationship between different training types using an alternative dataset – the Adult Education Survey (AES). This is useful as it provides an additional dataset with which we can address similar questions. The AES contains comprehensive information on EU individuals' participation in formal, non-formal, and informal education and training over the previous 12 months. For this study, we used the 2016 and 2022 waves of the AES. These waves were selected because they provide the most recent and relevant information on adult participation in non-formal education and exhibit a high degree of consistency in variable definitions and coding structures. Furthermore, they are the closest waves to the ESJS2, which was collected in 2021, and therefore represent the closest temporal comparisons. Using this data, we aim to replicate (as closely as possible) our analysis relating to the estimates in Tables 4 and 5.

We implement several sample restrictions on the AES. First, we include only individuals who are currently employed. Second, to increase the likelihood that the reported activity was undertaken in the context of the respondent's present job, we retain only those with at least one year of tenure in their current position. Third, we restrict the sample to individuals who reported only one non-formal training activity in the past year, to enable an unambiguous linkage between the activity and its reported outcomes. Lastly, we include only activities that were reported as having a job-related purpose, to ensure that the analysis remains focused on professional development. As a result of these selection criteria, the final sample comprised of 52,049 individuals drawn from the combined 2016 (25,494 individuals) and 2022 (26,555 individuals) AES waves.

We identify individuals that received tech-training based on the field specified of the non-formal activity they reported. For responders in 2022, individuals who indicated participation in training activities related to Computer use, Database and network design and administration; software and applications development and analysis (0611, 0612, 0613 fields in the ISCED-F 2013 Fields of Education and Training) were considered to have received technology-related training. For the 2016 wave, the same category was based on participation in non-formal learning activities related to Information and Communication technologies (06 field in the 2013 ISCED Fields of Education and Training). Based on this categorization, we construct a binary variable $TechTrained$ that takes the value 1 for individuals who reported one of the relevant technology-related fields and 0 for those who reported any other field.

To examine the relationship between non-formal tech-related learning and job-related outcomes, we estimated similar probit models to those outlined in Equations 4 and 5:

$$\Pr(IncreasePerformance_i \mid X_i = 1) = \Phi(\alpha + \beta TechTrained_i + Z_i'\theta + \epsilon_i) \quad (6)$$

$$\Pr(IncreasePerformance_i \mid X_i = 1) = \Phi(\alpha + \beta TrainignType_i + Z_i'\theta + \epsilon_i) \quad (7)$$

Where $IncreasePerformance$ denotes a binary variable that equals 1 if the respondent reported improved performance in their current job as a result of the non-formal training activity and 0 otherwise. $TechTrained$ denotes the binary variable (outlined above) relating to whether the respondent had received technology-oriented training in the previous twelve months or not. $TrainingType$ refers to a factor variable indicating the training type that respondent i had received in the previous twelve months: courses, workshops/seminars, on-the-job training or private lessons. These are converted to a series of dummy variables. The vector X_i' consists of control variables including gender, age, area of residence (densely, intermediate or thinly populated), country, net current monthly household income (categorised as either the bottom 60% (B60) or the top 40% (T40)), education level, employment status, tenure, ISCO-08 1-Digit Occupation, NACE Rev. 2 Sector, firm size and country dummies.

We report the marginal effects of these models in Table 6 below. Column (1) indicates that training receipt is associated with a 10 percentage-point increase in the likelihood of reporting improved performance, relative to those that did not receive training. This is consistent with our results using the ESJS2 data in Table 4. Furthermore, column (2) shows that respondents that experienced guided on-the-job training exhibited the highest comparative likelihood of reporting that their performance had improved in their current job, being approximately 6.7 percentage points more likely relative to the cohort of respondents that took courses.

Table 6: Worker Performance and Training (AES Data, 2016 and 2022, Marginal Effects)

Outcome Variable: $ImprovePerformance$	(1) dY/dX	(2) dY/dX
$TechTrained$	0.103***	--
	(0.014)	
Training Type		
Courses	--	*Ref.*
Workshops & Seminars	--	-0.023*
		(0.013)
Guided On-the-Job Training	--	**0.067*** **
		(0.011)
Private Lessons	--	0.029
		(0.037)
Controls	YES	YES
Country FE	YES	YES
Observations	40,570	41,432

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

4.1 Heterogeneous Effects

Our previous analysis provides a high-level examination of tech-underskilling and effective training across the EU economy. In this section, we test for the presence of heterogeneous effects by sector, gender, and age group. In the interest of brevity, we do not report all estimates in the main text below. Rather, we discuss the main results of our analysis and report all estimates in the appendix (Tables A2 – A17).

4.1.1 Sector

We begin with the sectoral analysis, reporting separate estimates for each NACE Rev. 1 sector. Table A2 shows the relationship between tech-underskilling and job satisfaction, job security, work-life balance and fear of job loss. The ICT sector emerges as a sector that displays strong effects across multiple indicators. Tech-underskilled employees in ICT are 12 percentage points more likely to fear job loss compared to ICT employees that are not tech-underskilled. In addition, tech-underskilled employees in ICT are 12 percentage points less likely to experience job security, and are 7 percentage points less likely to be satisfied with their work-life balance. In short, most of the negative impacts of tech-underskilling appear to be concentrated in the Information and Communication sector. Notably, when we examine the association between tech-underskilling and training receipt (Table A3), we find that tech-underskilled workers in the ICT sector do not have a higher likelihood of training receipt than matched workers in this sector. This is of some concern as it may indicate a lack of adequate training provision in the sector in which employees are most in need.

Table A4 shows that, for the majority of sectors, training allows employees to complete their tasks at a faster pace. Estimates range from an 8.7 percentage point improvement in task speed for workers in Wholesale and Retail Trade, to a 15.2 percentage point improvement for workers in Education.

In Table A5, we examine whether the effectiveness of different types / combinations of training differs across sectors. As in our pooled analysis, we focus on employees that received some type of training, with the reference group being the group that undertook training courses only. While there are differences across sectors in terms of the ranking of training combinations, the results support the finding that training intensity is important. Across sectors, multiple combinations of training are typically associated with better outcomes, particularly in terms of the ability of employees to do tasks faster and their perceived satisfaction with training provision.

4.1.2 Gender

We examine whether our estimates differ depending on whether the respondent is female or male. We estimate the impact of tech-underskilling on fear of job loss, job satisfaction, job security and perceptions of work-life balance in Table A6, with the inclusion of an interaction term between gender and tech-underskilling. The coefficient on the interaction term tells us how the impacts vary by gender. The results show that tech-underskilled women are approximately 3 percentage points less likely to be satisfied with their jobs than tech-underskilled men. We find no significant gender differences in relation to fear of job loss, job security and work-life balance.

We do not observe gender differences in the likelihood of receiving training on the basis of being tech-underskilled (Table A7). That is, tech-underskilled female and male respondents are equally likely to receive training. Additionally, we do not observe gender differences in the effectiveness of training, as measured by respondents self-reported ability to do their tasks faster or achieve improved performance at work (Table A8).

In Table A9 we investigate whether the types of training methods that are most effective differ for men and women. The first thing to note is that, for both men and women, training intensity is generally associated with better outcomes. Combining all three types of training (courses, seminars and on-the-job training) is associated with the greatest improvement in terms of task speed and training satisfaction for both men and women. However, there are differences when it comes to improved performance at work. Women that experience all three types of training are 7.5 percentage points more likely to report improved performance at work, relative to women that just took a training course. For men, however, there is no training type / combination that is associated with improved performance at work.

4.1.3 Age

To examine how our findings differ across age groups, we divide our sample into three categories – 1) those aged between 25 and 39, 2) those aged between 40 and 49, and 3) those aged between 50 and 65. Table A10 shows that older tech-underskilled workers (i.e. those aged between 50 and 64) are approximately 6.7 percentage points more likely to fear losing their job than non-tech-underskilled workers in the same age category, while there are no observable differences within the two younger age groups. While the overall rates of job loss fears decline as workers get older, the gap between tech-underskilled and non-tech-underskilled workers also widens with age, implying that the more harmful effects of tech-underskilling are likely to be felt among older workers.

When examining how tech-underskilling predicts training receipt, we find that both younger and older tech-underskilled workers are more likely to receive training than their non-tech-underskilled counterparts (Table A11). However, there is no statistically significant effect for the middle-aged employees (i.e. those aged between 40 and 49). Table A12 shows that, for all age groups, training is associated with an increased likelihood of reporting doing one's tasks at a faster pace following the introduction of technology, as well as reporting that technology improves performance at work. Finally, similar to our pooled estimates, the cohorts of respondents who took all three types of training were the most likely to report productivity benefits across all age groups (Table A13).

5. Conclusions

This paper set out to establish the impacts of technological change, skills mismatch and training in the EU labour market. Drawing on insights from the ESJS2 and AES, we sought to provide insight into four research questions. First, which sectors are the most impacted by recent waves of technological change and digital skill deficits? Second, what are the potential impacts of digital underskilling on employee wellbeing in Europe? Third, are digitally-underskilled workers receiving adequate training? Finally, is training beneficial to worker productivity, and if so, which types of training are the most effective?

We first examined which sectors are most likely to be impacted by technological change. Our analysis reveals that sectors with substantial digital task content – Information and Communication, Education and Finance and Insurance – experienced the highest rates of task-altering technological change across the European economy. Sectors that are typically characterised by lower digital task requirements, such as Accommodation and Food, Construction and Water and Waste Management were comparatively less affected by task-altering technological change. At the sectoral level, technological change is positively correlated with tech-underskilling, meaning that the sectors with high rates of technological change and substantial digital task content are also the sectors that are most likely to be impacted by digital skill deficits. As such, these sectors represent the most likely areas in which training policy interventions may be required.

For our second research question, we investigated the interplay between technological change, digital skill deficits (so-called ‘tech-underskilling’) and worker wellbeing. Specifically, we examine how job satisfaction, work-life balance, perceptions of job security and fear of job loss differ between underskilled and non-underskilled workers that were affected by technological change. Our primary findings from this analysis is that tech-underskilled employees were considerably more likely to fear losing their job. This is in line with previous literature (e.g. Cedefop, 2018), and underscores the importance of ensuring that tech-underskilled workers are supported with well-targeted training policies in order to adapt to the digital transition.

We found that most European workers that experienced recent technological change had recently undergone some form of training, with tech-underskilled workers being more likely to have done so than non-tech-underskilled workers. That is, workers with digital skill deficits were being trained more than workers without digital skill deficits. This may be partially indicative of efficient training resource allocation, in that workers whose digital training needs are most acute are more likely to have their needs met. Furthermore, this highlights a clear prioritisation of digital skills across the EU economy, in that digital skill deficits warrant more training.

Our findings also demonstrate that training is likely to incur favourable productivity effects (in terms of self-reported task efficiency) among workers who experience technological change. In addition, the quantity and type of training modes matter in this regard. Employees that experience high training volume and/or diverse range of training modes the most positive impacts. Focusing on individual types of training, on-the-job training stands out as a robust indicator of self-reported productivity improvements at work among workers who experience technological change, and is broadly complementary with other types of training (i.e. courses, seminars). Not only does this reiterate the importance of training for ensuring productivity, but it also identifies specific training modes that may prove more beneficial for worker productivity – a key piece of information for efficient allocation of training resources.

Our analysis also highlights sectoral variation. Workers in the Information and Communication sector appear to be the most likely to be exposed to the negative consequences of tech-underskilling. This is likely driven by the high technical skill requirements in Information and Communication jobs, meaning that digital skill deficits are more penalising in this area. In addition, tech-underskilled workers are no more likely to receive training than non-tech underskilled workers, despite training incurring productivity effects in this sector. That said, the overall training rate in the sector is high (approximately 83 percent), meaning that both tech-underskilled and non-tech-underskilled workers in this sector are quite likely to receive training.

We find that tech-underskilled women are more likely to be unsatisfied with their jobs than tech-underskilled men – a finding that is indicative of a gender gap in the negative impacts of tech-underskilling. Despite this, tech-underskilled women and men are equally likely to receive training. Older workers are more likely to experience negative outcomes as a result of tech-underskilling than younger workers, when compared to their non-tech-underskilled counterparts in the same age cohort. Specifically, older workers are more likely to fear job loss if they are tech underskilled, relative to older workers that are not tech-underskilled. While the overall fear of job loss declines with age, the gap between tech-underskilled and non-tech-underskilled workers is widest among older workers, with tech-underskilled workers being more likely to fear job loss. As such, tech-underskilled older workers may benefit from additional digital training, which the data shows they are more likely to receive than their non-tech-underskilled counterparts.

Finally, the groups that engage in all three training modalities – courses, seminars and on-the-job training – are most likely to reap the benefits of the introduction of new technology at work. This finding is persistent across genders, age groups and educational groups, and is consistent with the findings of our baseline pooled analysis. To reiterate, this finding could be indicative of both an *intensity* effect – in which more training is more beneficial to workers – or a *diversity* effect – in which combinations of different types of training are more beneficial.

A. Appendix

Table A1: Tech-Underskilling and Job Satisfaction, Job Security, Work-Life Balance and Fear of Job Loss (Marginal Effects, Overskilled Workers (that are not Tech-Underskilled) Excluded)

Variables	(1) Fear Job Loss	(2) Job Satisfaction	(3) Job Security	(4) Work-Life Balance
Tech-Underskilled	0.045***	0.006	-0.023	-0.028***
	(0.013)	(0.008)	(0.015)	(0.011)
Female	-0.040***	0.007	-0.011	-0.024
	(0.010)	(0.012)	(0.012)	(0.016)
Tenure	-0.002***	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ln(Wages)	-0.041**	0.035***	0.045***	0.037***
	(0.017)	(0.012)	(0.013)	(0.011)
Part-time	0.052***	-0.016	-0.025	0.005
	(0.014)	(0.012)	(0.022)	(0.024)
Digital Intensity	0.161***	0.072***	-0.031	0.008
	(0.028)	(0.017)	(0.025)	(0.032)
<u>Tech Change Type</u>				
Computer Programmes	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Computerised Machinery	0.046***	-0.009	-0.058**	-0.053**
	(0.017)	(0.018)	(0.025)	(0.025)
Both	0.060***	0.013	-0.055***	-0.024
	(0.013)	(0.010)	(0.016)	(0.016)
<u>Contract Type</u>				
Permanent	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Temporary	0.276***	-0.003	-0.113***	-0.021
	(0.022)	(0.012)	(0.024)	(0.018)
No Contract	0.051	-0.025	-0.161***	-0.096
	(0.042)	(0.034)	(0.059)	(0.066)
<u>Education</u>				
Lower Secondary	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Post-Secondary	-0.055**	0.026	0.102**	0.038
	(0.025)	(0.021)	(0.044)	(0.040)
Tertiary	-0.062***	0.021	0.146***	0.099***
	(0.023)	(0.016)	(0.039)	(0.035)
Country/Occupation/Industry	YES	YES	YES	YES
Pseudo R-Squared	0.114	0.064	0.066	0.050
Observations	13,528	13,589	8,568	8,568

Country-clustered standard errors in parentheses. Overskilled workers excluded.
**** p<0.01, ** p<0.05, * p<0.1*

Table A2: Tech-Underskilling and Job Satisfaction, Job Security, Work-Life Balance and Fear of Job Loss (NACE 1 Sector Models)

Fear of Job Loss

NACE 1 Sector	dY/dX	Standard Error	N
Manufacturing	0.025	(0.032)	1,657
Energy Supply	0.058	(0.089)	142
Construction	0.073	(0.085)	375
Wholesale & Retail Trade	0.053	(0.043)	1,157
Transportation & Storage	0.053	(0.046)	625
Accommodation & Food Services	0.016	(0.074)	303
Information & Communication	0.120***	(0.043)	1,243
Finance & Insurance	0.175***	(0.047)	704
Professional & Technical Services	0.023	(0.041)	1,123
Admin & Support Services	0.047	(0.043)	765
Public Admin & Defense	0.017	(0.038)	878
Education	0.025	(0.029)	2,027
Health & Social Work	0.018	(0.039)	1,259
Other Services	-0.269*	(0.154)	119

Job Security

NACE 1 Sector	dY/dX	Standard Error	N
Manufacturing	0.024	(0.037)	979
Energy Supply	0.000	(0.000)	41
Construction	-0.146	(0.102)	205
Wholesale & Retail Trade	0.005	(0.051)	824
Transportation & Storage	0.004	(0.050)	428
Accommodation & Food Services	-0.085	(0.106)	204
Information & Communication	-0.121***	(0.033)	784
Finance & Insurance	0.029	(0.053)	398
Professional & Technical Services	0.038	(0.046)	733
Admin & Support Services	0.015	(0.037)	552
Public Admin & Defense	0.049	(0.071)	529
Education	-0.042	(0.035)	1,102
Health & Social Work	-0.102**	(0.046)	763
Other Services	-0.331	(0.349)	63

Work-Life Balance

NACE 1 Sector	dY/dX	Standard Error	N
Manufacturing	-0.006	(0.045)	985
Energy Supply	0.000	(0.000)	62
Construction	-0.129	(0.114)	209
Wholesale & Retail Trade	0.003	(0.053)	830
Transportation & Storage	-0.004	(0.050)	429
Accommodation & Food Services	0.003	(0.087)	202

Information & Communication	-0.065*	(0.035)	787
Finance & Insurance	-0.038	(0.070)	399
Professional & Technical Services	-0.084*	(0.045)	743
Admin & Support Services	0.005	(0.043)	544
Public Admin & Defense	0.140**	(0.065)	531
Education	0.038	(0.046)	1,103
Health & Social Work	-0.074	(0.051)	770
Other Services	-0.000	(0.000)	67

Job Satisfaction

NACE 1 Sector	dY/dX	Standard Error	N
Forestry & Fishing	-0.000	(0.000)	59
Manufacturing	0.007	(0.030)	1,633
Energy Supply	0.147*	(0.087)	84
Construction	-0.044	(0.057)	329
Wholesale & Retail Trade	0.036	(0.039)	1,145
Transportation & Storage	0.013	(0.049)	608
Accommodation & Food Services	0.013	(0.056)	270
Information & Communication	0.015	(0.037)	1,109
Finance & Insurance	-0.021	(0.042)	657
Professional & Technical Services	0.036	(0.032)	1,063
Admin & Support Services	0.028	(0.040)	754
Public Admin & Defense	0.010	(0.043)	812
Education	0.034	(0.022)	2,011
Health & Social Work	-0.033	(0.039)	1,260
Arts & Recreation	0.227	(0.143)	160
Other Services	0.000	(0.000)	54

Table A3: Tech-Underskilling as a Predictor of Training (Marginal Effects, NACE 1 Sector Models)

NACE 1 Sector	dY/dX	Standard Error	N
Agriculture, Forestry & Fishing	-0.000	(0.000)	66
Manufacturing	0.050**	(0.023)	1,703
Energy Supply	0.337***	(0.084)	132
Construction	0.020	(0.034)	364
Wholesale & Retail Trade	0.032	(0.029)	1,214
Transportation & Storage	0.105***	(0.031)	640
Accommodation & Food Services	0.153	(0.115)	289
Information & Communication	0.037	(0.032)	1,209
Finance & Insurance	-0.033	(0.048)	683
Real Estate	0.000	(0.000)	48
Professional & Technical Services	0.075**	(0.032)	1,125
Admin & Support Services	0.075**	(0.036)	774
Public Admin & Defence	0.076*	(0.042)	856
Education	0.026	(0.021)	2,026
Health & Social Work	0.043*	(0.024)	1,310
Arts & Recreation	0.236***	(0.059)	197
Other Services	-0.072	(0.177)	129

Source: ESJS2, Authors' Calculations

Notes: dY/dX refers to marginal effect of tech-underskilling on training receipt.

Table A4: Training as a Predictor of Faster Task Efficiency and Performance Improvement (Marginal Effects, NACE 1 Sector Models)

Faster Tasks

NACE 1 Sector	dY/dX	Standard Error	N
Manufacturing	0.121***	(0.027)	1,723
Energy Supply	0.245***	(0.058)	156
Construction	0.074	(0.062)	384
Wholesale & Retail Trade	0.087***	(0.026)	1,216
Transportation & Storage	0.062	(0.045)	673
Accommodation & Food Services	0.069	(0.052)	309
Information & Communication	0.140***	(0.052)	1,278
Finance & Insurance	0.201***	(0.063)	729
Professional & Technical Services	0.066*	(0.040)	1,152
Admin & Support Services	0.113***	(0.039)	793
Public Admin & Defence	0.108**	(0.048)	915
Education	0.152***	(0.033)	2,085
Health & Social Work	0.100**	(0.046)	1,320
Arts & Recreation	0.181*	(0.096)	229
Other Services	0.108	(0.103)	160

Improve Performance

NACE 1 Sector	dY/dX	Standard Error	N
Agriculture, Forestry & Fishing	-0.000	(0.000)	36
Manufacturing	0.045	(0.030)	921
Construction	0.538***	(0.162)	125
Wholesale & Retail Trade	0.047	(0.030)	837
Transportation & Storage	0.245***	(0.042)	436
Accommodation & Food Services	-0.131**	(0.052)	193
Information & Communication	0.041	(0.027)	756
Finance & Insurance	0.010	(0.052)	319
Professional & Technical Services	0.052	(0.032)	686
Admin & Support Services	0.050	(0.041)	572
Public Admin & Defence	0.152***	(0.058)	545
Education	0.025	(0.057)	1,148
Health & Social Work	0.032	(0.044)	779
Other Services	0.000	(0.000)	44

Source: ESJS2, Authors' Calculations

Notes: dY/dX refers to marginal effect of training on either faster task efficiency or improved work performance.

Table A5: Training Types and Training Satisfaction, Faster Tasks and Improved Worker Performance (NACE 1 Sector Models)

Training Satisfaction

Variables	(1) Manufacturing	(2) Construction	(3) Wholesale & Retail Trade	(4) Transportation & Storage	(5) Accommodation & Food Services	(6) Information & Communication
Courses	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Seminars	0.122	0.169	-0.012	-0.035	0.089	-0.142*
	(0.078)	(0.259)	(0.091)	(0.148)	(0.145)	(0.082)
On-the-Job Training	0.185***	0.130	0.061	0.102	0.302***	-0.098*
	(0.062)	(0.220)	(0.089)	(0.078)	(0.105)	(0.057)
Courses & Seminars	0.170***	0.106	-0.032	0.079	0.632***	-0.041
	(0.065)	(0.257)	(0.095)	(0.133)	(0.137)	(0.066)
Courses & On-the-Job Training	0.190***	0.026	0.213***	0.101	0.395***	0.020
	(0.057)	(0.225)	(0.075)	(0.103)	(0.137)	(0.066)
Seminars & On-the-Job Training	0.321***	0.116	0.170	0.239**	0.301**	0.041
	(0.094)	(0.229)	(0.126)	(0.109)	(0.146)	(0.077)
All	0.229***	0.231	0.115	0.173*	0.358***	0.036
	(0.054)	(0.211)	(0.095)	(0.092)	(0.103)	(0.045)
Observations	836	170	656	347	172	683

Training Satisfaction (Contd.)

Variables	(7) Finance & Insurance	(8) Professional & Technical Services	(9) Admin & Support Services	(10) Public Admin & Defence	(11) Education	(12) Health & Social Work	(13) Arts & Recreation
Seminars	0.048	0.055	-0.077	-0.066	-0.115	-0.100	-0.255
	(0.111)	(0.082)	(0.114)	(0.128)	(0.074)	(0.086)	(0.000)
On-the-Job Training	0.142	-0.025	0.085	-0.040	0.044	-0.063	-0.287
	(0.167)	(0.078)	(0.111)	(0.115)	(0.089)	(0.069)	(0.000)
Courses & Seminars	0.038	-0.035	0.298***	0.007	0.024	0.028	0.289
	(0.113)	(0.061)	(0.115)	(0.071)	(0.077)	(0.078)	(0.000)
Courses & On-the-Job Training	0.167	-0.042	0.141*	0.093	-0.038	-0.068	0.636
	(0.113)	(0.076)	(0.077)	(0.110)	(0.088)	(0.069)	(0.000)
Seminars & On-the-Job Training	0.068	0.015	0.113	-0.049	0.021	0.042	0.061
	(0.158)	(0.084)	(0.094)	(0.127)	(0.074)	(0.080)	(0.000)
All	0.089	0.087	0.199***	0.193**	0.059	0.071	0.558
	(0.118)	(0.065)	(0.065)	(0.089)	(0.066)	(0.076)	(0.000)
Observations	354	603	454	454	1,024	671	64

Faster Tasks

Variables	(1) Manufacturing	(2) Construction	(3) Wholesale & Retail Trade	(4) Transportation & Storage	(5) Accommodation & Food Services	(6) Information & Communication
Seminars	0.100*	-0.211	0.023	0.044	-0.198	-0.149*
	(0.054)	(0.147)	(0.079)	(0.106)	(0.151)	(0.080)
On-the-Job Training	0.121**	0.087	0.051	0.130	0.056	0.041
	(0.052)	(0.135)	(0.058)	(0.081)	(0.111)	(0.069)
Courses & Seminars	0.077*	0.052	-0.029	0.108	-0.066	-0.024
	(0.040)	(0.145)	(0.090)	(0.091)	(0.179)	(0.050)
Courses & On-the-Job Training	0.154***	0.145	0.060	0.204***	0.121	0.013
	(0.046)	(0.101)	(0.067)	(0.077)	(0.168)	(0.064)
Seminars & On-the-Job Training	0.141**	0.072	0.003	0.161	-0.031	0.021
	(0.058)	(0.120)	(0.055)	(0.122)	(0.156)	(0.056)
All	0.152***	0.114	0.057	0.183**	0.183	0.079
	(0.047)	(0.083)	(0.060)	(0.092)	(0.167)	(0.056)
Observations	1,354	305	922	518	188	1,063

Faster Tasks (Contd.)

Variables	(7) Finance & Insurance	(8) Professional & Technical Services	(9) Admin & Support Services	(10) Public Admin & Defence	(11) Education	(12) Health & Social Work	(13) Arts & Recreation
Seminars	0.020	0.201***	0.050	0.111	0.019	0.024	0.311*
	(0.115)	(0.059)	(0.073)	(0.092)	(0.071)	(0.078)	(0.169)
On-the-Job Training	0.095	0.126*	-0.010	-0.000	-0.042	-0.010	0.143
	(0.094)	(0.070)	(0.087)	(0.073)	(0.074)	(0.073)	(0.182)
Courses & Seminars	0.156	0.069	-0.035	0.113	0.081	0.070	0.160
	(0.107)	(0.063)	(0.084)	(0.084)	(0.065)	(0.069)	(0.123)
Courses & On-the-Job Training	0.189**	0.063	0.063	0.138**	0.072	-0.059	0.279*
	(0.089)	(0.067)	(0.086)	(0.070)	(0.069)	(0.067)	(0.158)
Seminars & On-the-Job Training	0.203**	0.148**	0.117	0.037	0.116*	0.047	0.124
	(0.085)	(0.062)	(0.083)	(0.081)	(0.063)	(0.062)	(0.178)
All	0.170*	0.186***	0.082	0.184***	0.152**	0.038	0.035
	(0.092)	(0.051)	(0.069)	(0.064)	(0.060)	(0.055)	(0.165)
Observations	618	920	608	764	1,852	1,110	163

Improve Performance

Variables	(1) Manufacturing	(2) Wholesale & Retail Trade	(3) Transportation & Storage	(4) Accommodation & Food Services	(5) Information & Communication
Seminars	0.015	0.012	0.192**	-0.083	0.005
	(0.047)	(0.103)	(0.087)	(0.000)	(0.079)
On-the-Job Training	0.022	0.079	-0.043	0.176	0.073
	(0.044)	(0.061)	(0.088)	(0.000)	(0.053)
Courses & Seminars	0.037	0.077	0.125	-0.511	0.029
	(0.082)	(0.081)	(0.108)	(0.000)	(0.048)
Courses & On-the-Job Training	0.047	0.081	0.026	-0.141	-0.013
	(0.056)	(0.073)	(0.080)	(0.000)	(0.055)
Seminars & On-the-Job Training	0.079*	0.042	0.066	-0.113	-0.059
	(0.046)	(0.068)	(0.120)	(0.000)	(0.082)
All	0.025	0.057	0.146*	0.099	0.050
	(0.037)	(0.073)	(0.077)	(0.000)	(0.040)
Observations	701	621	324	121	606

Improve Performance (Contd.)

Variables	(6) Finance & Insurance	(7) Professional & Technical Services	(8) Admin & Support Services	(9) Public Admin & Defence	(10) Education	(11) Health & Social Work
Seminars	-0.441***	0.071	-0.127	-0.020	0.124**	-0.043
	(0.120)	(0.054)	(0.109)	(0.071)	(0.060)	(0.111)
On-the-Job Training	-0.113	-0.124*	-0.058	-0.104	0.037	0.055
	(0.103)	(0.067)	(0.101)	(0.081)	(0.079)	(0.059)
Courses & Seminars	-0.021	0.020	0.084	0.034	0.037	0.017
	(0.051)	(0.067)	(0.097)	(0.055)	(0.059)	(0.079)
Courses & On-the-Job Training	0.008	0.014	0.030	-0.072	0.035	0.053
	(0.068)	(0.068)	(0.089)	(0.070)	(0.067)	(0.065)
Seminars & On-the-Job Training	-0.150*	-0.088	-0.020	-0.078	-0.028	0.044
	(0.078)	(0.066)	(0.097)	(0.111)	(0.062)	(0.071)
All	-0.094*	0.024	0.011	-0.045	0.085*	0.066
	(0.049)	(0.051)	(0.085)	(0.056)	(0.046)	(0.054)
Observations	256	510	417	421	1,003	638

Source: ESJS2, Authors' Calculations

Table A6: Heterogeneous Effects of Tech-Underskilling and Gender on Worker Outcomes (Marginal Effects, No Overskilled)

Variables	(1) Fear of Job Loss	(2) Job Satisfaction	(3) Job Security	(4) Work-Life Balance
Tech-Underskilled	0.055***	0.026***	-0.006	-0.019
	(0.020)	(0.009)	(0.018)	(0.018)
Female	-0.016	0.030**	0.002	-0.020
	(0.021)	(0.012)	(0.023)	(0.029)
Tech-Underskilled × Female	**-0.031**	**-0.030****	**-0.017**	**-0.005**
	(0.023)	**(0.012)**	**(0.026)**	**(0.031)**
ln(Pay)	-0.039**	0.035***	0.042***	0.037***
	(0.017)	(0.013)	(0.012)	(0.011)
Part-Time	0.045***	-0.009	-0.022	0.005
	(0.015)	(0.013)	(0.023)	(0.025)
Digital Index	0.166***	0.063***	-0.038	0.006
	(0.028)	(0.018)	(0.026)	(0.034)
Education				
Low Education	*Ref.*	*Ref.*	*Ref.*	*Ref.*
Upper Secondary	-0.050*	0.017	0.093**	0.035
	(0.027)	(0.021)	(0.044)	(0.043)
Tertiary	-0.056**	0.015	0.139***	0.097***
	(0.025)	(0.017)	(0.038)	(0.036)
Observations	13,248	13,309	8,288	8,288

Standard errors in parentheses. Overskilled employees excluded from analysis.
*** p<0.01, ** p<0.05, * p<0.1

Source: ESJS2, Authors' Calculations

Table A7: Heterogeneous Effects of Tech-Underskilling and Gender on Training Receipt (Marginal Effects)

Variables	(1) Training	(2) Training
Underskilled	0.039***	
	(0.012)	
Tech-Underskilled		0.059***
		(0.010)
Female	0.035***	0.039***
	(0.013)	(0.013)
Underskilled × Female	**-0.015**	
	(0.016)	
Tech-Underskilled × Female		**-0.017**
		(0.014)
Ln(Pay)	0.027***	0.027***
	(0.006)	(0.006)
Part-Time	-0.014	-0.013
	(0.011)	(0.011)
Digital Index	0.152***	0.153***
	(0.020)	(0.020)
Education		
Low Education	*Ref.*	*Ref.*
Upper Secondary	-0.015	-0.015
	(0.016)	(0.016)
Tertiary	0.010	0.009
	(0.017)	(0.017)
Observations	13,780	13,784

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

Source: ESJS2, Authors' Calculations

Table A8: Heterogeneous Effects of Training and Gender on Faster Tasks / Technology Attitudes (Marginal Effects)

Variables	(1) Faster Tasks	(2) Faster Tasks (CAWI Only)	(3) Improve Performance
Trained	0.108***	0.130***	0.061***
	(0.020)	(0.024)	(0.015)
Female	-0.001	0.001	0.015
	(0.028)	(0.030)	(0.022)
Trained × Female	**-0.002**	**0.003**	**-0.002**
	(0.029)	**(0.035)**	**(0.024)**
ln(Pay)	-0.016**	-0.016*	0.011
	(0.008)	(0.010)	(0.008)
Part-Time	-0.044***	-0.038***	-0.011
	(0.010)	(0.012)	(0.012)
Digital Index	0.212***	0.213***	0.064***
	(0.026)	(0.032)	(0.021)
Education			
Low Education	*Ref.*	*Ref.*	*Ref.*
Upper Secondary	0.017	0.031	0.012
	(0.026)	(0.033)	(0.018)
Tertiary	-0.022	-0.008	0.023
	(0.026)	(0.030)	(0.018)
Observations	13,746	8,788	8,779

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

Source: ESJS2, Authors' Calculations

Table A9: Heterogeneous Effects of Training Type and Gender on Training Satisfaction / Faster Tasks / Technology Attitudes (Marginal Effects)

Variables	(1) Satisfied Training (Female)	(2) Satisfied Training (Male)	(3) Faster Tasks (Female)	(4) Faster Tasks (Male)	(5) Faster Tasks (CAWI Only Female)	(6) Faster Tasks (CAWI Only Male)	(7) Improve Performance (Female)	(8) Improve Performance (Male)
Seminars	-0.050	-0.054	0.061**	0.016	0.075**	0.009	0.021	0.026
	(0.034)	(0.042)	(0.029)	(0.027)	(0.037)	(0.026)	(0.035)	(0.027)
On-the-Job Training	0.030	-0.019	0.087***	0.027	0.102***	0.030	0.020	-0.001
	(0.040)	(0.038)	(0.029)	(0.026)	(0.034)	(0.033)	(0.026)	(0.025)
Courses & Seminars	0.067*	0.016	0.077***	0.034	0.076**	0.053*	0.034	0.024
	(0.039)	(0.035)	(0.028)	(0.025)	(0.037)	(0.028)	(0.035)	(0.027)
Courses & On-the-Job Training	0.127***	0.018	0.091***	0.059**	0.096***	0.030	0.016	0.006
	(0.039)	(0.035)	(0.025)	(0.024)	(0.026)	(0.025)	(0.024)	(0.031)
Seminars & On-the-Job Training	0.055	0.087**	0.098***	0.062**	0.132***	0.072**	0.036	-0.020
	(0.044)	(0.037)	(0.029)	(0.028)	(0.030)	(0.035)	(0.033)	(0.027)
All	0.133***	0.086***	0.123***	0.108***	0.140***	0.104***	0.075***	0.021
	(0.038)	(0.021)	(0.022)	(0.022)	(0.023)	(0.024)	(0.024)	(0.022)
Observations	3,252	3,866	5,382	5,869	3,238	3,864	3,238	3,823

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

Source: ESJS2, Authors' Calculations

Table A10: Heterogeneous Effects of Tech-Underskilling and Age on Worker Outcomes (Marginal Effects)

Variables	(1) Fear Job Loss	(2) Job Satisfaction	(3) Job Security	(4) Work-Life Balance
Tech-Underskilled (25-39)	0.026	0.029*	0.013	-0.007
	(0.022)	(0.015)	(0.020)	(0.021)
Tech-Underskilled (40-49)	0.039*	0.001	-0.040	-0.029
	(0.023)	(0.014)	(0.030)	(0.022)
Tech-Underskilled (50-64)	0.067***	-0.005	-0.033	-0.032
	(0.024)	(0.016)	(0.025)	(0.024)
Observations	13,390	13,452	8,374	8,374

Standard errors in parentheses. Reference group is corresponding age cohort that are not tech-underskilled.
*** p<0.01, ** p<0.05, * p<0.1

Source: ESJS2, Authors' Calculations

Table A11: Heterogeneous Effects of Tech-Underskilling and Age on Training Receipt (Marginal Effects)

Variables	(1) Training	(2) Training
Underskilled (25-39)	0.030**	--
	(0.014)	
Underskilled (40-49)	0.028	--
	(0.018)	
Underskilled (50-64)	0.038***	--
	(0.014)	
Tech-Underskilled (25-39)	--	0.046***
		(0.014)
Tech-Underskilled (40-49)	--	0.034*
		(0.020)
Tech-Underskilled (50-64)	--	0.072***
		(0.019)
Observations	13,927	13,932

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

Source: ESJS2, Authors' Calculations

Table A12: Heterogeneous Effects of Training and Age on Faster Tasks / Technology Attitudes (Marginal Effects)

Variables	(1) Faster Tasks	(2) Faster Tasks (CAWI Only)	(3) Improve Performance
Trained (25-39)	0.093***	0.151***	0.054***
	(0.022)	(0.025)	(0.020)
Trained (40-49)	0.131***	0.134***	0.048*
	(0.028)	(0.035)	(0.026)
Trained (50-64)	0.118***	0.122***	0.098***
	(0.021)	(0.025)	(0.016)
Observations	13,893	8,879	8,870

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

Source: ESJS2, Authors' Calculations

Table A13: Heterogeneous Effects of Training Type and Age on Training Satisfaction / Faster Tasks / Technology Attitudes (Marginal Effects)

Variables	(2) Seminars	(3) On-the-Job Training	(4) Courses & Seminars	(5) Courses and On-the-Job Training	(6) Seminars and On-the-Job Training	(7) All
Training Satisfaction						
Age Category						
25-39	-0.023	0.032	0.083**	0.078**	0.100**	0.123***
	(0.037)	(0.031)	(0.038)	(0.036)	(0.044)	(0.031)
40-49	-0.121***	0.001	-0.006	0.025	0.062	0.081**
	(0.043)	(0.051)	(0.042)	(0.045)	(0.041)	(0.034)
50-64	-0.012	-0.032	0.043	0.061	0.042	0.128***
	(0.058)	(0.057)	(0.055)	(0.059)	(0.060)	(0.050)
Observations	7,194	7,194	7,194	7,194	7,194	7,194

Faster Tasks						
Age Category						
25-39	0.036	0.072***	0.046	0.059*	0.083**	0.117***
	(0.037)	(0.027)	(0.034)	(0.032)	(0.035)	(0.028)
40-49	0.001	0.050	0.089**	0.109***	0.062	0.113***
	(0.039)	(0.033)	(0.038)	(0.031)	(0.049)	(0.028)
50-64	0.055	0.050	0.029	0.080***	0.087***	0.111***
	(0.036)	(0.036)	(0.025)	(0.031)	(0.030)	(0.025)
Observations	11,375	11,375	11,375	11,375	11,375	11,375
Faster Tasks (CAWI Only)						
Age Category						
25-39	0.078**	0.074***	0.064*	0.046	0.085**	0.119***
	(0.030)	(0.027)	(0.034)	(0.033)	(0.037)	(0.025)
40-49	-0.012	0.064	0.113**	0.086**	0.085	0.137***
	(0.038)	(0.042)	(0.049)	(0.038)	(0.060)	(0.036)
50-64	0.022	0.044	-0.001	0.095**	0.135***	0.093***
	(0.047)	(0.045)	(0.036)	(0.045)	(0.046)	(0.032)
Observations	7,191	7,191	7,191	7,191	7,191	7,191
Improve Performance						
Age Category						
25-39	0.011	0.012	0.027	-0.009	-0.038	0.019
	(0.036)	(0.024)	(0.026)	(0.030)	(0.033)	(0.025)
40-49	0.012	0.032	0.039	0.043	0.052	0.071**
	(0.031)	(0.040)	(0.034)	(0.033)	(0.039)	(0.033)
50-64	0.049	-0.026	0.014	0.017	0.013	0.051**
	(0.034)	(0.032)	(0.040)	(0.028)	(0.033)	(0.023)
Observations	7,186	7,186	7,186	7,186	7,186	7,186

Standard errors in parentheses. Reference group is the corresponding age group who undertook courses only.
**** p<0.01, ** p<0.05, * p<0.1*

Source: ESJS2, Authors' Calculations.

Chapter Two: Skills Mismatch and Household Well-being Across Europe

1. Introduction

This chapter turns to a critical yet often underexplored dimension: the relationship between skills mismatches and broader well-being outcomes across households in Europe. While Chapter 1 examined self-reported tech-related underskilling and its impact on individual level outcomes, this chapter extends the lens to examine how mismatches in formal qualifications and job requirements influence household economic security, poverty risks, financial resilience, and income inequality. By leveraging harmonised microdata and rigorous empirical strategies, this analysis provides a deeper understanding of the socio-economic consequences of skills mismatches, informing policy design aimed at mitigating vulnerability and enhancing social investment outcomes across diverse European contexts.

Skills mismatch—defined as the discrepancy between the skills individuals possess and those required by their jobs—is increasingly recognized as a structural labour market inefficiency influencing socio-economic outcomes. According to human capital theory (Becker, 1964; Schultz, 1961), individual productivity and consequently wages depend crucially on skill accumulation and their optimal utilization. Skills mismatch may undermine earnings potential and therefore elevate financial vulnerabilities and poverty risk (Hartog, 2000; Leuven & Oosterbeek, 2011).

Despite the growing political and academic consensus on the crucial role of skills in shaping employment trajectories and inclusive growth, the broader implications of skills mismatches for well-being remain under explored. Much of the existing research and monitoring – both in national strategies and the European Skills Agenda – has focused on improving training systems, addressing labour shortages and supporting transitions to employment. However, a deeper understanding of how mismatches in formal qualifications and job requirements affect well-being at the household level – such as income adequacy, financial resilience, and income inequality – is essential to advance both academic knowledge and effective policy design.

Labour market mismatches – especially those concerning educational attainment – are not only inefficient in terms of resource allocation but also carry potentially significant implications for income distribution and poverty risks. When workers are employed in roles that underutilize their qualifications (overeducation) or demand more than their formal qualifications (undereducation), the resulting productivity penalties and wage distortions may exacerbate existing inequalities or contribute to persistent forms of socio-economic disadvantage. These include lower household income, diminished financial buffers, and increased exposure to poverty. While previous research has consistently shown wage penalties associated with skills mismatch (McGuinness, 2006; Leuven & Oosterbeek, 2011), the evidence base linking mismatch to broader household-level economic outcomes remains relatively underdeveloped.

Most of the existing studies have focused on the direct labour market consequences of mismatch, such as reduced earnings, lower productivity, and weaker job satisfaction (Quintini, 2011; Ghignoni & Verashchagina, 2014). However, emerging work is beginning to address how mismatches interact with wider welfare outcomes. For example, Liu and Guo (2023) demonstrate that digital financial inclusion can mitigate vulnerability to poverty, underscoring how external resources may cushion the effects of mismatch on household well-being. Stephany and Teutloff (2022) similarly highlight that when workers possess skills complementary to digital technologies, their earnings potential rises—suggesting that mismatch in dynamic labour markets may suppress opportunities for income mobility.

Recent literature has also started to examine non-monetary consequences of mismatch, including effects on subjective well-being (Ilieva-Trichkova & Boyadjieva, 2021), job satisfaction (Allen & van der Velden, 2001; Green & Zhu, 2010), and intra-generational mobility (Verhaest & Omey, 2009). However, systematic evidence on whether and how mismatch affects key indicators of economic security – such as relative poverty risk, the ability to meet unexpected expenses, or household position within the national income distribution—remains scarce. When such studies do exist, they often focus on individual-level outcomes in single-country contexts, limiting broader conclusions across institutional settings (Green & Henseke, 2016). In a related context, Kim (2023) finds that social skills play a critical role in helping individuals recover from entering the labour market during a recession, suggesting that beyond formal qualifications, interpersonal capabilities can significantly influence financial resilience. This reinforces the view that underutilisation of skill sets, whether cognitive or social, can have long-term consequences for income security.

This analysis seeks to address that gap by examining the relationship between skills mismatch and multiple dimensions of well-being – including poverty risk, financial resilience, and relative income standing – across European countries. In doing so, it builds on the foundations of existing literature while extending the empirical lens to capture how mismatches affect the economic situation of households across different countries in Europe that have varied social, labour market, and welfare institutions.

This analysis contributes to the literature by providing a large-scale, comparative assessment of the relationship between educational mismatch and household well-being across 32 European countries over the period 2004–2023. Using harmonised microdata from the EU Survey on Income and Living Conditions (EU-SILC), we construct robust indicators of educational mismatch at both the individual and household levels and examine their association with three outcome dimensions: relative poverty (measured as equivalised disposable income below 60% of the national median), financial resilience (the ability of households to face unexpected expenses), and income inequality (proxied by the household's or individual's position in the national income distribution, scaled 0–100). This dual-level approach, capturing both individual mismatch and its accumulation within households, enables us to assess not only direct effects but also potential spillovers that may amplify vulnerability in multi-earner or dependent households.

This chapter examines three central questions: First, to what extent does educational mismatch increase the likelihood of experiencing relative poverty? Second, how is mismatch associated with households' financial resilience, particularly their ability to cope with unexpected expenses? Third, does educational mismatch influence an individual's or household's relative position within the national income distribution? These questions broaden the analysis of mismatch beyond labour market efficiency and wage penalties, towards a more comprehensive understanding of its implications on economic outcomes of the households and individuals.

The implications of this research are twofold. From a policy perspective, the findings provide valuable evidence for social investment strategies that integrate education, training, and income support policies. If educational mismatch is found to be systematically associated with higher poverty risks or weaker financial resilience, this would underscore the importance of preventive measures – such as better skills anticipation systems, targeted re-skilling programs, or social protection schemes for mismatched workers. The analysis bridges gaps between labour market dynamics and household-level welfare outcomes by linking individual educational mismatch to broader socio-economic conditions across Europe. It complements the previous chapter of this deliverable, by extending the focus from the individual level to the economic consequences of mismatch across European households.

2. Data and Measurement

We exploit the European Union Survey on Income and Living Conditions (EU-SILC) dataset to examine the relationship between skill mismatch and three key socio-economic outcomes: (i) the risk of relative poverty, (ii) household financial resilience, and (iii) income inequality, proxied through relative distance from the national median income. EU-SILC constitutes the primary microdata infrastructure in Europe for the analysis of income distribution, poverty, and social exclusion, and is widely used for monitoring progress under the European Pillar of Social Rights and related policy frameworks.

The EU-SILC survey, coordinated by Eurostat under a harmonised methodological framework, is conducted annually in all EU Member States as well as selected EFTA and candidate countries. It collects micro-level data from private households through standardised national protocols, ensuring comparability across countries and over time. Information is gathered at both the household and individual levels and includes detailed information on income sources, social benefits, material deprivation, housing conditions, and subjective well-being. The target population comprises individuals aged 16 years and older, with a particular focus on vulnerable groups such as single-parent households, the long-term unemployed, and elderly individuals living alone.

Both cross-sectional and longitudinal components are provided, allowing for both static snapshots and dynamic assessments of living conditions in European societies. The cross-sectional dataset offers nationally representative data for each calendar year, covering household income, labour market status, and living standards for the full sample. In contrast, the longitudinal dataset tracks a rotating sub-sample of individuals and households for up to four consecutive years, with longer panels possible in certain countries depending on national implementation. This structure enables medium-term analysis of income dynamics, poverty transitions, and labour market trajectories across diverse institutional contexts.

We rely on a structured set of variables derived from EU-SILC, encompassing four main domains: income poverty, material deprivation, income inequality, and financial resilience. These are complemented by detailed socio-demographic characteristics (such as age, gender, education, household composition, and migration background) and labour market indicators (including employment status, working time, occupation, and contract type). Income-related information is used to construct both household and individual measures of relative income positioning. The specific definitions and coding of all variables used in the empirical analysis are presented in the remainder of this section.

Our estimation strategy makes use of both components of the EU-SILC dataset. The cross-sectional data provides annual, nationally representative snapshots and are used as the primary source for the analysis due to their larger sample size and higher statistical power. To test the robustness of our results and assess the temporal dynamics of mismatch effects, we replicate the baseline models using the longitudinal dataset, which follows individuals and households for up to four consecutive years. Our sample includes 32 European countries over the 2004–2023 period, allowing for both extensive cross-country comparison and intertemporal variation.

All estimates are weighted using calibrated sampling weights provided by Eurostat to ensure representativeness at the national level. Harmonised metadata and methodological guidelines guarantee cross-country comparability and enable robust, generalisable insights. EU-SILC is thus particularly well suited for analysing the structural determinants of poverty, inequality, and vulnerability across the European social landscape.

By integrating EU-SILC into our empirical framework, we extend the scope of this deliverable, encompassing broader welfare impacts. This allows for a more comprehensive assessment of the socioeconomic implications of skill mismatch in the European labour market and the extent to which it translates into downstream inequality and poverty risks.

2.1 Outcome Variables

The analysis focuses on four key outcome variables that capture distinct dimensions of well-being and inequality. These outcomes allow us to assess the broad socio-economic implications of educational mismatch at the household level. In particular, they link mismatch conditions to (relative) poverty risk, household financial resilience, and income distribution outcomes at both the individual and household levels.

First, we examine the risk of relative poverty, measured through a binary indicator equal to 1 if the household's equivalised disposable income falls below 60% of the national median, and 0 otherwise. This variable corresponds to the standard EU definition of *at-risk-of-poverty* status, widely used for policy monitoring across Member States (see also Eurostat, 2023).

Second, we employ an indicator of household financial resilience, defined as the ability of the household to face unexpected financial expenses. This variable takes value 1 if the household reports being able to meet such expenses from its own resources, and 0 otherwise. It serves as a proxy for short-term economic buffer capacity and material stability, and complements the income-based poverty indicator by capturing financial vulnerability in the absence of income shocks.

The final two outcome variables capture inequality in income positioning at both the household and individual levels. These variables are constructed as continuous, percentile-based indicators scaled from 0 to 100, with higher values indicating a more advantageous position relative to the national median. The first is household income relative to the national median, which expresses a household's equivalised disposable income as a percentile rank within the national income distribution for the corresponding survey year. The second variable, individual earnings relative to the national median, reflects a person's position in the national earnings distribution based on their gross labour income, again scaled within their country and year.

To ensure comparability across countries and over time, all income amounts were first converted from national currencies into euros using the average annual exchange rate provided by Eurostat. Furthermore, we account for cross-country and intertemporal differences in purchasing power and inflation dynamics by adjusting all monetary values using the annual Consumer Price Index (CPI), normalised to real terms. These transformations allow us to construct consistent and inflation-adjusted indicators of income inequality, enabling robust comparative analysis across countries and over time. These relative income indicators allow us to assess the distributional consequences of mismatch and provide insight into whether mismatched individuals or households are systematically disadvantaged in terms of their placement within the income distribution.

The full set of outcome variables facilitates a multidimensional analysis of the socio-economic effects of mismatch. Their harmonised construction across countries and years ensures robust comparability and supports both cross-sectional and longitudinal perspectives. Taken together, these four outcome measures provide a comprehensive lens on the relationship between skills mismatch and well-being, highlighting how mismatch shapes broader dynamics of poverty, financial insecurity, and income inequality across European countries.

2.2 Educational Mismatch Measure

To capture the concept of educational mismatch, we construct individual-level and household-level indicators based on the alignment between an individual's educational attainment and the typical (modal) level of education observed within their occupational peer group. This approach follows a widely used empirical strategy in the educational mismatch literature and is adapted to the structure of the EU-SILC dataset.

These indicators are based on the alignment between an individual's educational attainment and the typical (modal) educational requirement for their occupation, as observed in the labour market of their country and year of observation. This approach follows a widely used empirical strategy in the educational mismatch literature (e.g., see McGuinness, 2006; McGuinness et al. 2018), and is adapted to the structure of the EU-SILC dataset. and offers a pragmatic means of assessing the extent to which workers are over- or underqualified relative to their peers.

At the individual level, a person is classified as matched or mismatched based on a comparison between their highest completed level of education and the modal education level observed among employees in the same occupation (at the 2-digit ISCO classification), country, and year. The educational mismatch is further disaggregated into two distinct types: overeducation that is when the individual's educational attainment is higher than the occupational modal level; undereducation that is when the individual's educational attainment is lower than the occupational modal level.

This classification results in three dummy variables:

- *Mismatched*: equals 1 if the individual is either overeducated or undereducated; 0 if matched.
- *Overeducated*: equals 1 if the individual is overeducated; 0 otherwise.

- *Undereducated*: equals 1 if the individual is undereducated; 0 otherwise.

In addition to these individual-level indicators, we construct household-level mismatch indicators, capturing the concentration of mismatch within households. These indicators reflect the share of mismatched individuals among all employed household members, and are scaled continuously between 0 and 1:

- % *Mismatched employees at household*: proportion of employed household members who are mismatched,
- % *Overeducated employees at household*: proportion of employed household members who are overeducated,
- % *Undereducated employees at household*: proportion of employed household members who are undereducated.

These household-level indicators allow us to assess how the accumulation of mismatch within households may exacerbate risks of poverty, financial resilience and household position in the income distribution, especially in contexts of economic stress or weak labour demand. The presence of multiple mismatched earners in a household may amplify the risk of falling into poverty or not being financially resilient, particularly under conditions of macroeconomic instability, weak labour demand or sectoral employment shocks.

All mismatch variables are constructed consistently across years, countries, and ISCO codes. In addition, we rely on harmonised education categories (based on ISCED classifications) to ensure comparability over time and across national education systems. This methodology aligns conceptually with existing measures of vertical mismatch in the literature, while also offering practical advantages in terms of data availability and empirical robustness across countries included in EU-SILC. By employing both individual- and household-level mismatch measures, our empirical framework allows us to explore both direct (personal labour market outcomes) and spillover effects of educational mismatch on socio-economic outcomes at the household level (broader economic resilience and welfare position of households).

2.3 Control Variables

To isolate the effect of educational mismatch, we control for a comprehensive set of individual and household-level characteristics. These variables are selected based on established findings in the poverty and labour market literature and are drawn directly from the harmonised EU-SILC dataset. Their inclusion ensures that the estimated relationship between mismatch and the outcome variable of interest is not confounded by underlying demographic, socio-economic, or labour market differences across individuals and households.

The set of demographic controls includes gender, generational cohort (classified into five categories: Traditionalists, Baby Boomers, Generation X, Generation Y, and Generation Z), marital status (single, married, widowed/divorced), and household size. These variables help account for life-cycle effects and family structures that are known to influence poverty risks, inequality and resilience.

Health status is proxied through a binary variable capturing whether the respondent reports a long-standing health limitation, given its known association with reduced earning capacity and increased vulnerability. Migration status is also included, distinguishing between native individuals, migrants from EU countries, and migrants from non-EU countries, to account for the socio-economic heterogeneity across origin groups.

In addition, we control for urban-rural residence status (city, town and rural), as spatial disparities are often closely tied to poverty outcomes due to differences in labour market access, public services, and cost of living.

2.4 Summary Statistics

To provide a descriptive overview of the analytical sample, Tables 1 and 2 report key summary statistics disaggregated by mismatch status for both the cross-sectional and panel components of EU-SILC. These statistics highlight important socio-demographic and labour market differences between matched and mismatched individuals and further distinguish between overeducated and undereducated subgroups.

Table 7: EU-SILC$_{\text{CROSS-SECTION}}$ –Differences in means of key variables by matching status

#Observations	Matched *3,072,007*	Mismatched *1,653,363*	Overeducated *702,694*	Undereducated *950,669*	Diff.	Sign.
Male	54.0%	54.0%	53.0%	54.0%	-0.002	***
Years of schooling	12.44	11.32	14.17	9.23	1.118	***
Age	42.03	42.36	40.23	43.93	-0.331	***
Generation Z: Born >1995	2.0%	2.0%	2.0%	3.0%	-0.007	***
Generation Y: Born 1977-1995	33.0%	32.0%	38.0%	27.0%	0.017	***
Generation X: Born 1965-1976	34.0%	32.0%	34.0%	30.0%	0.020	***
Generation B: Born 1946-1964	30.0%	32.0%	26.0%	38.0%	-0.024	***
Generation Traditionalists: Born before	1.0%	2.0%	1.0%	2.0%	-0.006	***
Single	34.0%	35.0%	38.0%	32.0%	-0.009	***
Married or in civil union	57.0%	55.0%	53.0%	56.0%	0.020	***
Separated, widowed, or divorced	10.0%	11.0%	9.0%	12.0%	-0.011	***
Household size	3.02	3.00	2.98	3.01	0.030	***
Health status: Good or very good	75.0%	73.0%	78.0%	70.0%	0.020	***
Health status: Neutral	14.0%	16.0%	13.0%	17.0%	-0.014	***
Health status: Bad or very bad	2.0%	3.0%	2.0%	3.0%	-0.005	***
Limitation in activities due to health	12.0%	14.0%	12.0%	16.0%	-0.016	***
Suffer from a chronic illness	20.0%	21.0%	18.0%	24.0%	-0.012	***
Year of immigration	1997	1999	2001	1997	-1.887	***
Individual was born in the native country	92.0%	87.0%	85.0%	88.0%	0.051	***
Immigrant born in another EU country	3.0%	4.0%	4.0%	3.0%	-0.011	***
Immigrant born outside EU	6.0%	9.0%	10.0%	9.0%	-0.040	***
Residence: City (densely populated area)	40.0%	40.0%	43.0%	38.0%	0.013	*
Residence: Town (semi-densely area)	28.0%	29.0%	28.0%	30.0%	-0.008	***
Residence: Rural (thinly populated area)	25.0%	23.0%	23.0%	24.0%	0.014	***
Homeownership: Outright	48.0%	45.0%	46.0%	44.0%	0.027	***
Homeownership: Mortgage	24.0%	22.0%	22.0%	22.0%	0.022	***
Homeownership: Rent at the market rate	19.0%	22.0%	22.0%	22.0%	-0.036	***
Homeownership: Rent at a reduced rate	5.0%	6.0%	5.0%	7.0%	-0.012	***
Homeownership: Free provided	5.0%	5.0%	5.0%	4.0%	-0.001	
NACE: (a) Agriculture, forestry & fishing	4.0%	5.0%	6.0%	4.0%	0.010	***
-“-: (b-e) Mining, Manufacturing,	18.0%	17.0%	18.0%	17.0%	0.007	***
-“-: (f) Construction	7.0%	7.0%	6.0%	7.0%	0.002	***
-“-: (g) Wholesale and retail trade	12.0%	14.0%	15.0%	13.0%	-0.023	***
-“-: (h) Transport and storage	5.0%	5.0%	6.0%	5.0%	-0.005	***

-“-: (i) Accommodation and food	3.0%	5.0%	5.0%	5.0%	-0.016	***
-“-: (j) Information and communication	3.0%	2.0%	2.0%	3.0%	0.006	***
-“-: (k) Financial and insurance activities	3.0%	4.0%	4.0%	3.0%	-0.005	***
-“-: (l-n) Real estate, Professional,	9.0%	9.0%	9.0%	8.0%	0.005	***
-“-: (o) Public administration and	7.0%	7.0%	8.0%	7.0%	-0.003	***
-“-: (p) Education	10.0%	4.0%	3.0%	5.0%	0.052	***
-“-: (q) Human health and social work	10.0%	10.0%	8.0%	11.0%	0.007	***
-“-: (r-u) Arts, recreation, other activities	5.0%	6.0%	7.0%	6.0%	-0.015	***
% Tertiary education (household)	38.0%	26.0%	50.0%	9.0%	0.116	***
Education attainment level: ISCED 0	0.0%	1.0%	0.0%	2.0%	-0.010	***
Education attainment level: ISCED 1	2.0%	9.0%	0.0%	15.0%	-0.072	***
Education attainment level: ISCED 2	7.0%	25.0%	3.0%	42.0%	-0.187	***
Education attainment level: ISCED 3	52.0%	28.0%	20.0%	34.0%	0.235	***
Education attainment level: ISCED 4	0.0%	11.0%	16.0%	7.0%	-0.105	***
Education attainment level: ISCED 5-8	40.0%	26.0%	60.0%	0.0%	0.139	***
Previous employment experience	100.0%	100.0%	100.0%	100.0%	0.001	
Years of experience in paid work	19.78	20.07	17.36	22.12	-0.291	***
Employed	86.0%	84.0%	83.0%	85.0%	0.021	***
Self-employed	13.0%	14.0%	16.0%	13.0%	-0.016	***
Family worker	1.0%	1.0%	1.0%	1.0%	-0.005	***
Actively looking for a job	11.0%	11.0%	16.0%	9.0%	-0.007	
Hours worked per week in the main job	38.83	38.10	38.53	37.78	0.731	***
Permanent contract	87.0%	84.0%	84.0%	84.0%	0.026	***
Managerial position	26.0%	23.0%	23.0%	23.0%	0.027	***
Change of job since last year	8.0%	9.0%	10.0%	8.0%	-0.007	***
Employee cash or near cash income	23,182	20,904	20,609	21,117	2,300	***
Cash or losses from self-employment	2,466	2,551	2,817	2,360	-84.89	***
HH at risk of (relative) poverty	8.0%	12.0%	10.0%	12.0%	-0.035	***
HH can face unexpected financial	74.0%	68.0%	72.0%	65.0%	0.055	***
HH can make ends meet with difficulty	44.0%	48.0%	47.0%	49.0%	-0.043	***
HH has a heavy financial burden	27.0%	30.0%	30.0%	31.0%	-0.037	***
Household income relative to the median	33.29	29.62	31.18	28.48	3.674	***
Personal income relative to the median	22.01	19.26	20.42	18.43	2.750	***

Notes: Data on income has been converted from the national currency into euros (where necessary) using the average exchange rate for each year and country and has been deflated using the GDP deflator specific to each country and year. *, **, *** denote statistical significance at 10%, 5%, 1%.

In both the cross-sectional and panel samples, mismatched individuals tend to be older, have fewer years of schooling, and are more likely to report poor health or activity limitations compared to their well-matched counterparts. Overeducated workers generally have the highest levels of formal education, yet they appear to earn lower average incomes and experience elevated financial vulnerability, relative to matched individuals. Undereducated workers are more likely to reside in larger households, work in manual or low-skill occupations, and report lower relative incomes and higher poverty risks. These disparities underscore the importance of accounting for educational mismatch in analyses of economic insecurity and income distribution.

Across both data structures, mismatched individuals consistently exhibit higher exposure to adverse welfare outcomes – including greater difficulty in meeting unexpected expenses, heavier financial burdens, and lower household income ranks within the national distribution. The differences are statistically significant in nearly all dimensions, confirming the relevance of mismatch status for understanding structural economic disadvantages across European labour markets. These patterns provide essential context for interpreting the empirical results presented in the next section.

Table 8: EU-SILC$_{PANEL}$ -Differences in means of key variables by matching status

	Matched	Mismatched	Overeducated	Undereducated	Diff.	Sign.
#Observations	*3,072,007*	*1,653,363*	*702,694*	*950,669*		
Male	53.0%	54.0%	53.0%	54.0%	-0.008	***
Years of schooling	12.48	11.19	14.31	9.05	1.294	***
Age	42.22	43.14	40.09	45.24	-0.920	***
Generation Z: Born >1995	1.0%	2.0%	1.0%	2.0%	-0.004	***
Generation Y: Born 1977-1995	32.0%	29.0%	38.0%	22.0%	0.030	***
Generation X: Born 1965-1976	35.0%	32.0%	35.0%	31.0%	0.030	***
Generation B: Born 1946-1964	31.0%	35.0%	24.0%	43.0%	-0.044	***
Generation Traditionalists: Born before	1.0%	2.0%	1.0%	2.0%	-0.007	***
Single	33.0%	33.0%	39.0%	29.0%	0.003	**
Married or in civil union	58.0%	57.0%	53.0%	59.0%	0.012	***
Separated, widowed, or divorced	9.0%	10.0%	8.0%	12.0%	-0.013	***
Household size	3.13	3.07	3.07	3.08	0.051	***
Health status: Good or very good	77.0%	75.0%	80.0%	72.0%	0.019	***
Health status: Neutral	15.0%	16.0%	13.0%	19.0%	-0.017	***
Health status: Bad or very bad	2.0%	3.0%	2.0%	4.0%	-0.006	***
Limitation in activities due to health	12.0%	14.0%	11.0%	16.0%	-0.019	***
Suffer from a chronic illness	21.0%	22.0%	18.0%	25.0%	-0.016	***
Residence: City (densely populated area)	41.0%	41.0%	43.0%	40.0%	0.001	
Residence: Town (semi-densely area)	27.0%	28.0%	28.0%	29.0%	-0.009	***
Residence: Rural (thinly populated area)	27.0%	26.0%	25.0%	27.0%	0.012	***
Homeownership: Outright	49.0%	47.0%	47.0%	47.0%	0.018	***
Homeownership: Mortgage	27.0%	24.0%	24.0%	23.0%	0.030	***
Homeownership: Rent at the market rate	14.0%	17.0%	17.0%	17.0%	-0.034	***
Homeownership: Rent at a reduced rate	6.0%	7.0%	6.0%	8.0%	-0.014	***
Homeownership: Free provided	5.0%	5.0%	5.0%	4.0%	-0.001	*
% Tertiary education (household)	38.0%	26.5%	52.3%	8.7%	0.115	***
Education attainment level: ISCED 0	0.0%	1.0%	0.0%	2.0%	-0.013	***
Education attainment level: ISCED 1	1.0%	10.0%	0.0%	17.0%	-0.090	***
Education attainment level: ISCED 2	7.0%	26.0%	2.0%	43.0%	-0.200	***
Education attainment level: ISCED 3	53.0%	28.0%	21.0%	34.0%	0.241	***
Education attainment level: ISCED 4	0.0%	7.0%	13.0%	4.0%	-0.072	***
Education attainment level: ISCED 5-8	40.0%	27.0%	65.0%	0.0%	0.131	***
Years of experience in paid work	19.73	20.53	16.84	23.10	-0.799	***
Employed	86.0%	84.0%	83.0%	85.0%	0.023	***
Self-employed	13.0%	15.0%	16.0%	14.0%	-0.019	***
Family worker	1.0%	1.0%	1.0%	1.0%	-0.004	***
Actively looking for a job	17.0%	15.0%	28.0%	11.0%	0.018	
Hours worked per week in the main job	38.82	38.02	38.42	37.74	0.806	***
Permanent contract	87.0%	85.0%	84.0%	85.0%	0.023	***
Change of job since last year	8.0%	9.0%	11.0%	7.0%	-0.008	***
Employee cash or near cash income	22,560	20,313	19,429	20,915	2,200	***
Cash or losses from self-employment	2,404	2,479	2,733	2,306	-75.71	***
HH at risk of (relative) poverty	9.0%	13.0%	12.0%	14.0%	-0.042	***
HH can face unexpected financial	74.0%	69.0%	73.0%	66.0%	0.055	***
HH can make ends meet with difficulty	49.0%	54.0%	52.0%	55.0%	-0.052	***
HH has a heavy financial burden	27.0%	31.0%	31.0%	32.0%	-0.040	***
Household income relative to the median	33.35	29.64	31.13	28.61	3.712	***
Personal income relative to the median	16.94	15.11	16.05	14.47	1.821	***

Notes: Data on income has been converted from the national currency into euros (where necessary) using the average exchange rate for each year and country and has been deflated using the GDP deflator specific to each country and year. *, **, *** denote statistical significance at 10%, 5%, 1%.

3. Empirical Strategy

To examine the relationship between educational mismatch and household well-being across Europe, we implement an empirical strategy grounded in repeated cross-sectional analysis using the EU Statistics on Income and Living Conditions (EU-SILC). The baseline estimates are derived from the cross-sectional component of EU-SILC, which provides nationally representative snapshots of income, labour market status, and living conditions across European countries each year. To assess the robustness and consistency of the results over time, we replicate the baseline model using the longitudinal (panel) version of EU-SILC, which follows individuals and households for up to four consecutive years. This two-step approach allows us to test the stability of the main findings and examine how mismatch relates to short-term versus medium-term household outcomes without combining the two datasets directly.

Building on this framework, our primary analysis uses pooled cross-sectional data from the EU-SILC cross-sectional sample over the period 2004–2023, covering 32 European countries. We estimate a series of ordinary least squares (OLS) regressions in which the dependent variables capture distinct dimensions of household and individual economic well-being: (1) the probability of being at risk of poverty (defined as having equivalised disposable income below 60% of the national median); (2) household financial resilience (defined as the ability to cope with unexpected financial expenses); (3) household relative income (a percentile-based indicator scaled 0–100, reflecting the household's position within the national income distribution); and (4) personal relative earnings (a similarly scaled indicator measuring the individual's earnings position relative to the national median).

Our main independent variable is the indicator of educational mismatch, operationalised at both the individual and household levels, as described in detail in the preceding section. We consider three individual-level mismatch dimensions – mismatched, overeducated, and undereducated – as well as corresponding household-level measures that capture the proportion of mismatched, overeducated, or undereducated household members among all employed individuals in the household. These allow us to examine both direct effects, capturing how individual-level mismatch influences a person's own economic outcomes, and compositional effects, which reflect how the presence of mismatch among other employed household members affects the household's overall economic situation.

To ensure that the estimated relationship between educational mismatch and outcome variables is not driven by other factors, we include an extensive set of control variables. These cover key socio-demographic characteristics (e.g. gender, age cohort, marital status, migrant background, household size, region of residence, health status), as well as employment-related factors such as employment status, job type (full-time/part-time), contract type, managerial position, and industry of employment. Additionally, we control for housing tenure status and the share of tertiary-educated household members, the latter serving as a proxy for household-level human capital. Variables related to individual education level or occupation (e.g. ISCO codes) are deliberately excluded from the models to avoid collinearity with the mismatch measure, which is constructed from these same dimensions.

We estimate each model under several specifications. The baseline specification includes only demographic and basic labour market controls. We then incrementally incorporate additional controls related to industry, household characteristics, and education composition. To account for unobserved heterogeneity across countries and over time, all regressions include country fixed effects to control for time-invariant institutional or structural factors, and year fixed effects to account for common macroeconomic shocks and policy changes.

All four models are estimated using OLS regressions, including those with binary dependent variables. While non-linear models such as probit or logit are theoretically more appropriate for modelling binary outcomes, OLS remains a practical and valid choice in this context. Its use is supported by the large sample size, the inclusion of robust control structures, and the application of clustered robust standard errors. OLS yields consistent estimates of average marginal effects and facilitates straightforward interpretation and comparability across models with both binary and continuous outcomes. To enhance the credibility of this approach, OLS results for binary models were cross validated against logit and probit specifications, with no substantive changes in the sign, magnitude, or statistical significance of the core findings (results are available upon request).

To strengthen the robustness and causal interpretability of our findings, we complement the OLS estimations with propensity score matching (PSM) techniques. Specifically, we use PSM to compare outcomes between matched and mismatched individuals who are similar along observable characteristics, thereby approximating a counterfactual comparison. Propensity scores are estimated using a logistic model that includes a similar set of covariates as the OLS specifications. Treatment effects from the PSM analysis are estimated under the assumption of conditional independence, meaning that once observable characteristics are accounted for, mismatch status is assumed to be unrelated to unobserved factors affecting outcomes. This allows for a credible comparison between matched and mismatched individuals with similar profiles. The resulting estimates are reported alongside the OLS benchmarks to assess the consistency and robustness of the findings.

Furthermore, we leverage the longitudinal dimension of EU-SILC, which follows individuals and households over up to four, five or six consecutive years, to replicate the cross-sectional baseline and PSM models using panel estimation techniques. This allows us to assess the consistency of the results over time and exploit within-individual variation over time. Panel data are estimated using fixed-effects models which control for unobserved individual-specific factors that remain constant over time and might otherwise bias cross-sectional estimates.

All estimations use sampling weights to ensure representativeness at the national level. Standard errors are robust and clustered at the household level to account for intra-household correlation and heteroskedasticity in the error structure. By applying complementary methodologies – OLS regressions, fixed-effects models, and propensity score matching – combined with rich control variables, our empirical strategy provides rigorous evidence on the link between eductional mismatch and well-being. This approach enables us to examine both short-term associations and medium-term dynamics in the distributional effects of mismatch across European labour markets.

4. Educational Mismatch and Poverty Incidence

This Section presents evidence on the relationship between educational mismatch and the likelihood of being at risk of poverty using a range of econometric approaches and different levels of analysis. Both individual- and household-level mismatch indicators are evaluated through ordinary least squares (OLS) estimations, propensity score matching (PSM), and panel fixed-effects models to ensure robustness and internal validity. The dependent variable throughout is a binary indicator equal to 1 if a household's equivalised disposable income falls below 60% of the national median – commonly referred to as being at risk of poverty.

4.1 Country-Level Heterogeneity in the Effect of Mismatch

Figure 11 displays the effects of individual-level educational mismatch on the risk of poverty, derived from separate OLS regressions per country. Each coefficient represents the estimated impact of being mismatched on poverty risk within a given national context, controlling for socio-demographic covariates and year fixed effects. Across countries, there is a consistent pattern of positive and statistically significant associations, indicating that educational mismatch tends to increase the probability of poverty. However, the magnitude of the effect varies substantially. Countries such as Bulgaria, Serbia, Hungary, Croatia, Belgium and Romania exhibit relatively large coefficients, pointing to a particularly strong link between mismatch and poverty in Eastern European settings. By contrast, the effects are smaller and more muted in Nordic and Western European countries, possibly reflecting stronger social protection systems or better job-matching mechanisms.

Figure 12 shifts the focus to the household level, examining how the proportion of mismatched workers within a household correlates with poverty risk. Again, separate country-specific regressions are estimated, and the pattern is broadly consistent with that observed at the individual level. In households where a greater share of employed members are mismatched, the probability of falling below the poverty line increases. The findings underline that educational mismatch is not only an individual labour market issue but also has wider household-level implications, particularly in multi-worker households.

4.2 Multivariate Regression Estimates

Table 9 presents the estimated effects of being mismatched at the individual level on the probability of falling below the relative poverty line. The coefficients for the educational mismatch variable are positive and statistically significant at the 1% level across all specifications. The estimated economic effect diminishes across the models as more controls are added and as alternative estimation strategies are applied. In the simplest OLS specification (column 1), being mismatched increases the risk of poverty by 23.2% relative to the average predicted probability (0.0938). This effect is gradually attenuated to 11.4% in column 4 with additional wealth, industry, and education controls. When using the PSM methodology (column 5), the estimated effect is similar in magnitude at 11.7%. Finally, in the longitudinal framework, the effect drops to 5.8% (pooled panel, column 6) and 5.2% (PSM-based panel estimate, column 7), suggesting the presence of unobserved individual heterogeneity that may inflate cross-sectional estimates. Nonetheless, the effect remains robust and consistently positive across all specifications.

Beyond mismatch, the demographic and labour market covariates exhibit expected patterns. Men are significantly more likely to be at risk of poverty, with an effect size of about 2.5% in the baseline and around 0.5–0.6% in panel models. Younger cohorts, especially Generation Z, show higher poverty risk relative to the reference group (pre-1945), with effects ranging from 3.1% to 15%, highlighting generational vulnerability. Marital status plays a protective role, as being married reduces the likelihood of poverty by approximately 1.8% in the baseline, whereas being widowed or divorced increases it by around 4%.

Larger household size is associated with higher poverty risk, with consistent positive and significant effects around 0.5% to 0.9%. Having a limiting health condition is another strong predictor, associated with an increase in poverty probability of around 2–2.7%. Regarding urbanicity, living in a rural area increases the probability of being at risk of poverty by about 3%, while city residence slightly decreases it. Migrants, particularly from non-EU countries, face substantially higher risks: the estimated effect is over 10% for this group.

Turning to employment characteristics, permanent contracts, full-time jobs, and managerial positions are strongly protective against poverty, reducing the probability by 10.4%, 6.4%, and 3.1% respectively in the baseline specification. In contrast, working in accommodation and food services, or in agriculture, is associated with elevated poverty risks. Ownership status also matters: individuals in mortgaged or outright ownership experience significantly lower poverty rates compared to those in free housing. For instance, outright ownership reduces poverty risk by 6.3–6.4%.

Sectoral affiliation also shapes poverty exposure: working in agriculture or accommodation services is associated with a higher probability of being poor, while employment in ICT, finance, public administration, education, and health services corresponds with reduced risk. Finally, household-level educational attainment (% of household members with a tertiary education) has a negative effect, reducing poverty probability by 5.6%, confirming the compositional importance of human capital.

Column (5) of Table 9 introduces the Propensity Score Matching (PSM) to strengthen causal inference. The matched comparison estimates indicate a positive and statistically significant relationship between educational mismatch and poverty, though the effect size is smaller than in the OLS models. The average treatment effect (ATE) for being mismatched is around 1.2 percentage points (Column 5), corresponding to an 11.66% effect, based on the predicted probability of poverty.

In columns (6)-(7) of Table 9 we replicate the main specification using panel data, allowing for within-individual comparisons over time. Although both the sign and statistical significance of the skill mismatch coefficient remain in the panel data results, underscoring its persistent influence even when accounting for time-invariant individual characteristics, the magnitude of the effect (5.2%) is more modest than in the cross-sectional results.

Table 10 shifts the focus from individuals to households, using the share of mismatched individuals in each household as the main independent variable. The estimated coefficients again show a consistent and statistically significant positive effect on poverty incidence across all specifications. In the baseline model, the economic magnitude of the effect is 34.7%, indicating that households with a greater proportion of mismatched members are significantly more likely to fall below the poverty line. This effect remains strong even after adding additional controls, with the % Effect gradually declining to 21.5% in the most demanding panel-PSM specification (column 7). Notably, the largest effect is observed in the cross-sectional PSM model (column 5), where the % Effect reaches 49.4%, suggesting that compositionally mismatched households face substantial income disadvantages.

Control variables mirror the individual-level results in direction and significance. Men, single individuals, and members of larger households face elevated risks. Generation Z remains the most exposed demographic group. Migrant status, especially for non-EU origins, carries a large and positive effect on poverty. Having a permanent contract, working full-time, and holding a managerial position are negatively associated with educational mismatch. Homeownership, both outright and mortgaged, substantially reduces poverty risks, with estimated negative effects between 7% and 9.8%. In contrast, reduced rent status is linked to elevated poverty risks. The results for industry categories remain consistent, highlighting higher poverty risks in agriculture and food services, and lower risks in ICT, finance, and public administration sectors.

Finally, Table 11 disaggregates the educational mismatch variable into overeducation and undereducation components at both individual and household levels. At the individual level, undereducation is associated with a significantly higher probability of poverty, with a % Effect of 34.7% in the baseline model, increasing to 51% for the household level mismatch. These results underscore the persistent vulnerability of undereducated workers across all estimation strategies. The effect remains statistically significant and sizeable in the panel and PSM models, with % Effects ranging from 5.1% to 11.6%.

The effect of overeducation is also statistically significant, but more nuanced. In the baseline model, overeducation increases poverty risk by 7.6%. However, in the PSM (column 3), the effect turns negative (-12.2%), suggesting potential heterogeneity in the nature of overeducation. In the panel data specifications, the effect is small and statistically insignificant under the PSM, indicating that overeducation may not be as strongly linked to poverty risk once longitudinal variation and selection are accounted for.

Overall, the results in this subsection provide robust and consistent evidence that educational mismatch, especially undereducation, is strongly associated with elevated risk of poverty. The analysis confirms this pattern across individual and household levels, a variety of estimation methods, and both cross-sectional and longitudinal data structures. The inclusion of detailed controls and the use of PSM techniques support the robustness of these findings and underscore the role of mismatch as a structural driver of economic vulnerability across European labour markets.

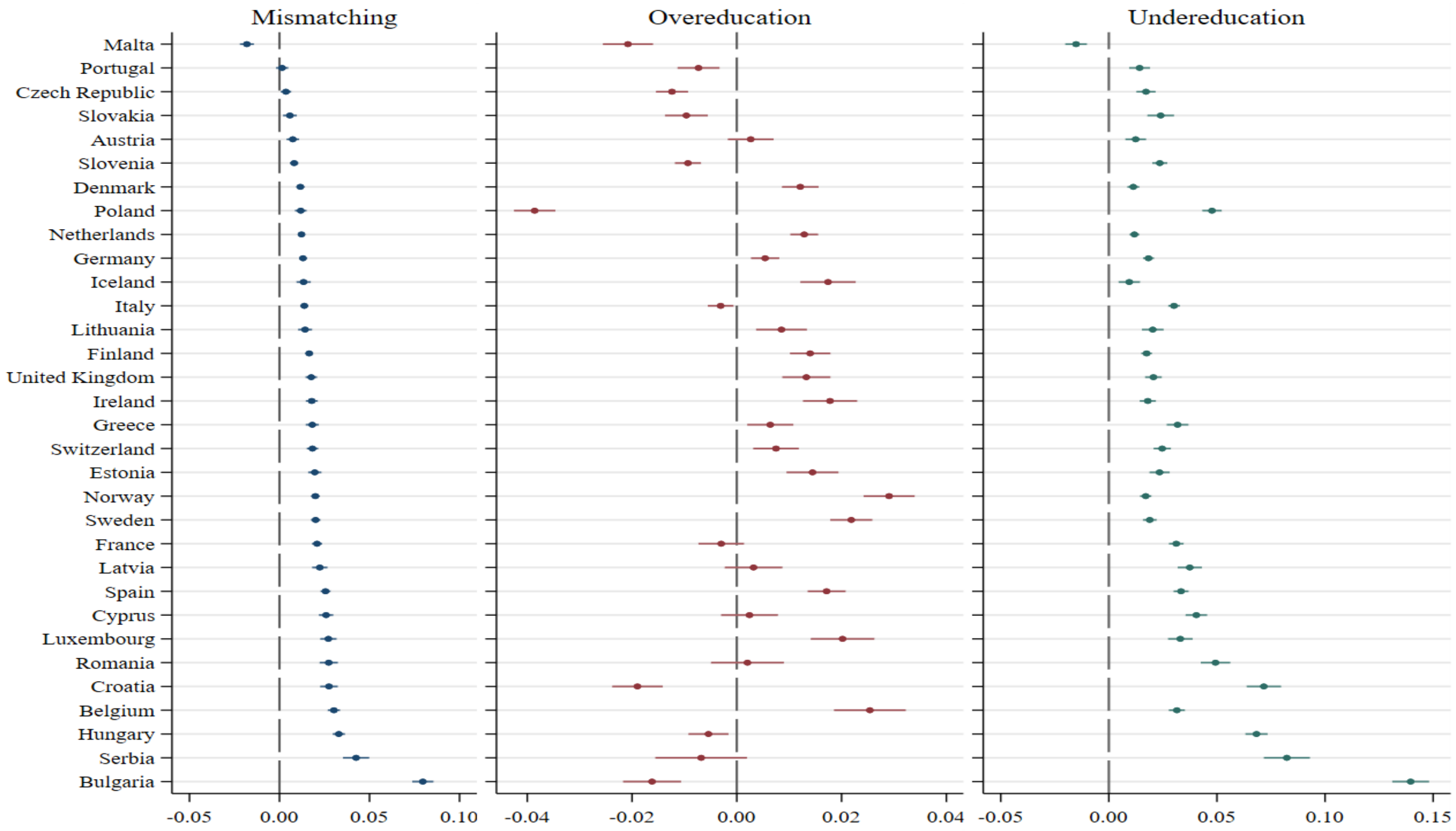

Figure 11: The effect of educational mismatch (individual level) on relative poverty by country

Notes: This figure shows the effects of educational mismatch on the likelihood of being at risk of poverty. Results from separate OLS regressions per country are presented. Coefficients correspond to the individual-level educational mismatch. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

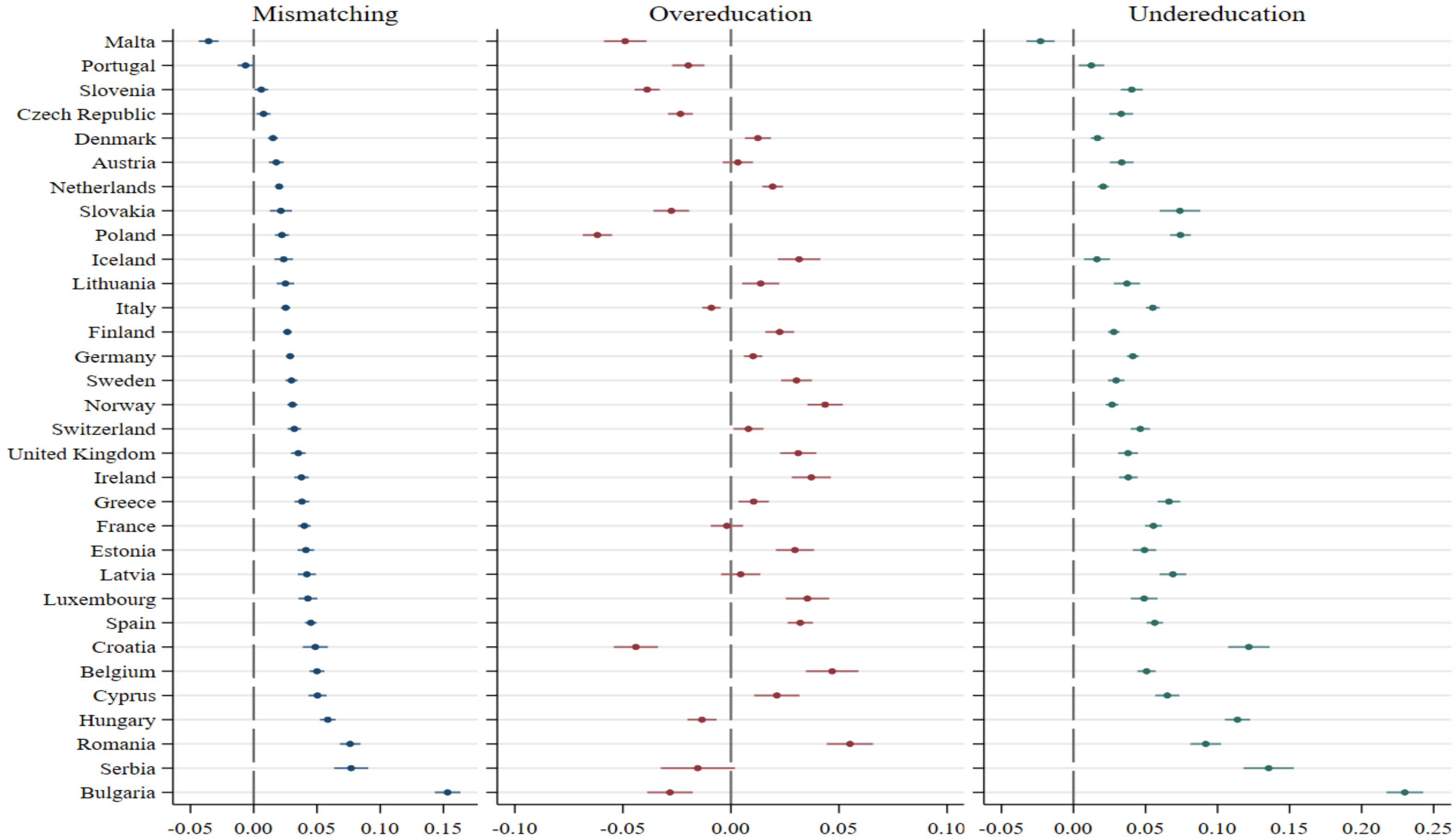

Figure 12: The effect of educational mismatch (% of household) on relative poverty by country

Notes: This figure shows the effects of educational mismatch on the likelihood of being at risk of poverty. Results from separate OLS regressions per country are presented. Coefficients correspond to the household-level educational mismatch. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

Table 9: The effects of educational mismatch (individual level) on relative poverty

	Repeated cross-sections					Longitudinal	
					PSM		PSM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mismatched employee	0.022***	0.020***	0.016***	0.011***	0.012***	0.006***	0.006***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]
Male	0.025***	0.024***	0.018***	0.019***	0.024***	0.005***	0.006
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.004]
Generation Z: Born >1995	0.048***	0.031***	0.041***	0.036***	0.072***	0.134***	0.150***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.013]	[0.022]
Generation Y: Born 1977-1995	0.031***	0.016***	0.025***	0.029***	0.055***	0.070***	0.083***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.009]	[0.013]
Generation X: Born 1965-1976	0.034***	0.025***	0.033***	0.035***	0.063***	0.058***	0.069***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.009]	[0.013]
Generation B: Born 1946-1964	0.025***	0.019***	0.026***	0.026***	0.052***	0.035***	0.041***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.009]	[0.012]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	-0.018***	-0.010***	-0.008***	-0.006***	-0.011***	-0.013***	-0.010***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
"-": Widow/Divorced	0.040***	0.038***	0.039***	0.037***	0.045***	0.023***	0.028***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	0.005***	0.009***	0.008***	0.006***	0.007***	0.005***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Limit Health	0.027***	0.024***	0.021***	0.019***	0.020***	0.004***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Residence: City	-0.007***	-0.014***	-0.008***	-0.004***	-0.009***	-0.014***	-0.014***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
"-": Rural	0.031***	0.033***	0.021***	0.018***	0.033***	0.019***	0.017***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
"-": Missing	0.008***	0.005***	0.006***	0.005***	0.014***	-0.068**	-0.091**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.028]	[0.046]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	0.053***	0.035***	0.030***	0.031***	0.057***	–	–
	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	–	–
"-": from non-EU country	0.108***	0.086***	0.081***	0.082***	0.107***	–	–
	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]	–	–
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	-0.104***	-0.103***	-0.084***	-0.086***	-0.115***	-0.056***	-0.060***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Full time job	-0.064***	-0.062***	-0.059***	-0.058***	-0.066***	-0.027***	-0.033***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Managerial position	-0.031***	-0.027***	-0.027***	-0.020***	-0.033***	–	–
	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]		
Homeownership: Outright	–	-0.063***	-0.064***	-0.062***	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Mortgage	–	-0.083***	-0.080***	-0.076***	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Rent	–	0.004**	0.002	0.001	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Reduced rent	–	0.021***	0.019***	0.015***	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Provided free	–	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–	–
Nace: (a) Agriculture	–	–	0.149***	0.150***	–	–	–

			[0.002]	[0.002]			
"-": (b-e) Mining, Manufacturing	–	–	-0.033***	-0.030***	–	–	–
			[0.001]	[0.001]			
"-": (g) Wholesale & retail trade	–	–	-0.011***	-0.010***	–	–	–
			[0.001]	[0.001]			
"-": (h) Transport and storage	–	–	-0.027***	-0.027***	–	–	–
			[0.001]	[0.001]			
"-": (i) Accom. & Food services	–	–	0.026***	0.025***	–	–	–
			[0.002]	[0.002]			
"-": (j) ICT services	–	–	-0.043***	-0.025***	–	–	–
			[0.002]	[0.002]			
"-": (k) Financial activities	–	–	-0.053***	-0.039***	–	–	–
			[0.001]	[0.001]			
"-": (l-n) Business &	–	–	-0.024***	-0.012***	–	–	–
			[0.001]	[0.001]			
"-": (o) Public administration	–	–	-0.046***	-0.034***	–	–	–
			[0.001]	[0.001]			
"-": (p) Education	–	–	-0.049***	-0.027***	–	–	–
			[0.001]	[0.001]			
"-": (q) Health & Care services	–	–	-0.035***	-0.023***	–	–	–
			[0.001]	[0.001]			
"-": (r-u) Arts, recreation, other	–	–	0.011***	0.017***	–	–	–
			[0.002]	[0.002]			
"-": Missing	–	–	-0.046***	-0.039***	–	–	–
			[0.002]	[0.002]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education	–	–	–	-0.056***	–	–	–
				[0.001]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	*23.20%*	*20.84%*	*16.68%*	*11.37%*	*11.66%*	*5.75%*	*5.19%*
Linear prediction	*0.0938*	*0.0938*	*0.0938*	*0.0938*	*0.1025*	*0.1001*	*0.1146*
No. of Observations	*4,712,988*	*4,709,880*	*4,709,880*	*4,709,702*	*2,519,565*	*3,715,060*	*1,434,545*

Notes: This table reports the effect of educational mismatch at the individual level on the likelihood of being at risk of poverty. The main independent variable is a binary indicator equal to 1 if the individual is employed in a job that does not match their formal educational qualifications (i.e., a mismatched employee), and 0 otherwise. The dependent variable is a binary indicator equal to 1 if a household's disposable income falls below 60% of the national median income, and 0 otherwise. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 10: The effects of educational mismatch (% of household) on relative poverty

	Repeated cross-sections					Longitudinal	
					P-scoreP		P-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% Mismatched employees at	0.040***	0.036***	0.032***	0.025***	0.056***	0.010***	0.030***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Male	0.010***	0.010***	0.013***	0.013***	0.025***	-0.005***	0.003
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.005]
Generation Z: Born >1995	0.049***	0.034***	0.040***	0.037***	0.098***	0.127***	0.243***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.010]	[0.034]
Generation Y: Born 1977-1995	0.043***	0.025***	0.038***	0.042***	0.066***	0.078***	0.093***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.007]	[0.016]
Generation X: Born 1965-1976	0.044***	0.034***	0.048***	0.050***	0.072***	0.064***	0.075***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.007]	[0.016]
Generation B: Born 1946-1964	0.033***	0.027***	0.038***	0.036***	0.061***	0.036***	0.044***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.007]	[0.015]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	-0.014***	-0.005***	-0.005***	-0.003***	-0.012***	-0.014***	-0.012***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.004]
"-": Widow/Divorced	0.041***	0.038***	0.041***	0.039***	0.040***	0.023***	0.025***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.004]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	0.012***	0.016***	0.013***	0.011***	0.012***	0.008***	0.010***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Limit Health	0.031***	0.026***	0.020***	0.017***	0.020***	0.006***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Residence: City	-0.007***	-0.015***	-0.011***	-0.006***	-0.008***	-0.014***	-0.019***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
"-": Rural	0.033***	0.036***	0.026***	0.023***	0.032***	0.023***	0.017***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.003]
"-": Missing	0.013***	0.009***	0.008***	0.008***	0.018***	-0.042	-0.07
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.026]	[0.056]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	0.060***	0.038***	0.033***	0.035***	0.057***	–	–
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]		
"-": from non-EU country	0.121***	0.095***	0.090***	0.091***	0.116***	–	–
	[0.002]	[0.002]	[0.002]	[0.002]	[0.001]		
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	-0.109***	-0.108***	-0.077***	-0.078***	-0.124***	-0.060***	-0.065***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Full time job	-0.046***	-0.045***	-0.054***	-0.052***	-0.071***	-0.017***	-0.039***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Managerial position	-0.036***	-0.031***	-0.027***	-0.018***	-0.035***	–	–
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]		
Homeownership: Outright	–	-0.074***	-0.074***	-0.071***	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Mortgage	–	-0.098***	-0.095***	-0.090***	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Rent	–	0.005**	0.005**	0.004*	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Reduced rent	–	0.027***	0.026***	0.020***	–	–	–
		[0.003]	[0.003]	[0.003]			
"-": Provided free	–	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–	–
Nace: (a) Agriculture	–	–	0.143***	0.144***	–	–	–

			[0.002]	[0.002]			
"-": (b-e) Mining, Manufacturing	–	–	-0.034***	-0.031***	–	–	–
			[0.001]	[0.001]			
"-": (g) Wholesale & retail trade	–	–	-0.012***	-0.010***	–	–	–
			[0.001]	[0.001]			
"-": (h) Transport and storage	–	–	-0.026***	-0.026***	–	–	–
			[0.001]	[0.001]			
"-": (i) Accom. & Food services	–	–	0.022***	0.021***	–	–	–
			[0.002]	[0.002]			
"-": (j) ICT services	–	–	-0.037***	-0.016***	–	–	–
			[0.002]	[0.002]			
"-": (k) Financial activities	–	–	-0.050***	-0.033***	–	–	–
			[0.001]	[0.001]			
"-": (l-n) Business & Professionals	–	–	-0.021***	-0.006***	–	–	–
			[0.001]	[0.001]			
"-": (o) Public administration	–	–	-0.043***	-0.030***	–	–	–
			[0.001]	[0.001]			
"-": (p) Education	–	–	-0.045***	-0.019***	–	–	–
			[0.001]	[0.001]			
"-": (q) Health & Care services	–	–	-0.032***	-0.018***	–	–	–
			[0.001]	[0.001]			
"-": (r-u) Arts, recreation, other	–	–	0.010***	0.018***	–	–	–
			[0.002]	[0.002]			
"-": Missing	–	–	0.039***	0.043***	–	–	–
			[0.001]	[0.001]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education (household)	–	–	–	-0.069***	–	–	–
				[0.001]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	34.69%	31.22%	28.15%	21.46%	49.37%	8.20%	21.53%
Linear prediction	0.1143	0.1143	0.1143	0.1143	0.1138	0.1230	0.1379
No. of Observations	5,900,319	5,895,640	5,895,640	5,895,448	1,775,726	4,787,646	867,466

Notes: This table reports the effect of educational mismatch at the household level on the likelihood of being at risk of poverty. The main independent variable is the proportion of mismatched employees within the household. The dependent variable is a binary indicator equal to 1 if a household's disposable income falls below 60% of the national median income, and 0 otherwise. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 11: The effects of educational mismatch types on relative poverty: Over- and Undereducation

	Repeated cross-sections				Longitudinal			
	Individual	**Household**	**P-score**	**P-score**	**Individual**	**Household**	**P-score**	**P-score**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overeducated employee	0.007***	0.012***	-0.012***	–	0.003***	0.005***	0.001	–
	[0.001]	[0.001]	[0.001]		[0.001]	[0.001]	[0.002]	
Undereducated employee	0.033***	0.058***	–	0.028***	0.008***	0.014***	–	0.006***
	[0.001]	[0.001]		[0.001]	[0.001]	[0.001]		[0.002]
Male	0.025***	0.010***	0.019***	0.027***	0.005***	-0.005***	-0.002	0.006
	[0.000]	[0.000]	[0.001]	[0.001]	[0.002]	[0.001]	[0.006]	[0.005]
Generation Z: Born >1995	0.049***	0.051***	0.088***	0.063***	0.135***	0.127***	0.195***	0.203***
	[0.003]	[0.003]	[0.004]	[0.003]	[0.013]	[0.010]	[0.030]	[0.035]
Generation Y: Born 1977-1995	0.035***	0.046***	0.064***	0.061***	0.070***	0.078***	0.106***	0.103***
	[0.002]	[0.002]	[0.003]	[0.002]	[0.009]	[0.007]	[0.020]	[0.016]
Generation X: Born 1965-1976	0.037***	0.047***	0.073***	0.066***	0.058***	0.064***	0.094***	0.074***
	[0.002]	[0.002]	[0.003]	[0.002]	[0.009]	[0.007]	[0.020]	[0.016]
Generation B: Born 1946-1964	0.027***	0.034***	0.063***	0.053***	0.035***	0.037***	0.066***	0.037**
	[0.002]	[0.002]	[0.003]	[0.002]	[0.009]	[0.007]	[0.020]	[0.015]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	-0.019***	-0.014***	-0.006***	-0.018***	-0.013***	-0.014***	-0.010***	-0.008**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.004]	[0.004]
"-": Widow/Divorced	0.039***	0.041***	0.051***	0.040***	0.023***	0.023***	0.030***	0.030***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.005]	[0.004]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	0.005***	0.011***	0.005***	0.008***	0.005***	0.008***	0.003**	0.003***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]
Limit Health	0.027***	0.030***	0.018***	0.020***	0.004***	0.006***	0.005***	0.003**
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.001]
Residence: City	-0.007***	-0.006***	-0.009***	-0.008***	-0.014***	-0.014***	-0.020***	-0.014***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.004]	[0.003]
"-": Rural	0.031***	0.033***	0.035***	0.030***	0.019***	0.023***	0.008*	0.013***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.004]	[0.003]
"-": Missing	0.007***	0.011***	0.017***	0.016***	-0.067**	-0.042	0.029	-0.112*
	[0.002]	[0.002]	[0.002]	[0.002]	[0.028]	[0.026]	[0.054]	[0.065]

"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	0.053***	0.061***	0.058***	0.059***	–	–	–	–
	[0.002]	[0.002]	[0.002]	[0.002]				
"-": from non-EU country	0.108***	0.122***	0.106***	0.115***	–	–	–	–
	[0.002]	[0.002]	[0.002]	[0.001]				
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	-0.104***	-0.109***	-0.117***	-0.116***	-0.056***	-0.060***	-0.055***	-0.060***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]
Full time job	-0.064***	-0.046***	-0.068***	-0.067***	-0.027***	-0.017***	-0.035***	-0.033***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]
Managerial position	-0.031***	-0.035***	-0.031***	-0.032***	–	–	–	–
	[0.001]	[0.001]	[0.001]	[0.001]				
Year Effects	+	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	+	+	+	+
% Effect overeducation	7.56%	10.50%	-12.18%	–	2.94%	4.01%	0.24%	–
% Effect undereducation	34.65%	51.02%	–	26.87%	8.30%	11.62%	–	5.09%
Linear prediction	0.0938	0.1143	0.1021	0.1055	0.1001	0.1230	0.1103	0.1226
No. of Observations	4,712,988	5,900,319	1,342,879	1,668,140	3,715,060	4,787,646	600,947	839,080

Notes: This table reports the effect of different types of educational mismatch on the likelihood of being at risk of poverty. The main independent variables are binary indicators identifying whether the individual is (i) overeducated – employed in a job that requires lower qualifications than their formal education or (ii) undereducated – employed in a job that requires higher qualifications than their formal education. The dependent variable is a binary indicator equal to 1 if a household's disposable income falls below 60% of the national median income, and 0 otherwise. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

5. Educational Mismatch and Household Financial Resilience

Financial resilience is defined as the ability of a household to cover unexpected expenses, serving as a key indicator of short-term economic stability. This subsection uses the same methodological structure as in the previous section, drawing on both individual- and household-level mismatch indicators, and applying OLS, propensity score matching (PSM), and panel data techniques.

5.1 Country-Level Heterogeneity in the Effect of Mismatch

Figure 13 illustrates the association between individual-level educational mismatch and the likelihood that a household can cover unexpected financial expenses, estimated through separate OLS regressions by country. Across most European countries, the estimated coefficients are negative and statistically significant, indicating that being mismatched is associated with lower household financial resilience. The strength of the association varies, with relatively larger negative effects observed in countries such as Ireland, Bulgaria, Hungary, Cyprus, Belgium, Spain, France, Latvia and Greece. These results are consistent with those in the poverty analysis, suggesting that mismatch reduces the ability of households to buffer financial shocks, especially in countries with weaker safety nets or more precarious labour markets.

Figure 14 shifts to household-level mismatch, using the share of mismatched individuals within a household as the key independent variable. The patterns mirror those at the individual level, with a general tendency for a higher proportion of mismatched workers in the household to be associated with reduced financial resilience. The estimates are statistically significant in most countries, reaffirming that mismatch has compositional effects beyond individual earnings, affecting the economic stability of entire households.

5.2 Multivariate Regression Estimates

Table 12 presents the estimated effects of individual-level mismatch on the probability that a household can meet unexpected financial expenses. The direction of the estimated effects is consistently negative and statistically significant across all specifications. In terms of economic magnitude, in the baseline model (column 1), being mismatched reduces financial resilience by 6.6%. The estimated effect declines slightly when additional controls are introduced, falling to -2.4% in column (4). Under PSM (column 5), the effect remains negative and significant (-3.5%), while the panel estimates indicate somewhat smaller effects of -1.3% (column 6) and -1.2% (column 7).

This attenuation across models is similar to the pattern observed in the poverty analysis, reinforcing the robustness of the negative association. Even after controlling for unobserved heterogeneity in panel specifications, the negative and significant relationship between mismatch and financial resilience remains, underscoring that mismatched workers are systematically more financially vulnerable.

Table 13 extends the analysis to household-level mismatch. The results are again negative and statistically significant in all model specifications. The economic magnitude of the effects is larger than those observed in Table 12, suggesting a cumulative impact when more household members are mismatched. In the baseline model (column 1), a higher share of mismatched workers in the household reduces financial resilience by 10.1%. This effect declines to -4.4% in the most saturated model (column 4). The largest effect is again observed under the PSM approach (column 5), where the reduction in resilience is -12.2%. Columns (6)-(7) present the panel specifications, where the results are similar in terms of sign and statistical significance but smaller in magnitude, reaches -4.6% in the panel-PSM specification (column 7).

These results highlight the household-level vulnerabilities induced by mismatch and point to the importance of considering household structures in assessing the socio-economic impacts of labour market inefficiencies.

Finally, Table 14 disaggregates the mismatch variable into overeducation and undereducation at both individual and household levels. At the individual level, undereducation is strongly and consistently associated with lower financial resilience across all specifications. The negative effect is -11.9% in the baseline model for the individual level mismatch, -17.3% for the household level mismatch. This negative effect remains significant across all models, including -11% in the panel-PSM. Overeducation exerts an opposite, but much smaller in size, effect on financial resilience, ranging from 4.6% in PSM specification (column 4) to 0.6% (column 2). In the panel specifications the effect of overeducation is statistically insignificant across columns (7) and (8).

Overall, the results presented here consistently show that educational mismatch – particularly undereducation – is negatively associated with household financial resilience. This relationship is evident at both the individual and household levels, robust across multiple specifications, and persists even when controlling for time-invariant unobserved characteristics. The economic magnitude of the effect is non-negligible, suggesting that skills mismatch undermines the capacity of households to absorb financial shocks.

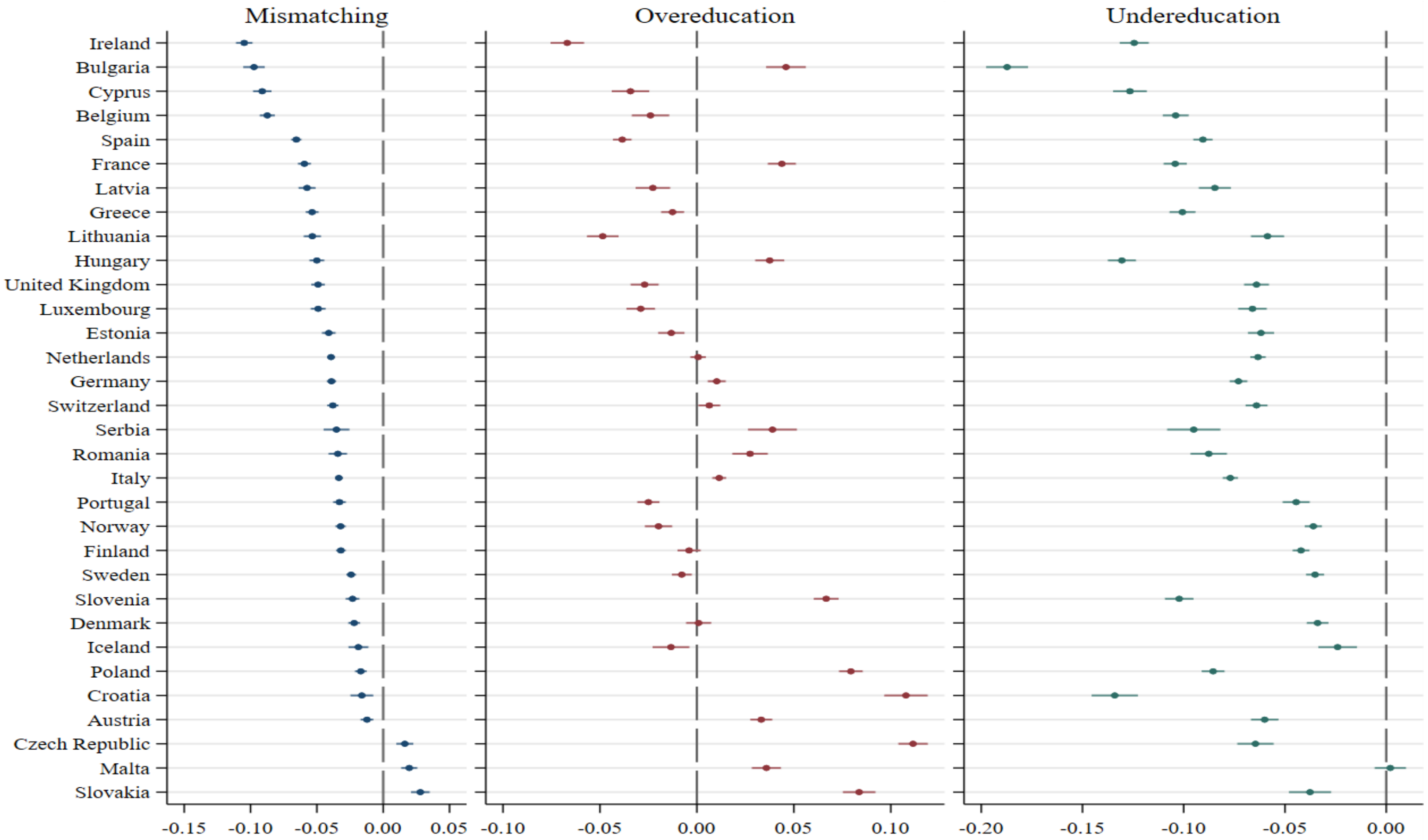

Figure 13: The effect of educational mismatch (individual level) on household financial resilience by country

Notes: This figure shows the effects of educational mismatch on the likelihood of a household being financially resilient. Results from separate OLS regressions per country are presented. Coefficients correspond to the individual-level mismatches. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

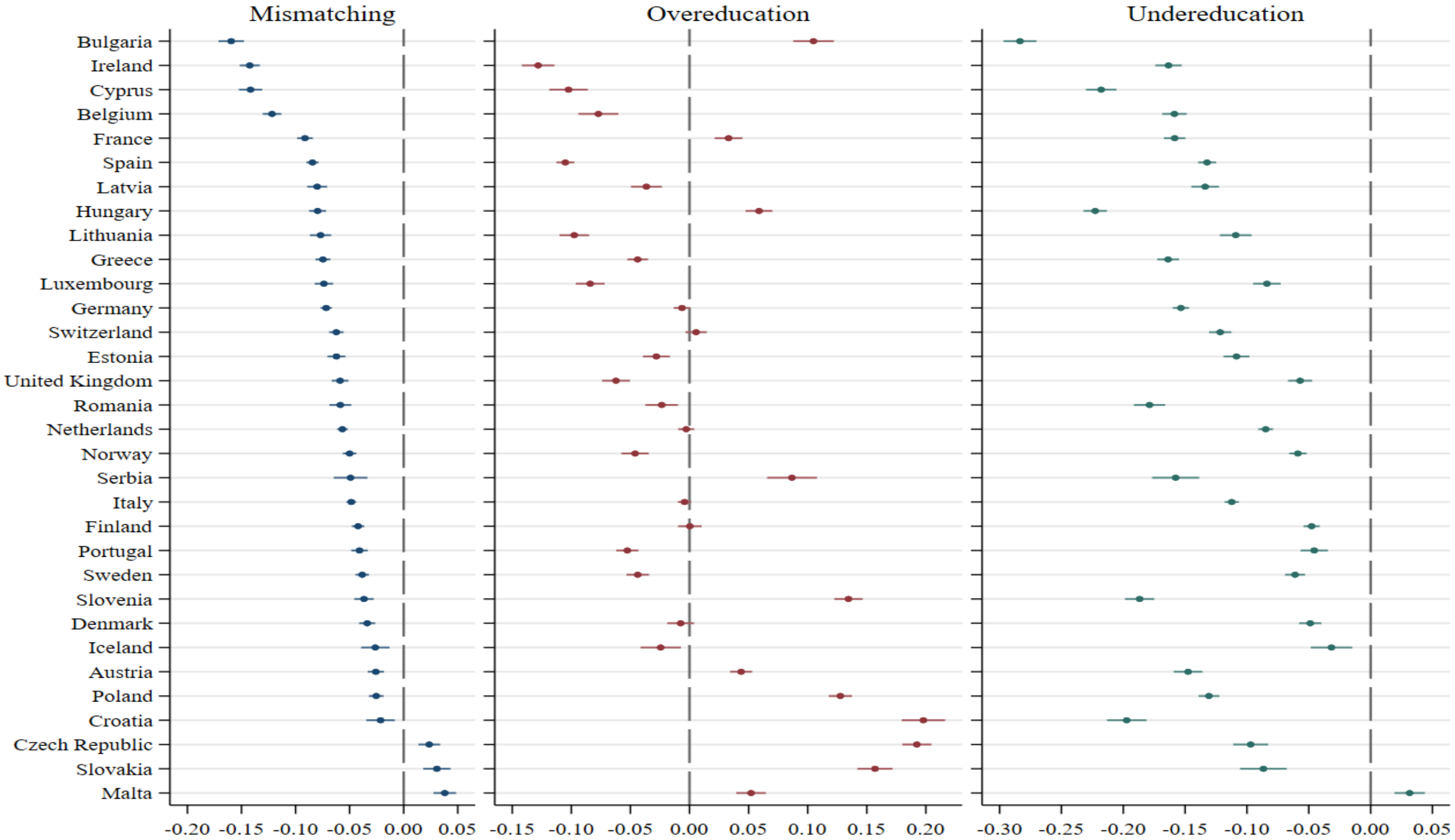

Figure 14:The effect of educational mismatch (% of household) on household financial resilience by country

Notes: This figure shows the effects of educational mismatch on the likelihood of a household being financially resilient. Results from separate OLS regressions per country are presented. Coefficients correspond to the household-level mismatches. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

Table 12: The effects of educational mismatch (individual level) on household financial resilience

	Repeated cross-sections					Longitudinal	
					P-score		P-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mismatched employee	-0.047***	-0.041***	-0.036***	-0.017***	-0.034***	-0.009***	-0.008***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Male	-0.013***	-0.011***	0	-0.002***	-0.012***	0.022***	0.035***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.005]
Generation Z: Born >1995	-0.201***	-0.137***	-0.132***	-0.120***	-0.183***	-0.284***	-0.308***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.017]	[0.028]
Generation Y: Born 1977-1995	-0.164***	-0.100***	-0.101***	-0.117***	-0.147***	-0.192***	-0.191***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.011]	[0.017]
Generation X: Born 1965-1976	-0.137***	-0.096***	-0.098***	-0.106***	-0.124***	-0.152***	-0.149***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.011]	[0.017]
Generation B: Born 1946-1964	-0.090***	-0.071***	-0.074***	-0.071***	-0.086***	-0.109***	-0.105***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.011]	[0.016]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	0.074***	0.058***	0.057***	0.051***	0.068***	0.046***	0.049***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.004]
"-": Widow/Divorced	-0.100***	-0.088***	-0.087***	-0.079***	-0.097***	-0.039***	-0.041***
	[0.002]	[0.002]	[0.002]	[0.001]	[0.001]	[0.003]	[0.005]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-0.011***	-0.022***	-0.020***	-0.015***	-0.010***	0.001	0.001
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Limit Health	-0.109***	-0.100***	-0.098***	-0.088***	-0.101***	-0.030***	-0.031***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Residence: City	0.006***	0.027***	0.019***	0.003***	0.004***	0.008***	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.004]
"-": Rural	-0.012***	-0.021***	-0.015***	-0.004***	-0.016***	0.001	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.004]
"-": Missing	0.016***	0.026***	0.023***	0.027***	-0.006**	0.174***	0.267***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.040]	[0.060]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-0.098***	-0.047***	-0.039***	-0.045***	-0.100***	–	–
	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]		
"-": from non-EU country	-0.201***	-0.136***	-0.127***	-0.130***	-0.194***	–	–
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]		
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	0.014***	0.014***	0.003***	0.011***	0.013***	0.021***	0.020***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Full time job	0.052***	0.049***	0.049***	0.043***	0.051***	0.021***	0.026***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Managerial position	0.086***	0.079***	0.077***	0.048***	0.092***	–	–
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]		
Homeownership: Outright	–	0.122***	0.120***	0.112***	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Mortgage	–	0.062***	0.057***	0.042***	–	–	–
		[0.003]	[0.002]	[0.002]			
"-": Rent	–	-0.119***	-0.117***	-0.114***	–	–	–
		[0.003]	[0.003]	[0.003]			
"-": Reduced rent	–	-0.182***	-0.179***	-0.163***	–	–	–
		[0.003]	[0.003]	[0.003]			
"-": Provided free	–	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–	–

Nace: (a) Agriculture	–	–	-0.013***	-0.015***	–	–	–
			[0.002]	[0.002]			
"-": (b-e) Mining, Manufacturing	–	–	0.036***	0.024***	–	–	–
			[0.002]	[0.002]			
"-": (g) Wholesale & retail trade	–	–	0.019***	0.013***	–	–	–
			[0.002]	[0.002]			
"-": (h) Transport and storage	–	–	0.019***	0.016***	–	–	–
			[0.002]	[0.002]			
"-": (i) Accom. & Food services	–	–	-0.023***	-0.021***	–	–	–
			[0.003]	[0.003]			
"-": (j) ICT services	–	–	0.144***	0.078***	–	–	–
			[0.003]	[0.003]			
"-": (k) Financial activities	–	–	0.158***	0.104***	–	–	–
			[0.002]	[0.002]			
"-": (l-n) Business &	–	–	0.075***	0.027***	–	–	–
			[0.002]	[0.002]			
"-": (o) Public administration	–	–	0.091***	0.047***	–	–	–
			[0.002]	[0.002]			
"-": (p) Education	–	–	0.109***	0.025***	–	–	–
			[0.002]	[0.002]			
"-": (q) Health & Care services	–	–	0.050***	0.006***	–	–	–
			[0.002]	[0.002]			
"-": (r-u) Arts, recreation, other	–	–	0.024***	-0.001	–	–	–
			[0.002]	[0.002]			
"-": Missing	–	–	0.051***	0.027***	–	–	–
			[0.002]	[0.002]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education	–	–	–	0.213***	–	–	–
				[0.001]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	-6.55%	-5.74%	-5.01%	-2.41%	-4.82%	-1.31%	-1.19%
Linear prediction	0.7151	0.7151	0.7151	0.7151	0.7018	0.7168	0.7070
No. of Observations	4,699,560	4,697,280	4,697,280	4,697,103	2,515,526	3,709,811	1,434,184

Notes: This table reports the effect of educational mismatch at the individual level on the likelihood of a household being financially resilient. The main independent variable is a binary indicator equal to 1 if the individual is employed in a job that does not match their formal educational qualifications (i.e., a mismatched employee), and 0 otherwise. The dependent variable is a binary indicator equal to 1 if the household has the capacity to face unexpected financial expenses, and 0 otherwise. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 13: The effects of educational mismatch (% of household) on household financial resilience

	Repeated cross-sections					Longitudinal	
					P-score		P-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% Mismatched employees at	-0.070***	-0.060***	-0.055***	-0.030***	-0.084***	-0.012***	-0.026***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Male	-0.001	-0.001	-0.003***	-0.005***	-0.010***	0.021***	0.039***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.002]	[0.006]
Generation Z: Born >1995	-0.158***	-0.101***	-0.092***	-0.087***	-0.209***	-0.199***	-0.371***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]	[0.012]	[0.039]
Generation Y: Born 1977-1995	-0.147***	-0.084***	-0.092***	-0.106***	-0.155***	-0.158***	-0.200***
	[0.003]	[0.002]	[0.002]	[0.002]	[0.003]	[0.009]	[0.021]
Generation X: Born 1965-1976	-0.121***	-0.080***	-0.092***	-0.099***	-0.128***	-0.120***	-0.155***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.009]	[0.020]
Generation B: Born 1946-1964	-0.077***	-0.060***	-0.069***	-0.066***	-0.088***	-0.086***	-0.100***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.009]	[0.020]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	0.066***	0.051***	0.051***	0.046***	0.070***	0.046***	0.049***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.005]
"-": Widow/Divorced	-0.102***	-0.087***	-0.088***	-0.080***	-0.088***	-0.044***	-0.035***
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.006]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-0.016***	-0.026***	-0.022***	-0.016***	-0.016***	-0.004***	-0.002
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]
Limit Health	-0.126***	-0.115***	-0.106***	-0.095***	-0.103***	-0.035***	-0.030***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Residence: City	0.002*	0.025***	0.019***	0.004***	0.002	0.006*	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.005]
"-": Rural	-0.010***	-0.020***	-0.017***	-0.005***	-0.014***	-0.003	0.003
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.005]
"-": Missing	0.012***	0.024***	0.023***	0.024***	-0.009***	0.147***	0.254***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.036]	[0.062]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-0.102***	-0.044***	-0.037***	-0.041***	-0.103***	–	–
	[0.003]	[0.003]	[0.003]	[0.003]	[0.002]		
"-": from non-EU country	-0.202***	-0.131***	-0.122***	-0.124***	-0.204***	–	–
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]		
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	0.034***	0.034***	0.005***	0.008***	0.012***	0.033***	0.020***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Full time job	0.028***	0.028***	0.046***	0.040***	0.052***	0.010***	0.027***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]
Managerial position	0.091***	0.082***	0.076***	0.047***	0.092***	–	–
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]		
Homeownership: Outright	–	0.135***	0.133***	0.124***	–	–	–
		[0.002]	[0.002]	[0.002]			
"-": Mortgage	–	0.073***	0.068***	0.052***	–	–	–
		[0.003]	[0.003]	[0.003]			
"-": Rent	–	-0.121***	-0.121***	-0.117***	–	–	–
		[0.003]	[0.003]	[0.003]			
"-": Reduced rent	–	-0.190***	-0.186***	-0.169***	–	–	–
		[0.003]	[0.003]	[0.003]			
"-": Provided free	–	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–	–

Nace: (a) Agriculture	–	–	-0.008***	-0.011***	–	–	–
			[0.002]	[0.002]			
"-": (b-e) Mining, Manufacturing	–	–	0.034***	0.023***	–	–	–
			[0.002]	[0.002]			
"-": (g) Wholesale & retail trade	–	–	0.016***	0.010***	–	–	–
			[0.002]	[0.002]			
"-": (h) Transport and storage	–	–	0.017***	0.014***	–	–	–
			[0.002]	[0.002]			
"-": (i) Accom. & Food services	–	–	-0.023***	-0.021***	–	–	–
			[0.003]	[0.003]			
"-": (j) ICT services	–	–	0.139***	0.071***	–	–	–
			[0.003]	[0.002]			
"-": (k) Financial activities	–	–	0.151***	0.097***	–	–	–
			[0.002]	[0.002]			
"-": (l-n) Business & Professionals	–	–	0.071***	0.021***	–	–	–
			[0.002]	[0.002]			
"-": (o) Public administration	–	–	0.086***	0.041***	–	–	–
			[0.002]	[0.002]			
"-": (p) Education	–	–	0.103***	0.016***	–	–	–
			[0.002]	[0.002]			
"-": (q) Health & Care services	–	–	0.043***	-0.002	–	–	–
			[0.002]	[0.002]			
"-": (r-u) Arts, recreation, other	–	–	0.022***	-0.004*	–	–	–
			[0.002]	[0.002]			
"-": Missing	–	–	-0.034***	-0.049***	–	–	–
			[0.002]	[0.002]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education (household)	–	–	–	0.225***	–	–	–
				[0.001]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	-10.07%	-8.70%	-7.99%	-4.38%	-12.24%	-1.81%	-3.88%
Linear prediction	0.6916	0.6916	0.6916	0.6916	0.6832	0.6920	0.6770
No. of Observations	5,879,829	5,876,648	5,876,648	5,876,457	1,772,732	4,778,221	867,263

Notes: This table reports the effect of educational mismatch at the household level on the likelihood of a household being financially resilient. The main independent variable is the proportion of mismatched employees within the household. The dependent variable is a binary indicator equal to 1 if the household has the capacity to face unexpected financial expenses, and 0 otherwise. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 14: The effects of educational mismatch types on household financial resilience: Over- and Undereducation

	Repeated cross-sections				Longitudinal			
	Individual	**Household**	**P-score**	**P-score**	**Individual**	**Household**	**P-score**	**P-score**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overeducated employee	0.006***	0.004**	0.032***	–	-0.001	-0.002	0.003	–
	[0.001]	[0.002]	[0.001]		[0.001]	[0.002]	[0.003]	
Undereducated employee	-0.085***	-0.119***	–	-0.076***	-0.017***	-0.021***	–	-0.014***
	[0.001]	[0.001]		[0.001]	[0.001]	[0.002]		[0.002]
Male	-0.013***	-0.001	-0.004***	-0.014***	0.022***	0.021***	0.039***	0.043***
	[0.001]	[0.000]	[0.001]	[0.001]	[0.003]	[0.002]	[0.008]	[0.007]
Generation Z: Born >1995	-0.207***	-0.164***	-0.193***	-0.178***	-0.286***	-0.200***	-0.313***	-0.365***
	[0.004]	[0.003]	[0.005]	[0.004]	[0.017]	[0.012]	[0.041]	[0.043]
Generation Y: Born 1977-1995	-0.176***	-0.157***	-0.149***	-0.167***	-0.194***	-0.159***	-0.178***	-0.260***
	[0.003]	[0.003]	[0.004]	[0.003]	[0.011]	[0.009]	[0.028]	[0.023]
Generation X: Born 1965-1976	-0.148***	-0.129***	-0.128***	-0.136***	-0.154***	-0.121***	-0.144***	-0.199***
	[0.003]	[0.002]	[0.004]	[0.003]	[0.011]	[0.009]	[0.027]	[0.022]
Generation B: Born 1946-1964	-0.096***	-0.081***	-0.093***	-0.088***	-0.110***	-0.086***	-0.094***	-0.145***
	[0.002]	[0.002]	[0.004]	[0.003]	[0.011]	[0.009]	[0.027]	[0.021]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	0.075***	0.064***	0.063***	0.077***	0.046***	0.046***	0.046***	0.046***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]	[0.005]	[0.005]
"-": Widow/Divorced	-0.099***	-0.102***	-0.102***	-0.088***	-0.039***	-0.044***	-0.041***	-0.033***
	[0.002]	[0.001]	[0.002]	[0.002]	[0.003]	[0.003]	[0.007]	[0.006]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-0.011***	-0.015***	-0.008***	-0.011***	-0.001	-0.004***	0.002	0.002
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.002]	[0.001]
Limit Health	-0.107***	-0.124***	-0.097***	-0.104***	-0.030***	-0.035***	-0.029***	-0.029***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.002]	[0.002]
Residence: City	0.005***	0.002	0.003**	0	0.008***	0.006*	0.005	0.002
	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.003]	[0.006]	[0.005]
"-": Rural	-0.012***	-0.010***	-0.013***	-0.013***	-0.001	-0.003	0.004	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.003]	[0.006]	[0.004]
"-": Missing	0.020***	0.018***	-0.015***	-0.004	0.173***	0.146***	0.239***	0.149*
	[0.003]	[0.003]	[0.004]	[0.003]	[0.040]	[0.036]	[0.090]	[0.077]

"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-0.101***	-0.106***	-0.110***	-0.102***	–	–	–	–
	[0.003]	[0.003]	[0.003]	[0.002]				
"-": from non-EU country	-0.203***	-0.205***	-0.209***	-0.198***	–	–	–	–
	[0.002]	[0.002]	[0.002]	[0.002]				
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	0.014***	0.034***	0.019***	0.010***	0.021***	0.033***	0.019***	0.019***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.002]
Full time job	0.052***	0.029***	0.053***	0.046***	0.021***	0.010***	0.030***	0.025***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.003]	[0.002]
Managerial position	0.086***	0.090***	0.082***	0.094***	–	–	–	–
	[0.001]	[0.001]	[0.001]	[0.001]				
Year Effects	+	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	+	+	+	+
% Effect overeducation	0.77%	0.59%	4.57%	–	-0.08%	-0.27%	0.37%	–
% Effect undereducation	-11.91%	-17.28%	–	-11.02%	-2.43%	-3.06%	–	-2.07%
Linear prediction	0.7151	0.6916	0.7095	0.6885	0.7168	0.6920	0.7201	0.6880
No. of Observations	4,699,560	5,879,829	1,341,056	1,665,178	3,709,811	4,778,221	601,266	838,762

Notes: This table reports the effect of different types of educational mismatch on the likelihood of a household being financially resilient. The main independent variables are binary indicators identifying whether the individual is (i) overeducated – employed in a job that requires lower qualifications than their formal education or (ii) undereducated – employed in a job that requires higher qualifications than their formal education. The dependent variable is a binary indicator equal to 1 if the household has the capacity to face unexpected financial expenses, and 0 otherwise. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

6. Educational Mismatch and Household Income Inequality

We now focus on the relationship between educational mismatch and household relative income, a percentile-based indicator measuring the household's position within the national income distribution. The analysis follows the same methodological structure as in the previous subsections, drawing on both individual- and household-level mismatch indicators, and applying OLS, propensity score matching (PSM), and panel data techniques.

6.1 Country-Level Heterogeneity in the Effect of Mismatch

Figure 15 presents the country-specific effects of individual-level educational mismatch on household relative income, as estimated through separate OLS regressions by country. Each coefficient reflects the association between an individual's mismatch status and their household's placement in the income distribution (scaled from 0 to 100). The pattern is strikingly consistent across countries: in nearly all national contexts, mismatch is associated with a statistically significant reduction in household relative income. The most substantial negative effects are observed in Ireland, Spain, Lithuania, Cyprus, Belgium, Latvia, Bulgaria, United Kingdom. By contrast, in some Northern and Western European countries with more generous welfare states, the negative effects are present but relatively modest, likely due to stronger social protections or more efficient labour markets.

Figure 16 shifts to the household-level mismatch indicator, measuring the proportion of mismatched workers in the household. The negative and statistically significant association persists across most countries. This reinforces the notion that the accumulation of mismatch within households compounds economic disadvantage, pushing families lower in the income distribution. The consistency across figures underscores the broader welfare consequences of mismatch and its spillover effects beyond the individual level.

6.2 Multivariate Regression Estimates

Table 15 examines the effects of being mismatched at the individual level on household relative income across a range of model specifications. The coefficients for the educational mismatch variable are negative and statistically significant in all seven models, indicating a meaningful reduction in household income rank for mismatched individuals. The baseline OLS model (column 1) estimates an effect of -9.3%, which gradually decreases to -3.9% after controlling for additional covariates (column 4). The PSM estimate (column 5) yields a slightly greater impact of -6.7%. In the panel regressions (columns 6 and 7), which account for time-invariant unobserved heterogeneity, the effect is smaller, -2.7% and -2.9%, respectively, but remains statistically significant, affirming the robustness of the negative relationship.

Table 16 extends the analysis to the household level by using the share of mismatched employed individuals in the household as the key predictor. The results are consistent with those in Table 15: the coefficients remain negative and significant throughout. In the baseline OLS model, the effect reaches -13.5%, indicating a substantial drop in household relative income for households with higher mismatch incidence. This effect gradually decreases as more controls are introduced into the model, reaching -6.4%. Importantly the PSM estimate (column 5) gives the greatest effect of -17.6%. After applying panel techniques, the effect remains strong and persistent but smaller in magnitude, around -3.2% in column (6) and -7.2% in column (7). These findings confirm that mismatch has implications not only for individual workers but also for the broader economic positioning of their households.

Table 17 decomposes the mismatch variable into its two components: overeducation and undereducation, at both individual and household levels. The results reveal important asymmetries. At the individual level, undereducation has the strongest and most robust negative effect on household relative income. In the baseline model, undereducation is associated with an effect of -12.6%, while in the panel model (column 6) it remains negative and significant at -3%. The PSM specifications in both cross-sectional and panel version confirm this pattern, suggesting that undereducation consistently undermines income positioning. Overeducation also exerts a negative impact, though the effects are more modest and less robust across all specifications.

At the household level, the compositional effects mirror the individual-level findings. The share of undereducated individuals in the household significantly reduces relative income ranking, with an effect of -17.8% in the baseline model and -4.1% in the panel data version. Overeducation, by contrast, produces a very smaller effect (-7.2% in baseline) and becomes insignificant in the final two specifications. These results suggest that undereducation is a more persistent and impactful driver of household income disadvantage, whereas the effect of overeducation is more heterogeneous and potentially mediated by other household or job characteristics.

Taken together, the results in this subsection indicate that skills mismatch, particularly undereducation, significantly reduces household standing in the national income distribution. This relationship holds across multiple estimation techniques and data structures, reinforcing the view that mismatch contributes not only to labour market inefficiencies but also to broader patterns of income inequality and social stratification in Europe.

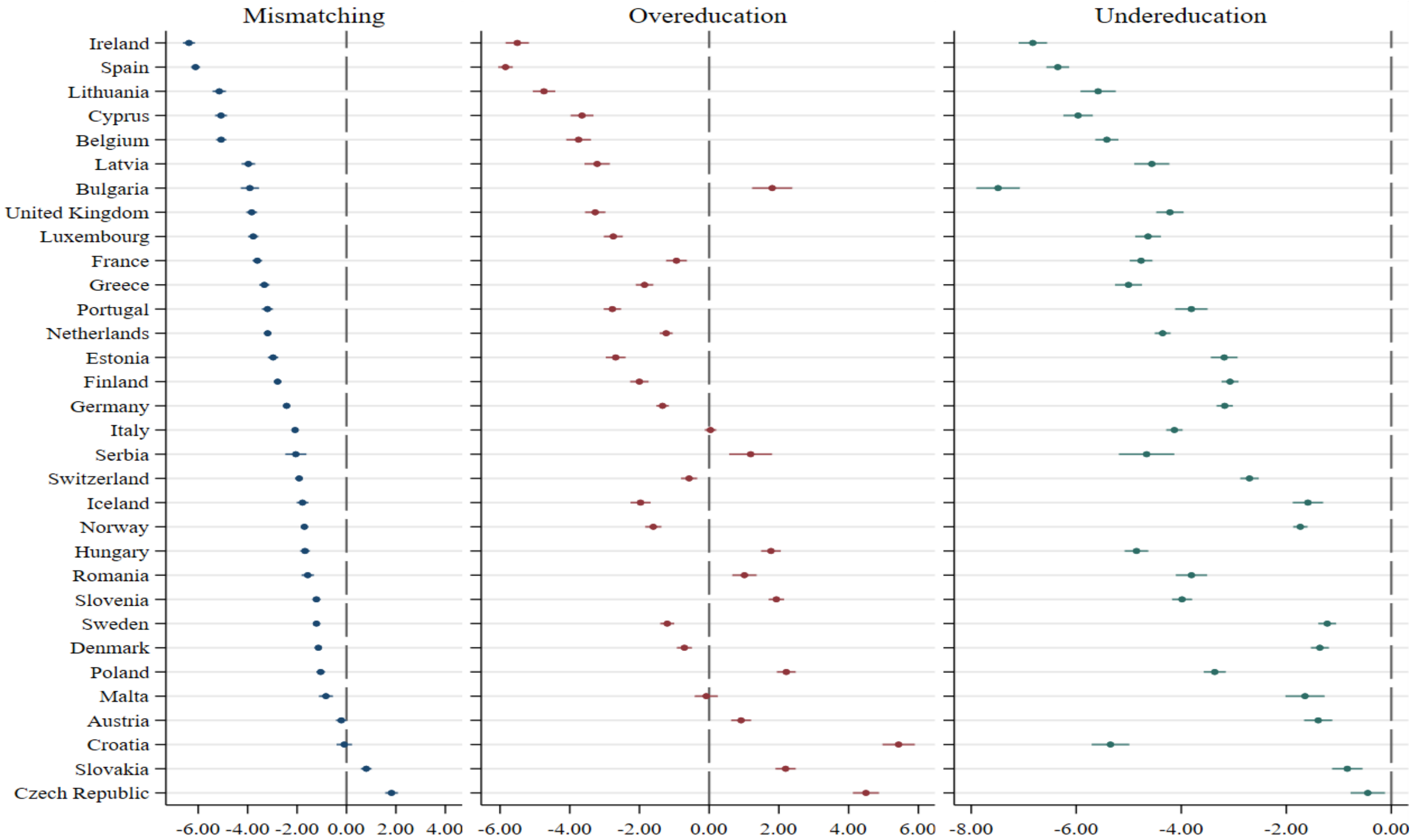

Figure 15: The effect of educational mismatch (individual level) on household relative income by country

Notes: This figure shows the effects of educational mismatch on household relative income. Results from separate OLS regressions per country are presented. Coefficients correspond to the individual-level educational mismatch. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

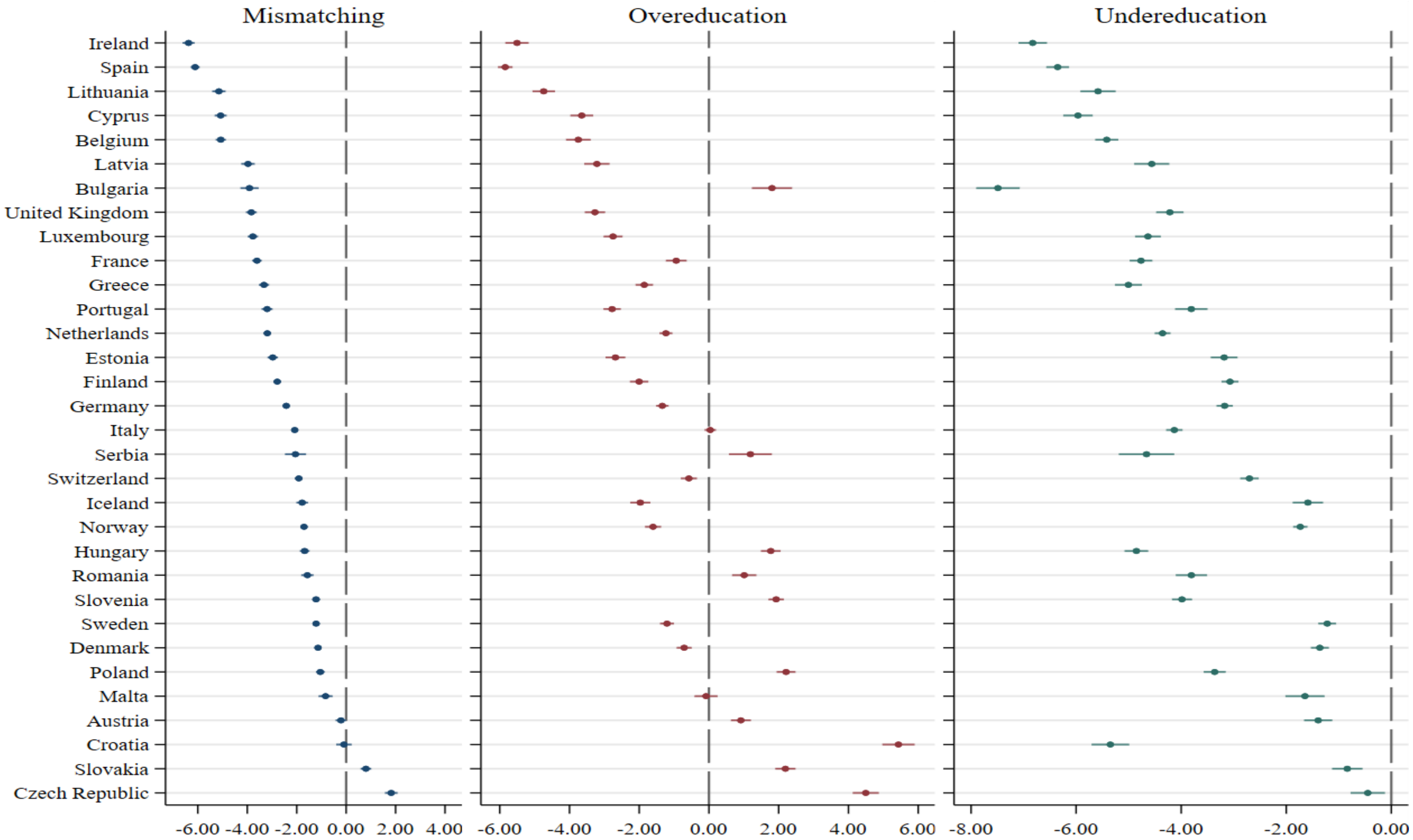

Figure 16: The effect of educational mismatch (% of household) on household relative income by country

Notes: This figure shows the effects of educational mismatch on household relative income. Results from separate OLS regressions per country are presented. Coefficients correspond to the household-level educational mismatch. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

Table 15: The effects of educational mismatch (individual level) on household relative income

	Repeated cross-sections					Longitudinal	
					P-score		P-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mismatched employee	-2.977***	-2.751***	-2.395***	-1.233***	-2.124***	-0.845***	-0.905***
	[0.035]	[0.034]	[0.034]	[0.032]	[0.027]	[0.041]	[0.066]
Male	-1.696***	-1.605***	-0.853***	-0.977***	-1.607***	0.234**	0.661***
	[0.024]	[0.024]	[0.027]	[0.026]	[0.024]	[0.109]	[0.209]
Generation Z: Born >1995	-7.881***	-6.001***	-6.109***	-5.322***	-9.370***	-10.910***	-10.423***
	[0.188]	[0.183]	[0.182]	[0.175]	[0.184]	[0.803]	[1.257]
Generation Y: Born 1977-1995	-6.619***	-4.852***	-5.280***	-6.237***	-7.763***	-6.861***	-6.036***
	[0.158]	[0.156]	[0.154]	[0.147]	[0.164]	[0.621]	[0.916]
Generation X: Born 1965-1976	-5.916***	-4.855***	-5.265***	-5.727***	-7.745***	-5.850***	-4.952***
	[0.154]	[0.152]	[0.150]	[0.143]	[0.162]	[0.612]	[0.899]
Generation B: Born 1946-1964	-3.432***	-2.856***	-3.198***	-3.039***	-5.322***	-3.108***	-2.038**
	[0.153]	[0.150]	[0.148]	[0.142]	[0.160]	[0.606]	[0.886]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	2.502***	1.728***	1.582***	1.200***	1.557***	1.698***	1.610***
	[0.050]	[0.048]	[0.048]	[0.046]	[0.038]	[0.098]	[0.152]
"-": Widow/Divorced	-4.158***	-3.899***	-3.873***	-3.388***	-4.272***	-1.716***	-1.802***
	[0.061]	[0.060]	[0.059]	[0.057]	[0.051]	[0.117]	[0.180]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-1.727***	-2.131***	-1.996***	-1.664***	-1.581***	-1.525***	-1.327***
	[0.016]	[0.016]	[0.016]	[0.016]	[0.012]	[0.033]	[0.048]
Limit Health	-3.273***	-2.969***	-2.745***	-2.105***	-2.722***	-0.446***	-0.416***
	[0.044]	[0.043]	[0.042]	[0.041]	[0.036]	[0.031]	[0.045]
Residence: City	3.164***	3.863***	3.208***	2.250***	3.013***	2.702***	2.360***
	[0.052]	[0.052]	[0.051]	[0.050]	[0.043]	[0.121]	[0.164]
"-": Rural	-2.846***	-3.124***	-2.356***	-1.690***	-2.792***	-1.231***	-1.184***
	[0.051]	[0.050]	[0.049]	[0.048]	[0.043]	[0.107]	[0.147]
"-": Missing	0.979***	1.317***	1.117***	1.329***	0.330***	5.721***	5.862***
	[0.116]	[0.114]	[0.112]	[0.108]	[0.110]	[1.327]	[1.906]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-3.135***	-1.344***	-0.795***	-1.195***	-3.881***	–	–
	[0.113]	[0.109]	[0.108]	[0.104]	[0.072]		
"-": from non-EU country	-6.409***	-4.208***	-3.621***	-3.795***	-6.616***	–	–
	[0.076]	[0.075]	[0.073]	[0.071]	[0.054]		
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	2.222***	2.147***	1.116***	1.569***	2.721***	2.089***	2.163***
	[0.047]	[0.045]	[0.049]	[0.050]	[0.034]	[0.045]	[0.072]
Full time job	4.311***	4.146***	4.021***	3.624***	4.284***	1.455***	1.542***
	[0.040]	[0.038]	[0.038]	[0.037]	[0.036]	[0.042]	[0.065]
Managerial position	6.959***	6.586***	6.492***	4.691***	7.103***	–	–
	[0.052]	[0.050]	[0.050]	[0.052]	[0.038]		
Homeownership: Outright	–	5.952***	5.857***	5.373***	–	–	–
		[0.086]	[0.084]	[0.083]			
"-": Mortgage	–	6.971***	6.606***	5.661***	–	–	–
		[0.100]	[0.099]	[0.097]			
"-": Rent	–	-1.296***	-1.156***	-1.023***	–	–	–
		[0.095]	[0.093]	[0.091]			
"-": Reduced rent	–	-3.666***	-3.439***	-2.436***	–	–	–
		[0.111]	[0.109]	[0.107]			
"-": Provided free	–	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–	–
Nace: (a) Agriculture	–	–	-5.536***	-5.641***	–	–	–

			[0.094]	[0.091]			
"-": (b-e) Mining, Manufacturing	–	–	2.603***	1.878***	–	–	–
			[0.066]	[0.063]			
"-": (g) Wholesale & retail trade	–	–	0.871***	0.477***	–	–	–
			[0.082]	[0.082]			
"-": (h) Transport and storage	–	–	1.596***	1.412***	–	–	–
			[0.082]	[0.079]			
"-": (i) Accom. & Food services	–	–	-1.538***	-1.417***	–	–	–
			[0.096]	[0.093]			
"-": (j) ICT services	–	–	9.583***	5.443***	–	–	–
			[0.136]	[0.132]			
"-": (k) Financial activities	–	–	11.545***	8.206***	–	–	–
			[0.121]	[0.117]			
"-": (l-n) Business &	–	–	5.707***	2.715***	–	–	–
			[0.085]	[0.082]			
"-": (o) Public administration	–	–	4.967***	2.223***	–	–	–
			[0.078]	[0.075]			
"-": (p) Education	–	–	6.081***	0.823***	–	–	–
			[0.080]	[0.079]			
"-": (q) Health & Care services	–	–	4.249***	1.478***	–	–	–
			[0.082]	[0.078]			
"-": (r-u) Arts, recreation, other	–	–	0.512***	-1.077***	–	–	–
			[0.087]	[0.085]			
"-": Missing	–	–	4.208***	2.727***	–	–	–
			[0.087]	[0.084]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education	–	–	–	13.257***	–	–	–
				[0.056]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	-9.32%	-8.62%	-7.50%	-3.86%	-6.76%	-2.66%	-2.89%
Linear prediction	31.9334	31.9360	31.9360	31.9376	31.4312	31.7597	31.3589
No. of Observations	4,712,988	4,709,880	4,709,880	4,709,702	2,519,565	3,715,060	1,434,545

Notes: This table reports the effect of educational mismatch at the household level on household relative income, a proxy for income inequality at the country-year level. The main independent variable is a binary indicator equal to 1 if the individual is employed in a job that does not match their formal educational qualifications (i.e., a mismatched employee), and 0 otherwise. The dependent variable is a continuous index capturing a household's disposable income relative to the national median (by country and year), scaled from 0 to 100. A value of 0 indicates income significantly below the median, while 100 indicates income far above it. Higher values reflect more advantaged positions in the income distribution, whereas lower values denote more disadvantaged positions. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 16: The effects of educational mismatch (% of household) on household relative income

	Repeated cross-sections					Longitudinal	
					P-score		P-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% Mismatched employees at	-4.131***	-3.789***	-3.436***	-1.967***	-5.362***	-1.079***	-2.142***
	[0.048]	[0.047]	[0.045]	[0.044]	[0.034]	[0.050]	[0.076]
Male	-0.447***	-0.441***	-0.447***	-0.543***	-1.570***	0.728***	0.554**
	[0.019]	[0.018]	[0.022]	[0.021]	[0.027]	[0.077]	[0.269]
Generation Z: Born >1995	-6.650***	-5.230***	-5.092***	-4.801***	-10.086***	-7.854***	-12.894***
	[0.148]	[0.145]	[0.143]	[0.137]	[0.193]	[0.548]	[1.571]
Generation Y: Born 1977-1995	-5.898***	-4.251***	-4.997***	-5.854***	-7.801***	-4.717***	-6.477***
	[0.126]	[0.125]	[0.122]	[0.117]	[0.169]	[0.462]	[1.019]
Generation X: Born 1965-1976	-5.108***	-4.127***	-5.037***	-5.435***	-7.539***	-3.797***	-5.204***
	[0.122]	[0.121]	[0.118]	[0.113]	[0.166]	[0.450]	[0.998]
Generation B: Born 1946-1964	-2.761***	-2.241***	-2.934***	-2.731***	-5.281***	-1.401***	-2.558***
	[0.120]	[0.119]	[0.117]	[0.112]	[0.164]	[0.445]	[0.985]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	1.705***	1.004***	1.023***	0.683***	1.607***	1.469***	1.527***
	[0.046]	[0.044]	[0.043]	[0.042]	[0.041]	[0.088]	[0.181]
"-": Widow/Divorced	-4.041***	-3.717***	-3.824***	-3.342***	-3.636***	-1.679***	-1.537***
	[0.057]	[0.056]	[0.055]	[0.053]	[0.053]	[0.106]	[0.206]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-1.833***	-2.188***	-1.907***	-1.590***	-1.810***	-1.503***	-1.427***
	[0.015]	[0.015]	[0.015]	[0.015]	[0.013]	[0.031]	[0.057]
Limit Health	-3.697***	-3.317***	-2.809***	-2.135***	-2.510***	-0.591***	-0.354***
	[0.038]	[0.037]	[0.036]	[0.035]	[0.039]	[0.029]	[0.054]
Residence: City	2.881***	3.600***	3.109***	2.181***	2.677***	2.607***	2.240***
	[0.051]	[0.050]	[0.049]	[0.048]	[0.045]	[0.117]	[0.193]
"-": Rural	-2.714***	-2.993***	-2.449***	-1.790***	-2.581***	-1.424***	-1.090***
	[0.049]	[0.048]	[0.047]	[0.046]	[0.045]	[0.104]	[0.176]
"-": Missing	0.758***	1.114***	1.066***	1.092***	0.005	4.513***	5.153**
	[0.113]	[0.111]	[0.108]	[0.105]	[0.117]	[1.339]	[2.469]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-3.217***	-1.303***	-0.829***	-1.108***	-3.771***	-3.217***	-1.303***
	[0.107]	[0.103]	[0.101]	[0.098]	[0.076]	[0.107]	[0.103]
"-": from non-EU country	-6.403***	-4.104***	-3.536***	-3.676***	-6.594***	-6.403***	-4.104***
	[0.069]	[0.067]	[0.065]	[0.064]	[0.056]	[0.069]	[0.067]
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	3.240***	3.119***	1.070***	1.270***	2.758***	2.573***	2.066***
	[0.039]	[0.038]	[0.042]	[0.043]	[0.037]	[0.036]	[0.085]
Full time job	2.854***	2.787***	3.703***	3.338***	4.136***	0.868***	1.608***
	[0.037]	[0.036]	[0.037]	[0.036]	[0.039]	[0.034]	[0.078]
Managerial position	7.108***	6.704***	6.301***	4.597***	6.837***	–	–
	[0.051]	[0.049]	[0.048]	[0.049]	[0.042]		
Homeownership: Outright	–	5.911***	5.799***	5.272***	–	–	–
		[0.082]	[0.080]	[0.078]			
"-": Mortgage	–	7.062***	6.667***	5.748***	–	–	–
		[0.096]	[0.094]	[0.092]			
"-": Rent	–	-1.343***	-1.322***	-1.129***	–	–	–
		[0.091]	[0.088]	[0.086]			
"-": Reduced rent	–	-3.713***	-3.467***	-2.470***	–	–	–
		[0.106]	[0.104]	[0.102]			
"-": Provided free	–	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–	–
Nace: (a) Agriculture	–	–	-5.075***	-5.265***	–	–	–

			[0.092]	[0.089]			
"-": (b-e) Mining, Manufacturing	–	–	2.681***	2.027***	–	–	–
			[0.065]	[0.062]			
"-": (g) Wholesale & retail trade	–	–	0.969***	0.621***	–	–	–
			[0.081]	[0.081]			
"-": (h) Transport and storage	–	–	1.581***	1.442***	–	–	–
			[0.081]	[0.078]			
"-": (i) Accom. & Food services	–	–	-1.351***	-1.226***	–	–	–
			[0.094]	[0.092]			
"-": (j) ICT services	–	–	9.387***	5.379***	–	–	–
			[0.134]	[0.131]			
"-": (k) Financial activities	–	–	11.553***	8.351***	–	–	–
			[0.120]	[0.117]			
"-": (l-n) Business & Professionals	–	–	5.625***	2.720***	–	–	–
			[0.084]	[0.080]			
"-": (o) Public administration	–	–	4.967***	2.341***	–	–	–
			[0.077]	[0.074]			
"-": (p) Education	–	–	6.059***	0.942***	–	–	–
			[0.079]	[0.078]			
"-": (q) Health & Care services	–	–	4.114***	1.472***	–	–	–
			[0.080]	[0.076]			
"-": (r-u) Arts, recreation, other	–	–	0.620***	-0.921***	–	–	–
			[0.085]	[0.084]			
"-": Missing	–	–	-1.509***	-2.365***	–	–	–
			[0.063]	[0.061]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education (household)	–	–	–	13.288***	–	–	–
				[0.054]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	-13.52%	-12.40%	-11.24%	-6.43%	-17.63%	-3.55%	-7.20%
Linear prediction	30.5641	30.5668	30.5668	30.5680	30.4126	30.3562	29.7424
No. of Observations	5,900,319	5,895,640	5,895,640	5,895,448	1,775,726	4,787,646	867,466

Notes: This table reports the effect of educational mismatch at the household level on household relative income, a proxy for income inequality at the country-year level. The main independent variable is the proportion of mismatched employees within the household. The dependent variable is a continuous index capturing a household's disposable income relative to the national median (by country and year), scaled from 0 to 100. A value of 0 indicates income significantly below the median, while 100 indicates income far above it. Higher values reflect more advantaged positions in the income distribution, whereas lower values denote more disadvantaged positions. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 17: The effects of educational mismatch types on household relative income: Over- and Undereducation

	Repeated cross-sections				Longitudinal			
	Individual	**Household**	**P-score**	**P-score**	**Individual**	**Household**	**P-score**	**P-score**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overeducated employee	-1.558***	-2.201***	0.133***	–	-0.739***	-0.876***	-0.763***	–
	[0.043]	[0.061]	[0.036]		[0.057]	[0.071]	[0.116]	
Undereducated employee	-4.015***	-5.435***	–	-3.141***	-0.941***	-1.244***	–	-0.681***
	[0.044]	[0.057]		[0.030]	[0.052]	[0.061]		[0.089]
Male	-1.681***	-0.447***	-1.209***	-1.748***	0.235**	0.729***	1.043***	0.892***
	[0.024]	[0.019]	[0.034]	[0.029]	[0.109]	[0.077]	[0.332]	[0.285]
Generation Z: Born >1995	-8.024***	-6.800***	-10.760***	-7.997***	-10.927***	-7.867***	-11.882***	-13.250***
	[0.188]	[0.148]	[0.259]	[0.191]	[0.803]	[0.548]	[1.855]	[1.698]
Generation Y: Born 1977-1995	-6.963***	-6.155***	-8.698***	-7.588***	-6.884***	-4.737***	-7.870***	-7.817***
	[0.158]	[0.126]	[0.233]	[0.167]	[0.621]	[0.462]	[1.371]	[1.147]
Generation X: Born 1965-1976	-6.200***	-5.322***	-8.548***	-7.417***	-5.868***	-3.813***	-6.547***	-6.148***
	[0.154]	[0.122]	[0.230]	[0.164]	[0.612]	[0.450]	[1.355]	[1.124]
Generation B: Born 1946-1964	-3.598***	-2.862***	-6.324***	-4.763***	-3.117***	-1.408***	-3.978***	-2.866***
	[0.152]	[0.120]	[0.229]	[0.162]	[0.606]	[0.445]	[1.341]	[1.107]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	2.508***	1.676***	1.089***	2.036***	1.698***	1.468***	1.538***	1.511***
	[0.050]	[0.046]	[0.049]	[0.042]	[0.098]	[0.088]	[0.209]	[0.180]
"-": Widow/Divorced	-4.118***	-4.022***	-4.817***	-3.691***	-1.715***	-1.679***	-1.763***	-1.432***
	[0.061]	[0.057]	[0.069]	[0.056]	[0.117]	[0.106]	[0.271]	[0.204]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-1.710***	-1.806***	-1.474***	-1.597***	-1.525***	-1.504***	-1.268***	-1.214***
	[0.016]	[0.015]	[0.016]	[0.013]	[0.033]	[0.031]	[0.074]	[0.053]
Limit Health	-3.227***	-3.647***	-2.542***	-2.580***	-0.446***	-0.590***	-0.318***	-0.387***
	[0.044]	[0.038]	[0.050]	[0.039]	[0.031]	[0.029]	[0.073]	[0.051]
Residence: City	3.149***	2.862***	3.038***	2.629***	2.701***	2.605***	2.709***	1.996***
	[0.052]	[0.051]	[0.053]	[0.046]	[0.121]	[0.117]	[0.232]	[0.181]
"-": Rural	-2.842***	-2.709***	-2.798***	-2.490***	-1.230***	-1.422***	-0.926***	-0.928***
	[0.051]	[0.049]	[0.054]	[0.046]	[0.107]	[0.104]	[0.214]	[0.160]
"-": Missing	1.103***	0.913***	0.264*	0.047	5.711***	4.495***	3.786	2.89
	[0.116]	[0.113]	[0.143]	[0.117]	[1.327]	[1.338]	[2.912]	[2.839]

"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-3.217***	-3.325***	-4.415***	-3.868***	–	–	–	–
	[0.113]	[0.107]	[0.092]	[0.082]				
"-": from non-EU country	-6.465***	-6.474***	-7.173***	-6.547***	–	–	–	–
	[0.077]	[0.069]	[0.068]	[0.060]				
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	2.224***	3.223***	3.244***	2.507***	2.089***	2.572***	2.041***	1.978***
	[0.047]	[0.039]	[0.044]	[0.038]	[0.045]	[0.036]	[0.104]	[0.083]
Full time job	4.312***	2.860***	4.398***	4.011***	1.455***	0.869***	1.677***	1.481***
	[0.040]	[0.037]	[0.048]	[0.040]	[0.042]	[0.034]	[0.098]	[0.075]
Managerial position	6.946***	7.076***	6.936***	6.616***	–	–	–	–
	[0.052]	[0.051]	[0.050]	[0.042]				
Year Effects	+	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	+	+	+	+
% Effect overeducation	-4.88%	-7.20%	0.42%	–	-2.33%	-2.89%	-2.38%	–
% Effect undereducation	-12.57%	-17.78%	–	-10.28%	-2.96%	-4.10%	–	-2.26%
Linear prediction	31.9334	30.5641	31.9160	30.5679	31.7597	30.3562	32.0138	30.2098
No. of Observations	4,712,988	5,900,319	1,342,879	1,668,140	3,715,060	4,787,646	600,947	839,080

Notes: This table reports the effect of different types of educational mismatch on household relative income, a proxy for income inequality at the country-year level. The main independent variables are binary indicators identifying whether the individual is (i) overeducated – employed in a job that requires lower qualifications than their formal education or (ii) undereducated – employed in a job that requires higher qualifications than their formal education. The dependent variable is a continuous index capturing a household's disposable income relative to the national median (by country and year), scaled from 0 to 100. A value of 0 indicates income significantly below the median, while 100 indicates income far above it. Higher values reflect more advantaged positions in the income distribution, whereas lower values denote more disadvantaged positions. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

7. Educational Mismatch and Individual Income Inequality

This section presents the results on the effect of educational mismatch on individual's earnings income positioning within national earnings distribution. The dependent variable is a continuous index scaled from 0 to 100, indicating the individual's relative gross earnings position compared to others in the same country and year. The analysis covers both individual- and household-level mismatch measures, disaggregates mismatch types (over- and undereducation), and applies cross-sectional, panel, and PSM estimation techniques to ensure robustness.

7.1 Country-Level Heterogeneity in the Effect of Mismatch

Figure 17 presents country-specific OLS estimates of the effect of being skills-mismatched (at the individual level) on one's position in the national earnings distribution. Most coefficients are negative and statistically significant, indicating that mismatched individuals tend to occupy lower positions in their country's earnings hierarchy. Country patterns are similar to those for household relative income in the previous subsection.

Figure 18 shifts to the household-level mismatch measure and illustrates how the share of mismatched workers within a household affects individual earnings ranks. The results generally align with those of Figure 17. In households where more members are mismatched, individuals are systematically positioned lower in the earnings distribution, although cross-country heterogeneity remains. The effects are particularly pronounced in Eastern and Southern European countries, reaffirming the broader vulnerability associated with mismatch under weaker institutional settings.

7.2 Multivariate Regression Estimates

Table 18 reports the association between individual-level mismatch and personal relative income. Across all model specifications, the coefficient on the mismatch indicator is negative and statistically significant at the 1% level. In the baseline cross-sectional OLS (column 1), the economic impact is substantial, with mismatch reducing earnings rank by -12.4% relative to the average position. This effect attenuates slightly as more controls are added, falling to -7% in column 4. The PSM model in column 5 yields a similar negative effect of 8.6%. In the panel models (columns 6 and 7), which control for unobserved individual heterogeneity, the magnitude drops further to 5.5% (column 6) and 4.8% (PSM – column 7), but remains statistically significant. These results suggest a consistent earnings penalty associated with educational mismatch that persists even after controlling for time-invariant factors and selection on observables.

Table 19 evaluates household-level mismatch effects on personal relative income. The share of mismatched earners in the household is again negatively and significantly associated with an individual's earnings position. The baseline model shows a -15.5% effect, while the model, including all the control variables, indicates the smallest -8.4% effect for repeated cross-sectional analysis. PSM in cross-sectional (column 5) and panel version (column 7) do not improve the results.

Finally, Table 20 disaggregates mismatch into overeducation and undereducation at both the individual and household levels. Undereducation is consistently associated with significant and substantial earnings penalties. At the individual level, the effect reaches -14.2% in the baseline and -10% in PSM model (column 4). In the panel the effect remains between -5.2% (column 5) and -3.5% (PSM - column 8). At the household level, the undereducation effect is even larger, peaking at -18.6% in the cross-sectional specification and remaining significant at -6.4% in the panel estimates. These results confirm that undereducation is a strong determinant of lower income positioning, both individually and within households.

Overeducation, by contrast, shows a more nuanced pattern. The individual-level effect is negative and statistically significant across all models, ranging from -2.9% to -9.8%, but smaller than for undereducation. Similarly at the household level, the effect of overeducation is negative and statistically significant but again smaller in size across all models, suggesting more heterogeneity in how overeducation translates into income outcomes.

Together, these findings provide robust evidence that educational mismatch, especially undereducation, exerts a persistent and statistically significant downward pressure on individuals' positioning in national income distributions.

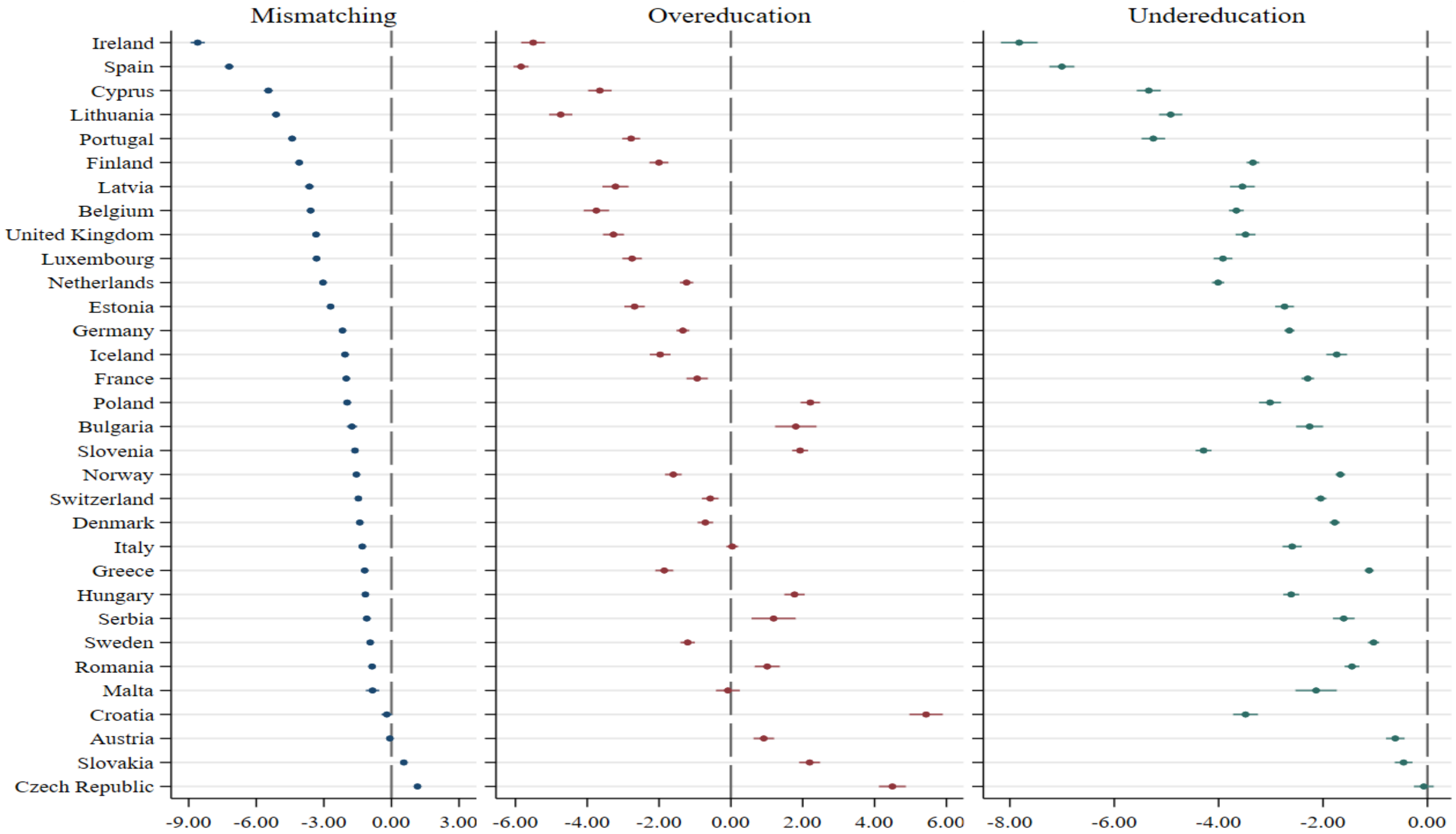

Figure 17: The effect of educational mismatch (individual level) on personal relative income by country

Notes: This figure shows the effects of educational mismatch on personal relative income. Results from separate OLS regressions per country are presented. Coefficients correspond to the individual-level educational mismatch. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

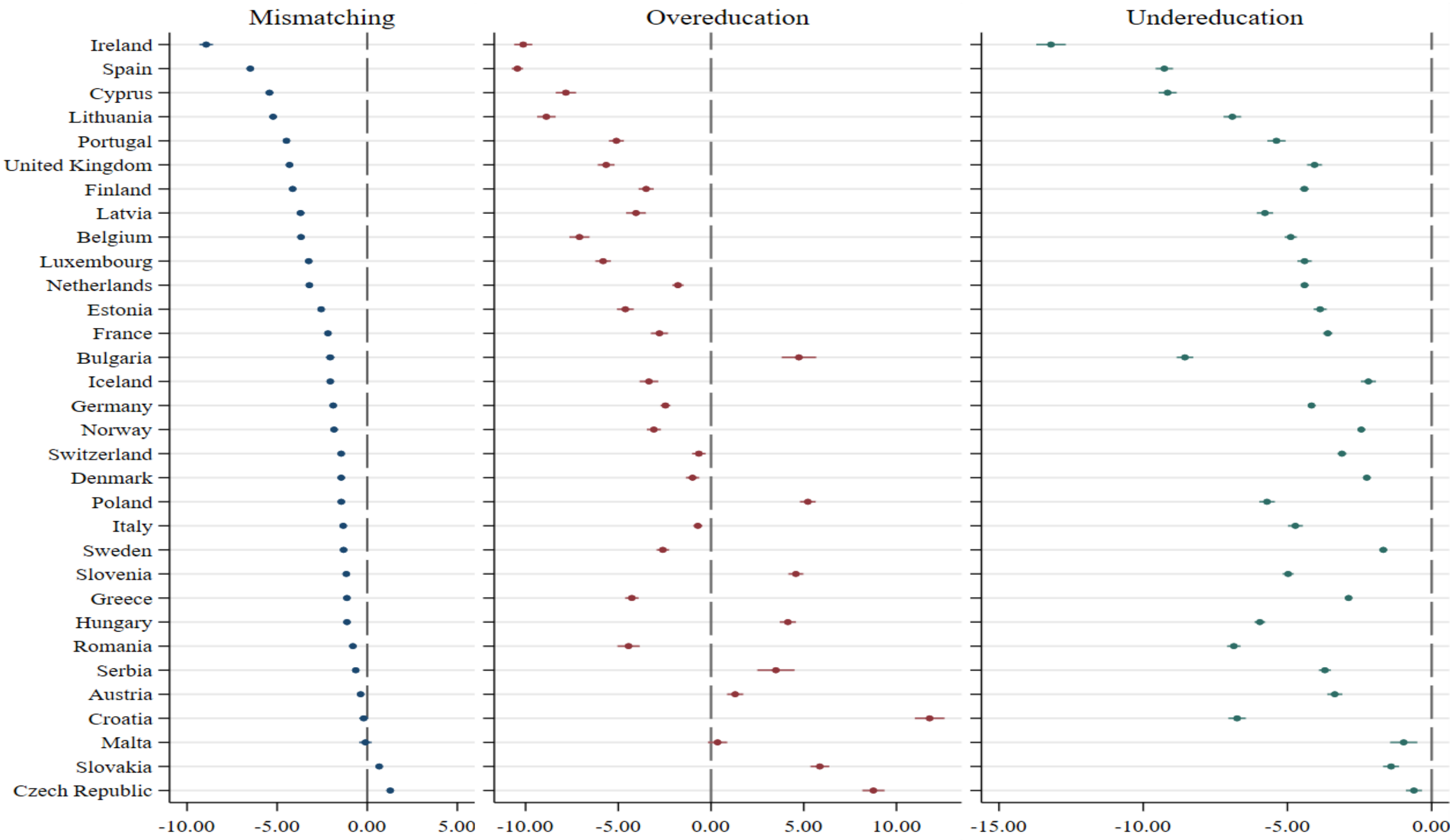

Figure 18: The effect of educational mismatch (% of household) on personal relative income by country

Notes: This figure shows the effects of educational mismatch on personal relative income. Results from separate OLS regressions per country are presented. Coefficients correspond to the household-level educational mismatch. All regressions control for the full set of socio-demographic covariates included in the main analysis, incorporate year fixed effects, and apply robust standard errors clustered at the household level.

Table 18: The effects of educational mismatch (individual level) on personal relative income

	Repeated cross-sections					Longitudinal	
					P-score		P-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mismatched employee	-2.596***	-2.510***	-2.107***	-1.467***	-1.812***	-0.857***	-0.766***
	[0.029]	[0.029]	[0.028]	[0.028]	[0.025]	[0.033]	[0.054]
Male	3.021***	3.051***	3.647***	3.580***	3.062***	2.876***	3.263***
	[0.025]	[0.025]	[0.027]	[0.026]	[0.025]	[0.106]	[0.179]
Generation Z: Born >1995	1.191***	1.283***	1.490***	1.888***	1.506***	-2.063***	-2.087**
	[0.135]	[0.135]	[0.134]	[0.133]	[0.147]	[0.571]	[0.833]
Generation Y: Born 1977-1995	2.362***	2.381***	2.247***	1.723***	2.892***	1.366***	1.322**
	[0.115]	[0.115]	[0.114]	[0.112]	[0.134]	[0.462]	[0.629]
Generation X: Born 1965-1976	4.752***	4.659***	4.430***	4.187***	4.727***	3.445***	3.758***
	[0.112]	[0.112]	[0.111]	[0.109]	[0.132]	[0.459]	[0.617]
Generation B: Born 1946-1964	5.096***	5.164***	4.874***	4.975***	4.781***	3.571***	4.053***
	[0.110]	[0.110]	[0.109]	[0.108]	[0.130]	[0.453]	[0.614]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	2.431***	1.963***	1.702***	1.489***	1.898***	0.797***	0.553***
	[0.037]	[0.037]	[0.036]	[0.035]	[0.033]	[0.071]	[0.112]
"-": Widow/Divorced	0.549***	0.444***	0.455***	0.719***	0.716***	-0.039	-0.094
	[0.050]	[0.049]	[0.048]	[0.047]	[0.045]	[0.087]	[0.136]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-0.325***	-0.442***	-0.363***	-0.181***	-0.261***	-0.082***	-0.075**
	[0.012]	[0.012]	[0.012]	[0.012]	[0.010]	[0.024]	[0.037]
Limit Health	-2.703***	-2.595***	-2.310***	-1.961***	-2.090***	-0.584***	-0.476***
	[0.036]	[0.036]	[0.035]	[0.035]	[0.032]	[0.025]	[0.037]
Residence: City	2.743***	2.936***	2.497***	1.969***	2.519***	1.849***	1.492***
	[0.040]	[0.040]	[0.039]	[0.039]	[0.037]	[0.089]	[0.128]
"-": Rural	-1.562***	-1.615***	-1.004***	-0.636***	-1.441***	-0.442***	-0.347***
	[0.037]	[0.037]	[0.036]	[0.036]	[0.035]	[0.076]	[0.110]
"-": Missing	1.930***	2.018***	1.848***	1.957***	3.121***	0.343	-1.385*
	[0.068]	[0.068]	[0.066]	[0.064]	[0.082]	[0.583]	[0.812]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-1.267***	-0.702***	0.022	-0.192**	-1.700***	–	–
	[0.093]	[0.091]	[0.089]	[0.087]	[0.066]		
"-": from non-EU country	-3.026***	-2.344***	-1.610***	-1.701***	-3.131***	–	–
	[0.063]	[0.062]	[0.060]	[0.059]	[0.046]		
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	14.311***	14.231***	13.223***	13.471***	15.956***	5.366***	6.038***
	[0.037]	[0.036]	[0.039]	[0.040]	[0.033]	[0.043]	[0.068]
Full time job	7.109***	7.024***	6.592***	6.367***	6.903***	2.008***	2.025***
	[0.031]	[0.031]	[0.031]	[0.030]	[0.031]	[0.035]	[0.054]
Managerial position	9.681***	9.499***	9.483***	8.503***	9.998***	–	–
	[0.045]	[0.044]	[0.044]	[0.044]	[0.040]		
Homeownership: Outright	–	-0.629***	-0.809***	-1.087***	–	–	–
		[0.081]	[0.079]	[0.078]			
"-": Mortgage	–	2.149***	1.709***	1.185***	–	–	–
		[0.088]	[0.086]	[0.086]			
"-": Rent	–	-2.001***	-1.787***	-1.723***	–	–	–
		[0.085]	[0.083]	[0.082]			
"-": Reduced rent	–	-2.996***	-2.760***	-2.211***	–	–	–
		[0.095]	[0.093]	[0.092]			
"-": Provided free	–	-0.629***	-0.809***	-1.087***	–	–	–
Nace: (a) Agriculture	–	–	-3.952***	-4.011***	–	–	–

			[0.071]	[0.070]			
"-": (b-e) Mining, Manufacturing	–	–	4.850***	4.449***	–	–	–
			[0.058]	[0.057]			
"-": (g) Wholesale & retail trade	–	–	-0.099	-0.313***	–	–	–
			[0.066]	[0.067]			
"-": (h) Transport and storage	–	–	3.113***	3.022***	–	–	–
			[0.075]	[0.073]			
"-": (i) Accom. & Food services	–	–	-2.363***	-2.294***	–	–	–
			[0.080]	[0.079]			
"-": (j) ICT services	–	–	8.831***	6.572***	–	–	–
			[0.116]	[0.115]			
"-": (k) Financial activities	–	–	11.881***	10.056***	–	–	–
			[0.108]	[0.106]			
"-": (l-n) Business &	–	–	2.253***	0.616***	–	–	–
			[0.069]	[0.069]			
"-": (o) Public administration	–	–	7.331***	5.829***	–	–	–
			[0.068]	[0.067]			
"-": (p) Education	–	–	7.855***	4.990***	–	–	–
			[0.070]	[0.071]			
"-": (q) Health & Care services	–	–	4.401***	2.894***	–	–	–
			[0.067]	[0.066]			
"-": (r-u) Arts, recreation, other	–	–	-0.065	-0.949***	–	–	–
			[0.075]	[0.074]			
"-": Missing	–	–	8.693***	7.876***	–	–	–
			[0.074]	[0.072]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education	–	–	–	7.237***	–	–	–
				[0.041]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	-12.36%	-11.95%	-10.03%	-6.99%	-8.75%	-5.54%	-4.77%
Linear prediction	20.9982	21.0014	21.0014	21.0028	20.7152	15.4718	16.0621
No. of Observations	4,580,360	4,577,251	4,577,251	4,577,074	2,427,990	3,617,209	1,374,514

Notes: This table reports the effect of educational mismatch at the household level on personal relative income, a proxy for income inequality at the country-year level. The main independent variable is a binary indicator equal to 1 if the individual is employed in a job that does not match their formal educational qualifications (i.e., a mismatched employee), and 0 otherwise. The dependent variable is a continuous index capturing an individual's gross earnings relative to the national median (by country and year), scaled from 0 to 100. A value of 0 indicates earnings significantly below the median, while 100 indicates earnings far above it. Higher values reflect more advantaged positions in the income distribution, whereas lower values denote more disadvantaged positions. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 19: The effects of educational mismatch (% of household) on personal relative income

	Repeated cross-sections					Longitudinal	
					P-score		P-score
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
% Mismatched employees at	-2.752***	-2.628***	-2.209***	-1.496***	-1.822***	-0.825***	-0.647***
	[0.033]	[0.032]	[0.031]	[0.030]	[0.030]	[0.032]	[0.058]
Male	5.055***	5.051***	4.086***	4.040***	3.121***	4.000***	3.158***
	[0.023]	[0.023]	[0.023]	[0.023]	[0.028]	[0.088]	[0.224]
Generation Z: Born >1995	2.062***	1.938***	2.629***	2.754***	1.645***	-0.371	-2.680**
	[0.107]	[0.106]	[0.101]	[0.101]	[0.156]	[0.382]	[1.157]
Generation Y: Born 1977-1995	4.641***	4.599***	3.456***	3.036***	3.025***	4.152***	1.586**
	[0.093]	[0.092]	[0.088]	[0.087]	[0.139]	[0.338]	[0.730]
Generation X: Born 1965-1976	7.201***	7.067***	5.447***	5.259***	4.919***	6.194***	4.254***
	[0.090]	[0.090]	[0.085]	[0.084]	[0.137]	[0.336]	[0.724]
Generation B: Born 1946-1964	6.572***	6.614***	5.368***	5.473***	4.976***	5.333***	4.352***
	[0.088]	[0.087]	[0.083]	[0.082]	[0.135]	[0.331]	[0.709]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	2.006***	1.581***	1.585***	1.415***	1.829***	0.727***	0.532***
	[0.033]	[0.033]	[0.031]	[0.031]	[0.037]	[0.061]	[0.142]
"-": Widow/Divorced	0.983***	0.892***	0.560***	0.791***	0.722***	0.075	-0.087
	[0.047]	[0.046]	[0.045]	[0.044]	[0.047]	[0.078]	[0.157]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-0.769***	-0.863***	-0.366***	-0.212***	-0.243***	-0.265***	-0.084*
	[0.010]	[0.010]	[0.010]	[0.010]	[0.011]	[0.020]	[0.046]
Limit Health	-4.241***	-4.114***	-3.103***	-2.778***	-2.072***	-0.874***	-0.482***
	[0.031]	[0.031]	[0.029]	[0.029]	[0.035]	[0.022]	[0.045]
Residence: City	2.242***	2.424***	2.119***	1.668***	2.321***	1.643***	1.364***
	[0.035]	[0.035]	[0.033]	[0.033]	[0.041]	[0.078]	[0.157]
"-": Rural	-1.292***	-1.338***	-0.908***	-0.588***	-1.441***	-0.521***	-0.513***
	[0.033]	[0.032]	[0.031]	[0.031]	[0.039]	[0.067]	[0.139]
"-": Missing	0.671***	0.757***	0.882***	0.888***	2.795***	0.05	-2.198*
	[0.062]	[0.062]	[0.058]	[0.057]	[0.093]	[0.541]	[1.207]
"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-1.097***	-0.554***	0.114	-0.017	-1.838***	–	–
	[0.081]	[0.079]	[0.075]	[0.074]	[0.071]		
"-": from non-EU country	-2.692***	-2.048***	-1.200***	-1.263***	-3.343***	–	–
	[0.051]	[0.051]	[0.048]	[0.047]	[0.049]		
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	14.593***	14.485***	10.479***	10.573***	15.918***	5.823***	5.937***
	[0.031]	[0.030]	[0.032]	[0.033]	[0.036]	[0.034]	[0.080]
Full time job	4.007***	3.964***	5.860***	5.678***	6.635***	1.036***	1.930***
	[0.028]	[0.028]	[0.029]	[0.028]	[0.034]	[0.028]	[0.066]
Managerial position	10.330***	10.139***	9.427***	8.610***	9.624***	–	–
	[0.044]	[0.043]	[0.042]	[0.042]	[0.044]		
Homeownership: Outright	–	-0.347***	-0.562***	-0.825***	–	–	–
		[0.069]	[0.066]	[0.065]			
"-": Mortgage	–	2.467***	1.901***	1.454***	–	–	–
		[0.076]	[0.073]	[0.072]			
"-": Rent	–	-1.472***	-1.485***	-1.397***	–	–	–
		[0.074]	[0.070]	[0.069]			
"-": Reduced rent	–	-2.625***	-2.274***	-1.791***	–	–	–
		[0.082]	[0.078]	[0.078]			
"-": Provided free	–	*{Ref.}*	*{Ref.}*	*{Ref.}*	–	–	–
Nace: (a) Agriculture	–	–	-4.588***	-4.685***	–	–	–

			[0.067]	[0.066]			
"-": (b-e) Mining, Manufacturing	–	–	5.566***	5.248***	–	–	–
			[0.057]	[0.056]			
"-": (g) Wholesale & retail trade	–	–	0.288***	0.122*	–	–	–
			[0.064]	[0.064]			
"-": (h) Transport and storage	–	–	3.534***	3.475***	–	–	–
			[0.074]	[0.073]			
"-": (i) Accom. & Food services	–	–	-2.039***	-1.977***	–	–	–
			[0.075]	[0.075]			
"-": (j) ICT services	–	–	8.943***	7.016***	–	–	–
			[0.117]	[0.116]			
"-": (k) Financial activities	–	–	12.545***	11.004***	–	–	–
			[0.109]	[0.108]			
"-": (l-n) Business & Professionals	–	–	2.334***	0.934***	–	–	–
			[0.068]	[0.067]			
"-": (o) Public administration	–	–	7.987***	6.721***	–	–	–
			[0.068]	[0.067]			
"-": (p) Education	–	–	8.332***	5.877***	–	–	–
			[0.070]	[0.070]			
"-": (q) Health & Care services	–	–	4.438***	3.175***	–	–	–
			[0.066]	[0.065]			
"-": (r-u) Arts, recreation, other	–	–	0.189***	-0.566***	–	–	–
			[0.072]	[0.071]			
"-": Missing	–	–	-6.363***	-6.779***	–	–	–
			[0.055]	[0.054]			
"-": (f) Construction	–	–	*{Ref.}*	*{Ref.}*	–	–	–
% Tertiary education (household)	–	–	–	6.393***	–	–	–
				[0.036]			
Year Effects	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	–	+	+
% Effect	-15.50%	-14.80%	-12.44%	-8.43%	-8.79%	-6.46%	-4.03%
Linear prediction	17.7476	17.7507	17.7507	17.7516	20.7247	12.7660	16.0841
No. of Observations	5,723,543	5,718,858	5,718,858	5,718,667	1,708,588	4,657,705	828,854

Notes: This table reports the effect of educational mismatch at the household level on personal relative income, a proxy for income inequality at the country-year level. The main independent variable is the proportion of mismatched employees within the household. The dependent variable is a continuous index capturing an individual's gross earnings relative to the national median (by country and year), scaled from 0 to 100. A value of 0 indicates earnings significantly below the median, while 100 indicates earnings far above it. Higher values reflect more advantaged positions in the income distribution, whereas lower values denote more disadvantaged positions. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

Table 20: The effects of educational mismatch types on personal relative income: Over- and Undereducation

	Repeated cross-sections				Longitudinal			
	Individual	**Household**	**P-score**	**P-score**	**Individual**	**Household**	**P-score**	**P-score**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Overeducated employee	-2.068***	-1.924***	-0.546***	–	-0.913***	-0.832***	-0.477***	–
	[0.039]	[0.044]	[0.033]		[0.045]	[0.045]	[0.089]	
Undereducated employee	-2.974***	-3.298***	–	-2.109***	-0.806***	-0.818***	–	-0.548***
	[0.035]	[0.038]		[0.028]	[0.043]	[0.040]		[0.075]
Male	3.028***	5.055***	3.247***	3.065***	2.875***	4.000***	3.423***	3.153***
	[0.025]	[0.023]	[0.032]	[0.028]	[0.106]	[0.088]	[0.247]	[0.247]
Generation Z: Born >1995	1.149***	2.004***	1.207***	2.668***	-2.054***	-0.37	-3.275***	-3.468***
	[0.135]	[0.107]	[0.198]	[0.156]	[0.571]	[0.382]	[1.185]	[1.315]
Generation Y: Born 1977-1995	2.246***	4.536***	3.117***	3.090***	1.378***	4.153***	0.618	1.333*
	[0.115]	[0.093]	[0.179]	[0.141]	[0.462]	[0.338]	[0.891]	[0.810]
Generation X: Born 1965-1976	4.659***	7.117***	5.257***	4.812***	3.454***	6.194***	3.411***	3.676***
	[0.112]	[0.090]	[0.177]	[0.139]	[0.459]	[0.336]	[0.875]	[0.804]
Generation B: Born 1946-1964	5.044***	6.534***	5.090***	4.993***	3.577***	5.333***	3.218***	4.244***
	[0.110]	[0.088]	[0.175]	[0.137]	[0.453]	[0.331]	[0.874]	[0.793]
Traditionalists: Born before 1945	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Marital status: Married	2.432***	1.994***	1.934***	1.852***	0.797***	0.727***	0.414***	0.564***
	[0.037]	[0.033]	[0.042]	[0.037]	[0.071]	[0.061]	[0.150]	[0.141]
"-": Widow/Divorced	0.563***	0.992***	0.583***	0.822***	-0.04	0.075	0.01	-0.135
	[0.050]	[0.047]	[0.060]	[0.049]	[0.087]	[0.078]	[0.189]	[0.159]
"-": Single	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Household size	-0.319***	-0.758***	-0.320***	-0.195***	-0.082***	-0.265***	-0.046	-0.090**
	[0.012]	[0.010]	[0.013]	[0.011]	[0.024]	[0.020]	[0.052]	[0.041]
Limit Health	-2.687***	-4.220***	-1.854***	-2.104***	-0.584***	-0.874***	-0.425***	-0.463***
	[0.036]	[0.031]	[0.044]	[0.035]	[0.025]	[0.022]	[0.057]	[0.041]
Residence: City	2.737***	2.233***	2.478***	2.303***	1.849***	1.643***	1.498***	1.237***
	[0.040]	[0.035]	[0.047]	[0.042]	[0.089]	[0.078]	[0.172]	[0.151]
"-": Rural	-1.560***	-1.289***	-1.414***	-1.393***	-0.443***	-0.521***	-0.377**	-0.149
	[0.037]	[0.033]	[0.045]	[0.040]	[0.076]	[0.067]	[0.156]	[0.126]
"-": Missing	1.976***	0.738***	3.427***	2.764***	0.348	0.051	0.286	-2.817**
	[0.068]	[0.062]	[0.115]	[0.088]	[0.583]	[0.541]	[1.423]	[1.181]

"-": Town	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Migrant status: from EU country	-1.297***	-1.143***	-1.911***	-1.819***	–	–	–	–
	[0.093]	[0.081]	[0.083]	[0.074]				
"-": from non-EU country	-3.045***	-2.719***	-3.458***	-3.116***	–	–	–	–
	[0.063]	[0.051]	[0.058]	[0.051]				
"-": Native	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*	*{Ref.}*
Permanent contract	14.312***	14.585***	16.384***	15.437***	5.366***	5.823***	5.679***	5.533***
	[0.037]	[0.031]	[0.040]	[0.036]	[0.043]	[0.034]	[0.095]	[0.082]
Full time job	7.110***	4.011***	7.112***	6.607***	2.008***	1.036***	1.922***	1.881***
	[0.031]	[0.028]	[0.040]	[0.035]	[0.035]	[0.028]	[0.079]	[0.064]
Managerial position	9.677***	10.317***	9.993***	9.341***	–	–	–	–
	[0.045]	[0.045]	[0.052]	[0.044]				
Year Effects	+	+	+	+	+	+	+	+
Country Fixed Effects	+	+	+	+	+	+	+	+
Individual Fixed Effects	–	–	–	–	+	+	+	+
% Effect overeducation	-9.85%	-10.84%	-2.64%	–	-5.90%	-6.52%	-2.98%	–
% Effect undereducation	-14.16%	-18.58%	–	-10.43%	-5.21%	-6.41%	–	-3.51%
Linear prediction	20.9982	17.7476	20.6780	20.2230	15.4718	12.7660	15.9878	15.6000
No. of Observations	4,580,360	5,723,543	1,282,936	1,613,708	3,617,209	4,657,705	570,665	806,984

Notes: This table reports the effect of different types of educational mismatch on personal relative income, a proxy for income inequality at the country-year level. The main independent variables are binary indicators identifying whether the individual is (i) overeducated – employed in a job that requires lower qualifications than their formal education or (ii) undereducated – employed in a job that requires higher qualifications than their formal education. The dependent variable is a continuous index capturing an individual's gross earnings relative to the national median (by country and year), scaled from 0 to 100. A value of 0 indicates earnings significantly below the median, while 100 indicates earnings far above it. Higher values reflect more advantaged positions in the income distribution, whereas lower values denote more disadvantaged positions. Columns 1 through 5 present estimates based on a time-series cross-sectional dataset using OLS regressions. Column 1 provides the baseline specification with demographic controls. Columns 2 to 4 insert the wealth, industry and education controls. Column 5 reports treatment effect estimates derived using the propensity score matching (PSM) method. Columns 6 and 7 use panel data to replicate the baseline model and the PSM-based treatment effect estimation, respectively. All regressions include two-way fixed effects. All standard errors are robust and clustered at the household level. The asterisks denote the following levels of significance: ***: <0.01, ** : <0.05, *<0.1.

8. Concluding Remarks

This chapter has provided robust empirical evidence on the broader household-level impacts of educational mismatch across Europe, extending the literature beyond its predominant focus on individual earnings and labour market outcomes. Our findings show a clear and significant association between educational mismatch and higher risks of household poverty, weaker financial resilience, and less favourable positions within national income distributions. In particular, undereducation within households emerges as a persistent determinant of vulnerability, indicating that when household members collectively hold qualifications below those typically required by their occupations, the entire household faces elevated risks of poverty and diminished capacity to absorb financial shocks. This finding suggests that the consequences of mismatch are not merely personal or occupational but have structural implications for household economic security across European welfare regimes.

Moreover, the analysis highlighted substantial cross-country variation in the magnitude of these effects. Countries with stronger welfare systems and active labour market policies appear better positioned to mitigate the adverse consequences of educational mismatch, while households in countries with weaker safety nets are exposed to greater risks when mismatch occurs. This variation underlines the importance of integrating skills policies with social protection frameworks to shield households from the vulnerabilities induced by mismatch. In practice, it suggests that EU-level recommendations to address skills mismatch must be tailored to national institutional contexts to effectively reduce household-level poverty risks and income inequality.

Importantly, our results indicate that the consequences of mismatch extend beyond immediate income effects, influencing households' broader financial resilience and their ability to cope with unexpected expenses. This has implications for inclusive growth strategies, as households unable to invest in education, health, or entrepreneurial activities due to financial vulnerability may become trapped in persistent low-income trajectories. Thus, policies aiming to reduce mismatch must combine better skills anticipation systems, improved alignment between education and labour market needs, and targeted reskilling or upskilling programmes for those in vulnerable household contexts. Such an integrated approach can strengthen not only individual labour market outcomes but also household well-being and social cohesion.

Finally, this chapter complements the preceding analysis by emphasising that skills mismatch is a multi-level challenge with both microeconomic and macro-distributional implications. Addressing educational mismatch should therefore be seen as a social investment priority that can enhance economic security, reduce inequality, and improve resilience to future economic shocks. Future work within the TRAILS project will deepen this analysis by examining dynamic transitions into and out of mismatch over time and exploring how digitalisation, automation, and green transitions reshape the risk profiles of mismatch across European households. This will further support evidence-based policy design for a more inclusive and resilient European labour market.

References

Acemoglu, D., & Restrepo, P. (2019). Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives*, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2021). *The Wrong Kind of AI? Artificial Intelligence and the Future of Labor Demand*. NBER Working Paper No. 25682. https://doi.org/10.3386/w25682

Allen, J., & van der Velden, R. (2001). Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers, 53*(3), 434–452.

Becker, G. S. (1964). Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education. *University of Chicago Press*, Chicago.

Cedefop. (2018). *Insights into skill shortages and skill mismatch*. Available at: https://www.cedefop.europa.eu/en/publications/3075#group-details

Dolton, P., & Silles, M. (2008). The effects of overeducation on earnings in the graduate labour market. *Economics of Education Review, 27*(2), 125–139.

Ghignoni, E., & Verashchagina, A. (2014) Educational qualifications mismatch in Europe. Is it demand or supply driven? *Journal of Comparative Economics*, Volume 42, Issue 3, 2014, 670-692.

Goldin, C., & Katz, L. F. (2008). *The Race Between Education and Technology*. Harvard University Press.

Green, F., & Henseke, G. (2016). The changing graduate labour market: analysis using a new indicator of graduate jobs. *IZA J Labor Policy* 5, 14.

Green, F., & Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers, 62*(4), 740–763.

Hartog, J. (2000). Over-education and earnings: Where are we, where should we go? *Economics of Education Review, 19*(2), 131–147.

Ilieva-Trichkova, P., & Boyadjieva, P. (2021). The Fragile Axes of Life: A Capability Approach Perspective towards Graduates' Education–Job Mismatches and Subjective Well-Being. *Social Sciences*, *10*(7), 262, 1-18.

ILO. (2021). *Skills Development and Lifelong Learning: A Review of Policies and Practices*. International Labour Office.

Kampelmann, S., & Rycx, F. (2012). The impact of educational mismatch on firm productivity: Evidence from linked panel data. *Economics of Education Review*, *31*(6), 918-931.

Kampelmann, S., Mahy, B., Rycx, F., & Vermeylen, G. (2020). Over-, Required, and Undereducation: Consequences on the Bottom Lines of Firms. *Labour*, *34*(1), 80-112.

Kim, S.H., (2023) - The importance of social skills in recovery from graduating in a recession. *Journal of Economic Behavior & Organization*, 205, 387–411,

Leuven, E., & Oosterbeek, H. (2011). Overeducation and mismatch in the labor market. In E. A. Hanushek, S. Machin & L. Woessmann (Eds.), *Handbook of the Economics of Education, Vol. 4* (pp. 283–326). Amsterdam: Elsevier.

Liu, L., & Guo, L. (2023). Digital Financial Inclusion, Income Inequality, and Vulnerability to Relative Poverty. *Social Indicator Research*, 170(3), 1155–1181.

Mahy, B., Rycx, F., & Vermeylen, G. (2015). Educational mismatch and firm productivity: do skills, technology and uncertainty matter?. *De Economist*, *163*, 233-262.

McGuinness, S. (2006). Overeducation in the labour market. *Journal of Economic Surveys, 20*(3), 387–418.

McGuinness, S., & Ortiz, L. (2016). Skill gaps in the workplace: measurement, determinants and impacts. *Industrial Relations Journal*, *47*(3), 253-278.

McGuinness, S., Pouliakis, K. & Redmond, P. (2018). Skill Mismatch: Concepts, Measurement and Policy Approaches*, Journal of Economic Surveys*, 32(4), 985–1005.

McGuinness, S., Redmond, P., Pouliakas, K., Kelly, L., & Brosnan, L. (2025). *Technological Change and the Upskilling of European Workers* (No. 17753). IZA Discussion Papers.

OECD. (2019). *OECD Skills Outlook 2019: Thriving in a Digital World*. OECD Publishing. https://doi.org/10.1787/df80bc12-en

Pouliakas, K., & Souto-Otero, M. (2022). Setting Europe on course for a human digital transition: new evidence from Cedefop's second European skills and jobs survey. Available at: https://orca.cardiff.ac.uk/id/eprint/154841/

Quintini, G. (2011). Over-qualified or under-skilled: A review of existing literature. *OECD Social, Employment and Migration Working Papers*, No. 121, OECD Publishing.

Sánchez-Sánchez, N., & McGuinness, S. (2015). Decomposing the impacts of overeducation and overskilling on earnings and job satisfaction: an analysis using REFLEX data. *Education Economics*, *23*(4), 419-432.

Schultz, T. W. (1961). Investment in human capital. *American Economic Review, 51*(1), 1–17.

Stephany, F., & Teutloff, O. (2024). What is the price of a skill? The value of complementarity. *Research Policy*, 53(1), 104898, 1-23.