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New and changing risks of labour market attachment – the future of work

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PATHS2INCLUDE

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European Labour Markets Under Pressure – New knowledge on pathways to include persons in vulnerable situations

Title: New and changing risks of labour market attachment – the future of work

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Contents

Introduction

This working paper analyses labour market vulnerability, understood as workers' weak labour market attachment and low labour force participation rates. Establishing a clear understanding of this vulnerability is critical for two reasons. First, it is necessary to identify the socio-demographic groups that have faced persistent, historical challenges. Second, changing economic circumstances and significant megatrends—such as demographic change, climate change, and especially technological advances—are actively redefining the pool of "gainers" and "losers," creating a need to anticipate future risks as well.

For the past two decades, certain social groups have consistently faced greater challenges. Our analysis indicates that the primary risk groups are migrants, parents, and individuals without a tertiary education. These groups have persistently experienced higher rates of underemployment, lower labour force participation, and greater exposure to economic slack. Moreover, vulnerability is often compounded at the intersection of these characteristics, with groups such as migrant mothers without tertiary education facing particularly significant barriers in the labour market.

However, these established patterns of vulnerability are being challenged by the megatrends reshaping the labour market. The second part of this paper, therefore, analyses which socio-demographic groups are potentially most at risk from future technological disruption. We identify a high-risk group based on a critical intersection of two factors: (1) individuals who do not currently perform significant digital tasks in their jobs—and are therefore unlikely to possess future-proof digital skills—and (2) individuals who are employed in occupations that are highly exposed to Artificial Intelligence (AI). We argue that these individuals are particularly vulnerable because, although they do not currently need relevant digital skills, their job content may change in the near future due to the implementation of digital tools in their workplaces or displacement.

The main research questions we ask in this paper are:

1. Which socio-economic groups of workers have faced the most significant challenges on the labour market over the previous 20 years?
2. What individual characteristics are likely to be correlated with future vulnerabilities when Artificial Intelligence (AI) is widely introduced in the workplace?
3. Which groups are most likely to be adversely affected by future technological changes in the labour market?
4. How do current vulnerabilities interact with the future ones?

Our analysis additionally examines the differing labour market patterns between "Old" EU member states (EU15, those that joined before 2004) and "New" EU member states (NMS, those that joined in and after 2004). We use this distinction for several key reasons. These two country groups have experienced different economic trajectories over the last 20 years, with NMS countries in an economic "catching up" phase. They differ in their general levels of economic development, wage levels, and the structure of their labour market institutions (e.g., labour unions, active labour market policies). Furthermore, the two groups have distinct historical migration patterns and significantly different demographic structures, with the EU15 population being, on average, older.

This paper is organised into two main parts. The first part provides a descriptive analysis of historical vulnerabilities, plotting trends in labour force participation, underemployment, and labour market slack from 2006 to 2023. This analysis confirms that migrants, parents, and individuals without college degrees have been the most vulnerable, with intersections like non-tertiary educated migrant mothers facing acute challenges. The findings highlight a clear EU15-NMS divide: the education divide is starker in the EU15, while in the NMS, different systemic barriers appear to be at play, particularly concerning labour market slack for migrants and mothers.

The second part of the paper examines the potential future vulnerability due to "low digital adaptability," identifying a high-risk group of workers in high-AI-exposure jobs who currently use few digital skills. Our findings show that this "adaptability-risk" group disproportionately includes women, mid- and later-career workers, the tertiary-educated, and the native-born. This profile, however, differs markedly across Europe. Notably, the correlation between this future risk and current weak labour-market attachment diverges: in the NMS, the two risks appear largely separate (a reassuring result), whereas in the EU15, current weak attachment is more prevalent also among those who are at high adaptability risk.

Background

This section sets out the macroeconomic and institutional context for analysing how risk factors for weak labour-market attachment have evolved across EU countries over the past two decades. Initial disparities in economic, institutional, and social conditions across EU15 and NMS motivate their separate analysis. We document substantial labour market transformations in both groups during the two decades since the 2004 accession of ten NMS, alongside pronounced economic volatility that affected both EU15 and NMS.

Macroeconomic Shocks and Their Asymmetric Impact on EU Member States

Following moderate economic growth in the immediate post-accession years, the 2008 financial crisis—originating in the United States—had profound global repercussions, with severe implications for EU banks that quickly transmitted into the real economy. Subsequently, the sovereign debt crisis of 2011–2013 further exacerbated the economic challenges faced by Member States, particularly those in Southern Europe. Full economic recovery across the EU was not achieved until 2017 (Rovelli, 2024a). In the following years, economic growth resumed but was accompanied by recurring political crises, including the arrival of Syrian refugees and the United Kingdom's withdrawal from the EU (“Brexit”). In late 2019, the COVID-19 pandemic brought renewed disruption, imposing public health and economic shocks due to widespread lockdowns and the breakdown of global supply chains. A swift policy response by individual Member States and the EU mitigated some of the long-term damage to workers and firms. However, this came at the cost of unprecedented increases in public debt levels.

These crises have had asymmetric impact on the EU15 and NMS. The Great Recession of 2008–2009 led to a more pronounced economic contraction, sharper declines in employment, and a steeper rise in unemployment in the New Member States, compared to EU15. In contrast, the post-Sovereign Debt Crisis of 2011–2013 had more severe consequences for the EU15 across all three indicators. Similarly, the economic fallout from the COVID-19 recession disproportionately affected the EU15, with greater declines in both GDP and employment.

Pandemic and the gender gap in employment

Previous research has shown that women lost jobs more often than men during the Covid-19 pandemic, because they were more concentrated in contact-intensive (primarily services) sectors and because increased childcare needs during school and daycare closures prevented many from working (Alon et al., 2021). This was more pronounced in the countries where the schools and businesses were closed for longer (See OECD (2021) for a comparison). Gender gaps in employment increased mainly among workers who could not work from home. However, among teleworking workers, women with children experienced a greater reduction in productivity than men with children, due to the increased time spent on childcare by women (Alon et al., 2021). The issue is most relevant for EU15 states, where the share of teleworking persons is higher than in NMS (Eurofound and European Commission Joint Research Centre, 2024). This is a stark contrast to previous recessions in which there were consistent patterns: men, nonwhites, youth, and less-educated workers were most sensitive to economic cycles. (Hoynes et al., 2012) Another relevant heterogeneity of how the recessions affect workers is the scarring effect on the youngest employees. Research has shown that graduating in a recession leads to persistent effects on the labour income of workers (Altonji et al., 2016).

Structural Economic and Institutional Labour Market Differences

In 2006, the average wage in Purchasing Power Standard of workers in the EU15 was 149% higher than for their counterparts in the NMS, this has decreased to around 53% in 2022. NMS unemployment rate in 2005 averaged 8.2% vs 7.0% in the EU-15, but by 2023 was lower: 5.1% vs 6.3%. However, inactivity has been higher in the NMS, especially among women and older workers, but also among young people, who often remain neither in employment, education, nor training. Finally, NMS are ageing faster than EU-15 countries.

In terms of labour market institutions, by 2008, trade union density in the EU15 had reached 35.9% of workers; in the NMS it stood at just 15.6% (Rovelli, 2024a). Similar disparities were observed in collective bargaining coverage, with 82.6% of workers covered in the EU15 compared to 74.3% in the NMS. Differences in the strictness of employment protection legislation for regular and temporary contracts were less pronounced. In 2008, the EU15 states had slightly stricter regulations for temporary contracts, alongside more liberal rules governing regular contracts. Furthermore, public expenditure on labour market policies differed substantially: NMS spent, on average, three times less (as a percentage of GDP) on active labour market measures, and nearly four times less on passive measures, relative to the EU15 (Rovelli, 2024b).

Weaker institutions in the NMS—lower union density, thinner bargaining coverage, and far lower spending on active/passive labour-market policies (LMP)—tend to raise weak labour-market attachment by increasing inactivity and underemployment and lengthening non-employment spells (including NEETs). In the EU15, stronger coverage and higher LMP spending cushion shocks and support activation, so detachment is more likely to appear as shorter, registered unemployment rather than persistent inactivity.

1. The Persistence of Weak Labour Market Attachment

This section outlines our methodology for identifying vulnerable groups in the labour market between 2006 and 2023. We first define our measures of weak labour market attachment and the risk factors examined in the analysis. We then present the descriptive findings and discuss their implications.

1.1. Data

The data we use comes from the EU Labour Force Survey. We focus on the period from 2006 to 2023. We choose this timeframe due to data availability in the EU LFS. We aggregate the indicators of weak labour market attachment for EU15 and NMS. We weight our data using country weights COEFFY such that the weight of each country by group is 1, as described in detail in the Appendix Note.

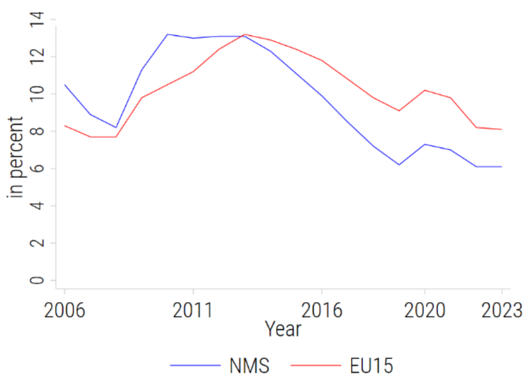
Weak labour market attachment

We employ three measures of weak labour market attachment: labour market slack, the underemployment rate, and the inactivity rate. This selection is necessary because these indicators directly operationalise our paper's core definition of vulnerability, which is workers' weak labour market attachment and low labour force participation rates. Labour market slack and the underemployment rate capture different dimensions of weak attachment. Using these three metrics allows us to quantify the exact "persistent, historical challenges" that our introduction identifies—specifically faced by vulnerable groups. They were selected because they are standard measures used in the literature and are the most reliable measures of weak labour market attachment among those available in the EU LFS.

Labour market slack

As defined by (Eurostat, 2025) the *labour market slack* captures a broader scope of labour market vulnerability than the standard unemployment rate. It measures weak attachment to the labour market by including the unemployed and certain groups of the employed and the traditionally classified inactive population. We present the average rates of labour market slack for NMS and EU15 on the Figure 1.

Figure 1. Labour market slack by country group



Source: Own elaboration based on EU LFS data 2006-2023

To be officially classified as unemployed, individuals must meet specific criteria regarding an active job search and availability for work. The labour market slack indicator relaxes these requirements to incorporate two additional groups who, although neither employed nor formally unemployed, demonstrate some degree of labour market attachment.

The first group includes individuals seeking employment but not immediately available to start work. Specifically, these are persons who:

a) have actively sought work during the past four weeks but are not available to begin work within the next two weeks;
b) have secured a job that will start within the next three months but are not available to begin work within the next two weeks; or
c) have secured a job that will start in more than three months and are similarly unavailable to start work within the next two weeks.

The second group among the inactive population comprises individuals available to work but not actively seeking employment. This group includes persons who:

a) have not actively sought employment during the past four weeks but are available to start work within the next two weeks;
b) have passively sought employment during the past four weeks and are available to start within the next two weeks; or
c) have secured a job that will commence in more than three months and are available to start work within the next two weeks.

These two groups together constitute what Eurostat terms the *potential additional labour force.*

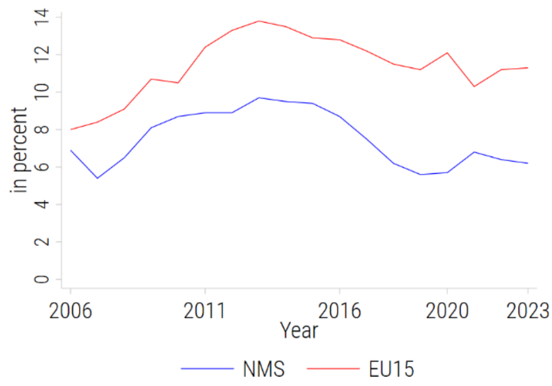
The third component comprises underemployed part-time workers: individuals in self-reported part-time work who desire and are available for additional working hours. These three groups together constitute the supplementary indicators of labour market slack, capturing underutilization beyond conventional unemployment measures.

The labour market slack is thus defined as the share of unemployed individuals, along with the potential additional labour force and underemployed part-time workers, relative to the extended labour force—the sum of the labour force and the potential additional labour force.

Underemployment rate

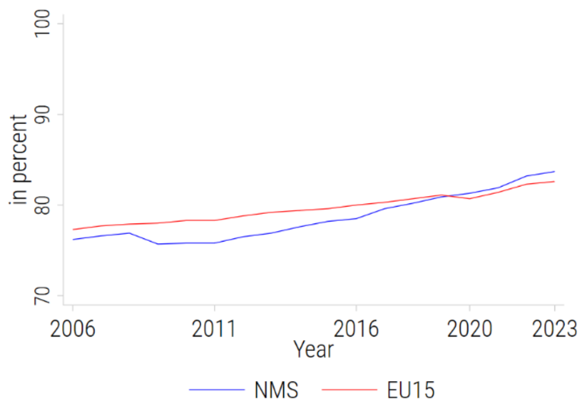
We define an underemployed person as an individual who is employed but expresses a desire to work more hours, either by explicitly stating this preference or by indicating a preferred number of working hours that exceeds their usual working hours by at least five hours. This is in consequence a broader definition than in the case of underemployed part-time workers. The data on underemployment in NMS and EU15 is presented on the Figure 2.

Figure 2. Underemployment rate by country group



Source: Own elaboration based on EU LFS data 2006-2023

Figure 3. Labour force participation by country group.



Source: Own elaboration based on EU LFS data 2006-2023

We define inactive persons as those who are not working or unemployed but who are between 25 and 64 years of age. Although the inactivity rate does not signify weak labour market attachment but rather a lack thereof, we understand that factors that influence the inactivity rate might also be driving the unemployment rate.

Overall, the situation on the EU15 labour markets was better than in the NMS at the beginning of the considered period (2006-2023), featuring higher labour force participation and lower labour market slack. However, this reversed by the end of the period, as those rates became more favourable for the NMS. Underemployment was higher in the EU15 throughout the period.

Risk groups

Our first research aim is to identify groups that have faced the most significant labour market challenges over the past two decades. We acknowledge that complex individual factors, including personal characteristics, background, aspirations, structural barriers, and life choices, shape labour market outcomes. Nevertheless, drawing on the extensive literature reviewed below, we adopt a socio-demographic lens to identify systematic patterns that may correlate with weak labour market attachment measures.

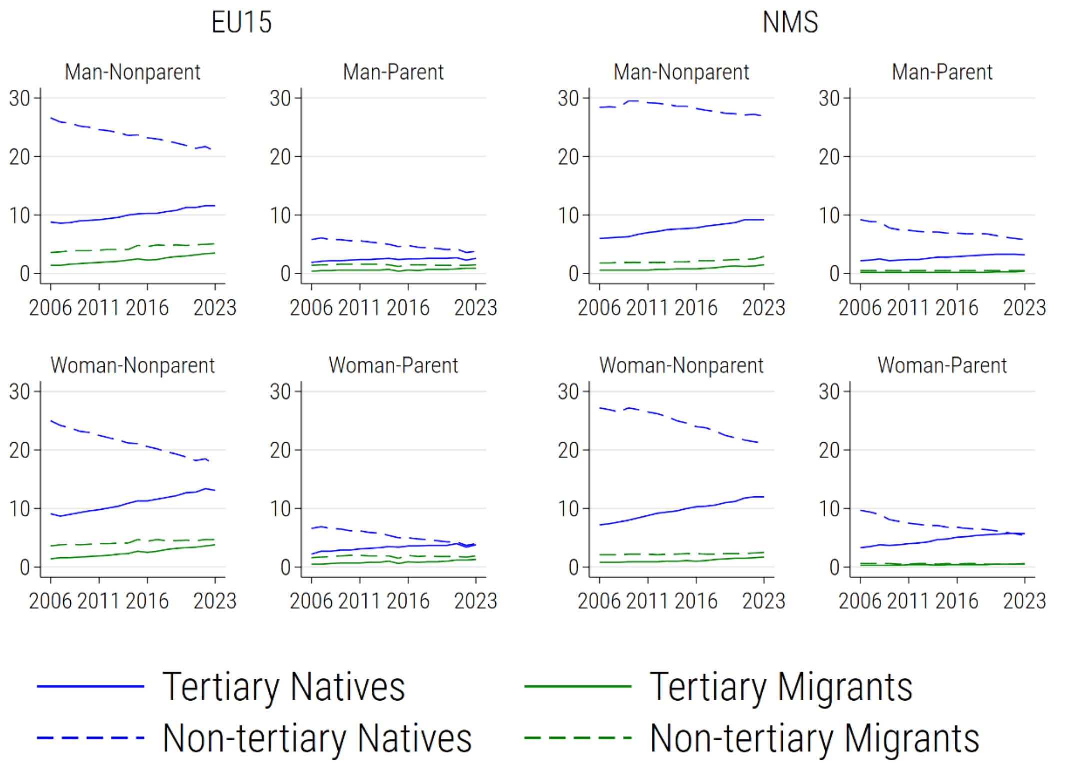
We build on the PATHS2INCLUDE framework (Valls et al., 2024) that lists the at-risk groups on the labour market and outlines the possibility of identifying them in the data. In our analysis, which examines trends in weak labour market attachment measures, we focus on the risk factors commonly linked in the literature to differential labour market outcomes: parental status, gender, migrant status, educational attainment, and age. We restrict the analysis to individuals aged 25–64. We examine the indicators listed in the previous section across these factors—and their intersections—to assess labour-market performance and identify particularly vulnerable profiles.

Parental obligations are widely considered a factor reducing labour force participation and creating a risk of a worsening labour market situation for women due to career breaks (Kleven, Landais, & Søgaard, 2019; Olivetti et al., 2024) and employer discrimination (Baert, 2018; Blau & Kahn, 2017; Buttler et al., 2025). A growing number of researchers investigate the motherhood wage penalty, also known as the motherhood gap (difference in wages of mothers and childless women) (Kleven, Landais, & Søgaard, 2019). In OECD countries, motherhood penalties account for most of the overall gender inequality (Kleven, Landais, Posch, et al., 2019). A vast body of literature discusses the impact of gender on labour market attachment, covering topics such as gender-based discrimination in hiring (Baert, 2018) and societal norms that influence women's labour market choices (Olivetti et al., 2024). This literature also discusses the potential risk factor of a migrant background in the labour market due to discrimination in hiring (Baert, 2018) and occupational downgrading (Brell et al., 2020). The economic literature also widely discusses how tertiary education can improve one's labour market position in terms of wage levels (Patrinos, 2024) and labour market participation (OECD, 2023). Finally, the relationship between age and labour market attachment has been the subject of numerous studies, particularly with regard to the impact of economic crises on young people (Bell & Blanchflower, 2011) and older people (Coile & Levine, 2011; Eiffe et al., 2025).

Figure 4 illustrates changes in the composition of the 25–64 age group, highlighting a steady increase in the proportion of migrants in EU15 states. As of 2023, migrants accounted for 24% of the EU-LFS sample in the EU15 (and 8% in the NMS).

While migration background explains meaningful differences in labour-market attachment, and we will report results by migrant status where relevant, our primary analysis focuses on gender and educational attainment gaps. Therefore, to sharpen this focus and maintain a clear analysis, we will frequently present statistics that are not further stratified by migration status.

Figure 4. Share of population (in percent) for the 25–64 age group, broken down by gender, education, parental status, and migration status (by country group).



Source: Own elaboration based on EU LFS data 2006-2023

Note: Tertiary and non-tertiary relate to the highest achieved education level.

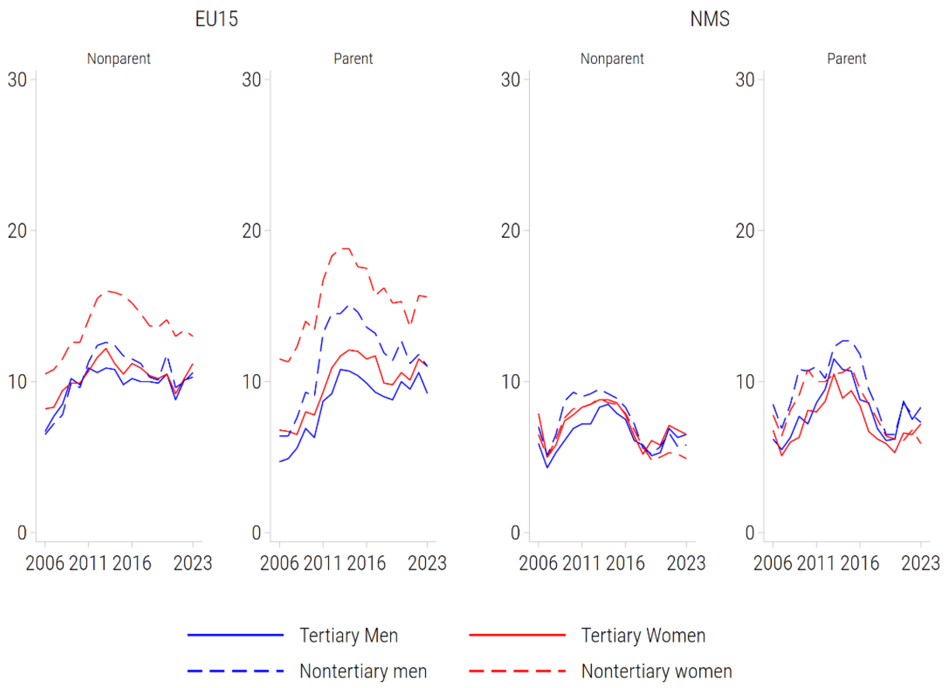
1.2. Results – descriptive analysis

We begin by presenting results for the core working-age group (35–54) to compare levels of underemployment, labour force participation and labour market slack across key socio-demographic groups. The first figure for each indicator shows average rates of the variable by gender, parental status, and education. Focusing first on this group allows us to highlight the main differences in labour market outcomes across the entire population. Once these patterns are established, we introduce the distinction between migrants and natives to show how migration background modifies these differences. Comparisons for younger workers (under 35) and older workers (55+) are provided in the Appendix.

Underemployment

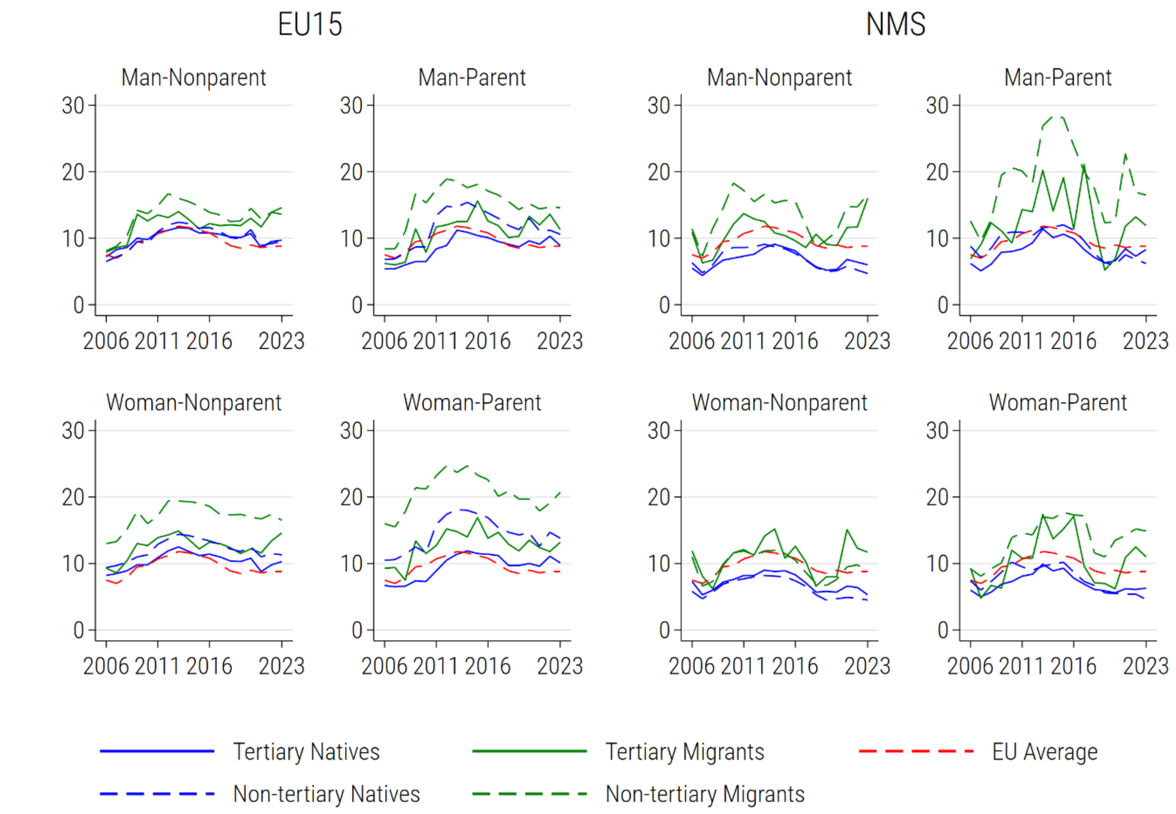
Across the EU, migrants have higher rates of underemployment than their native peers, when looking at people of the same gender, age, education and parental status. In the EU-15, the following strongest risk factors, in order, are being under 34, having no tertiary education, and being a woman. Risks compound for mothers without tertiary education—especially if they are migrants. In the NMS, lacking tertiary education is as important a correlate as gender for parents. On the other hand, for non-parents, the differences across gender and education groups are not as stark. Figures 5 and 6 align with these patterns. Figure 5 shows that in the EU-15, the non-tertiary educated are especially vulnerable, and parenthood adds a further risk. Figure 6 confirms that being a migrant is the leading risk factor, with non-tertiary-educated mothers facing markedly higher underemployment if they are migrants. Figure A1 in the Appendix indicates that while parent–non-parent gaps among younger workers resemble those for the 35–54 group, overall underemployment levels are higher for the young, reaching about 20%. Figure A2 in the Appendix shows that while among those aged 55+, the level of underemployment is lower than in other age groups, there is a significant gender gap in underemployment for the non-tertiary educated in the EU-15, whereas in the NMS, there are no sizable gaps by gender or education.

Figure 5. Underemployment among 35-54



Source: Own elaboration based on EU LFS data 2006-2023
Note: Tertiary and non-tertiary relate to the highest achieved education level.

Figure 6. Underemployment among 35-54, by migration status.



Source: Own elaboration based on EU LFS data 2006-2023
Note: Tertiary and non-tertiary relate to the highest achieved education level.

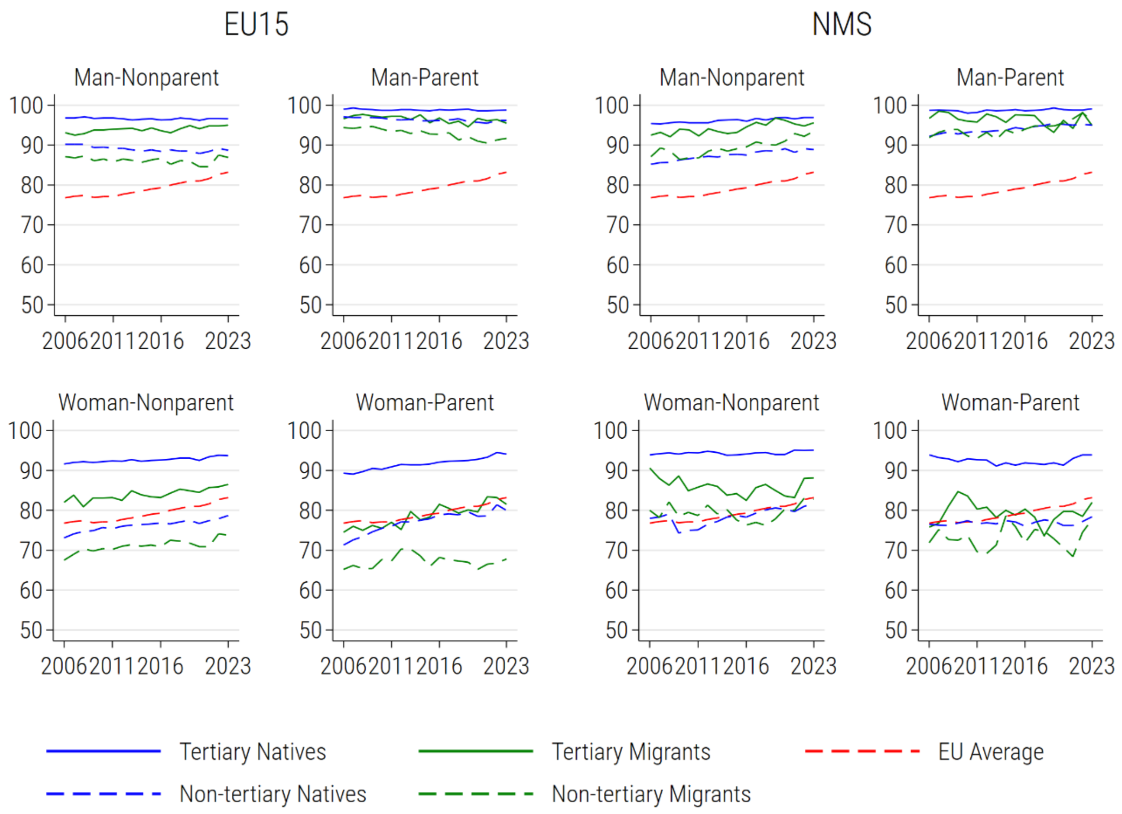
Labour force participation

Across the EU, significant differences in labour-force participation can be observed when stratified by gender and education (see Figure 7). The lowest participation rates are found among two groups: migrant women and women aged 54+ without tertiary education (Figures 10 and A4 in the Appendix). In the NMS, women's participation is lower overall, especially among migrant mothers and mothers without a tertiary education. In contrast, in the EU-15, the highest risks cluster among non-tertiary-educated migrant mothers, highlighting the protective role of tertiary education (Figure 8). Trajectories also diverge by age. For the 25–34 age group, participation is generally higher; yet sizeable gaps persist for women with children. In the NMS, non-tertiary-educated mothers experienced a significant decline that has only partially recovered since 2020 (Figure A3 in the Appendix). Participation is particularly low for the oldest cohort, with large gender gaps and a pronounced education gradient persisting (Figure A4 in the Appendix). Two additional patterns emerge over time: the absence of sustained growth in the participation of mothers with and without tertiary education in the NMS, and the decline in the participation of fathers in the EU-15, most notably among those without tertiary education (Figure 7). Throughout the period, native mothers — whether tertiary-educated or not — are more likely to be active in the EU-15 than in the NMS, and the education gap between mothers with and without tertiary education is wider in the NMS (Figure 7).

Figure 7. Labour force participation among 35-54 year old

Source: Own elaboration based on EU LFS data 2006-2023
Note: Tertiary and non-tertiary relate to the highest achieved education level.

Figure 8. Labour force participation among 35-54 year old, by migration status.



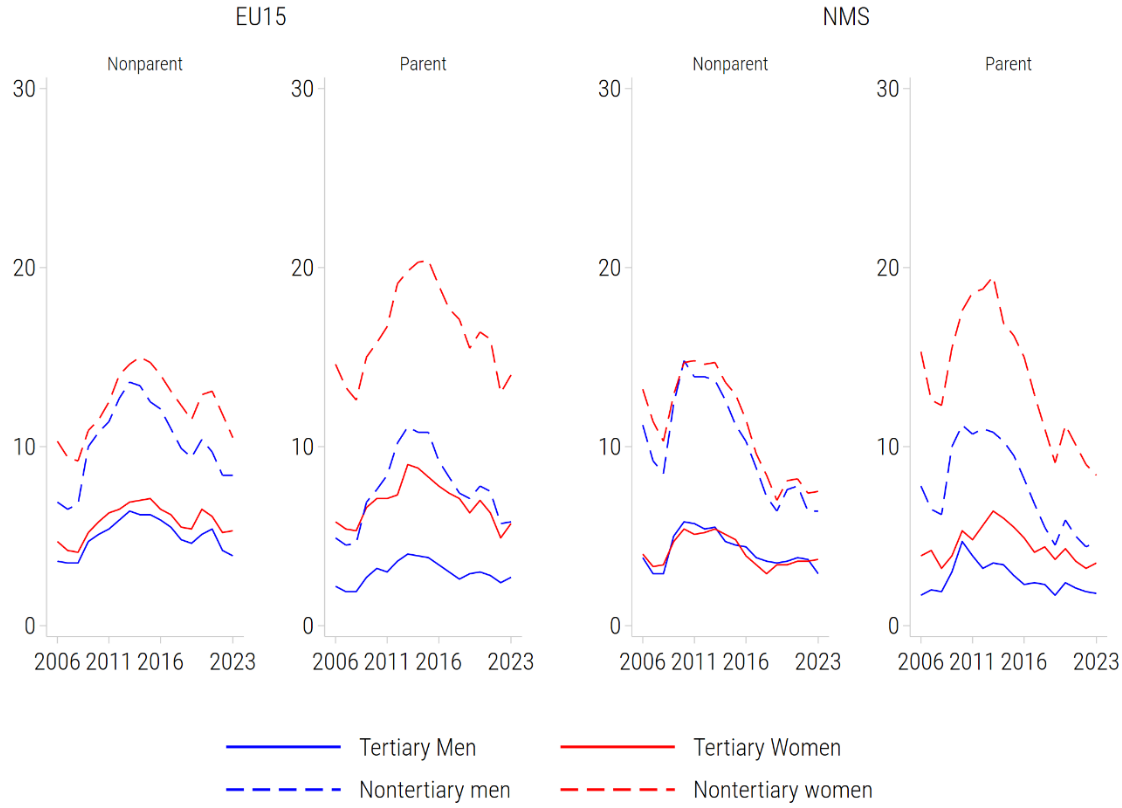
Source: Own elaboration based on EU LFS data 2006-2023
Note: Tertiary and non-tertiary relate to the highest achieved education level.

Labour market slack

Across the EU, when considering socio-demographic categories, migrants and those with non-tertiary education have higher rates of labour market slack. Among younger, non-tertiary-educated women, the proportion of women who were in the labour market slack group rose above 30% in the EU-15 between 2011 and 2016, with similarly high levels in the NMS. The gap between women who had children and those who did not was especially pronounced. In the NMS, once education and migration are held constant, differences between mothers and non-mothers are modest; however, at comparable education–migration profiles, mothers in the NMS have similar labour market slack levels as mothers in the EU-15.

Figure 9 shows that the core drivers of slack are education and gender: among non-parents aged 35–54, women and those without tertiary education face higher slack; among parents, lacking tertiary education is a particularly strong risk factor. Figure 10 adds that migration background amplifies slack risk—most strongly in the EU-15, but also for mothers in the NMS. Age gradients further shape the picture: for the youngest group, participation shortfalls translate into much higher slack for mothers, while fathers tend to experience lower slack than non-parent men (Figure A5 in the Appendix). For the oldest group, overall slack in the EU-15 is similar to that of the 35–54 cohort, whereas in the NMS it is higher across education levels; within education groups, gender gaps are not statistically significant (Figure A6 in the Appendix).

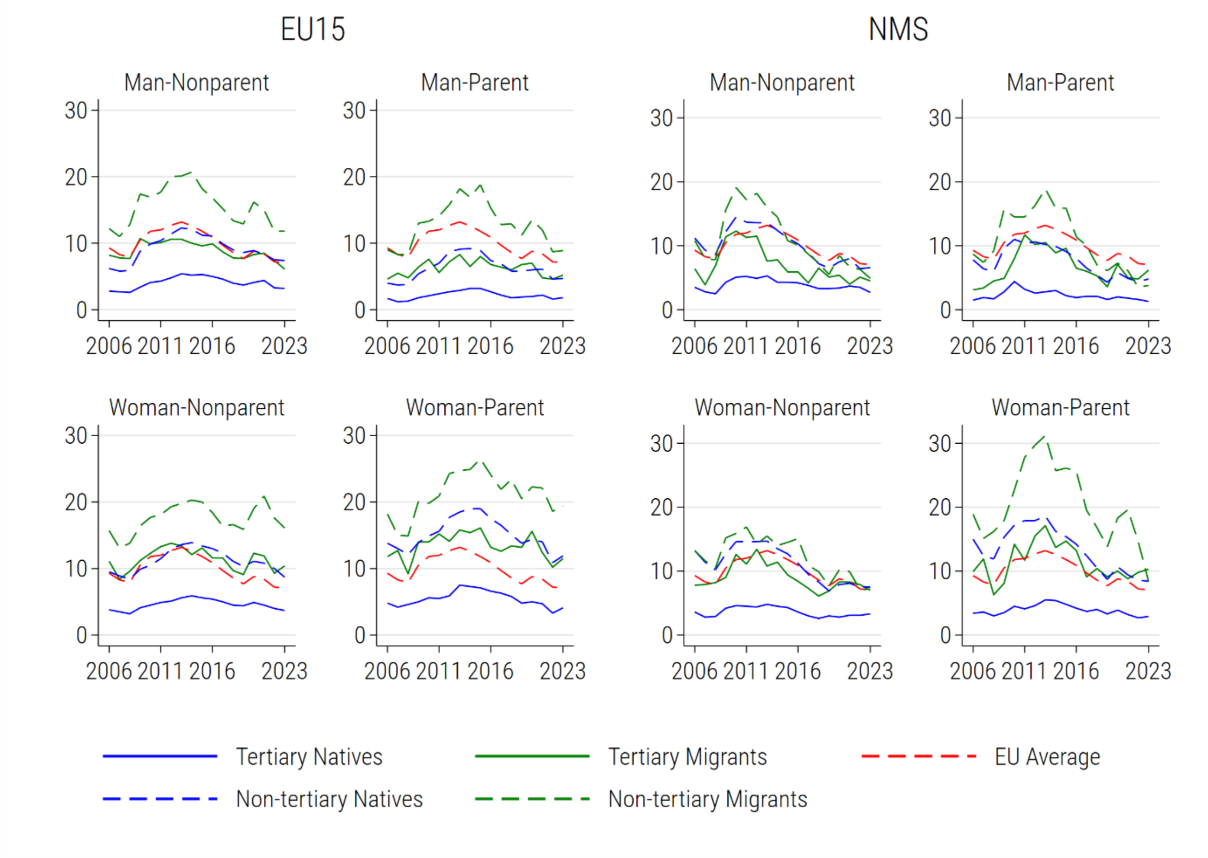
Figure 9. Labour market slack among 35-54 year old



Source: Own elaboration based on EU LFS data 2006-2023

Note: Tertiary and non-tertiary relate to the highest achieved education level.

Figure 10. Labour market slack among 35-54, by migration status.



Source: Own elaboration based on EU LFS data 2006-2023
Note: Tertiary and non-tertiary relate to the highest achieved education level.

2. Future of work

2.1. Background

Technological change throughout the 20th century created both winners and losers in terms of job access, job quality, and wages (Acemoglu & Restrepo, 2022; Autor et al., 2003; Goldin & Katz, 2008). This raises concerns about the potential disruptions that emerging technologies may bring to labour markets (Mokyr et al., 2015). The previous chapter documented EU trends in weak labour-market attachment over the past two decades. In this chapter, we develop hypotheses about who is most at risk from current workplace transformations by focusing on occupations that combine high exposure to AI with limited digital use.

Our empirical strategy assumes that workers in these occupations are particularly vulnerable to technological change. We construct an indicator identifying these "high-exposure, low-digital" jobs and use regression analysis to examine the socio-demographic characteristics associated with them. It has been proven that ICT skills are highly rewarded in the labour market (Falck et al., 2021). It has also been shown that predictions about automatability of jobs are mostly correct in showing which jobs will be reduced and which will not (Albinowski & Lewandowski, 2024; Autor et al., 2003; OECD, 2018). In case of Generative Artificial Intelligence impacts, one should expect a decline in the share of people employed in occupations that can have their core tasks automated by AI; however, an effect on occupations in which only a part of the tasks will be replaced is not trivial to predict (Machovec et al., 2025). It is hard to forecast whether the change in job task content due to technological disruptions will have a net positive or negative impact on the exposed occupations. The answer depends on multiple factors, and primarily, the job creation due to an increased product demand (Acemoglu & Restrepo, 2020; Gregory et al., 2022). Nevertheless, as research on recent technological change impacts shows, some demographic groups, concentrated in affected occupations, may be particularly negatively affected. This was the case of women with an intermediate level of education working in routine cognitive occupations between the 1980s and 2010s (Cortes et al., 2017). Previous waves of automation have contributed to the transition of many middle-skilled workers to low-skilled employment and an increase in involuntary part-time employment (Doorn & Vliet, 2024). The objective is to identify who will possibly be affected in the current wave of technological changes.

As shown earlier, several groups are over-represented among workers with weak labour-market attachment—particularly those with lower education, migrants, mothers with care responsibilities, and individuals facing discrimination or institutional barriers (e.g., limited childcare, recognition of qualifications). We now ask whether the AI-related adaptability risk identified above aligns with these existing vulnerabilities. In other words, do the groups with weaker attachment today also face disproportionately higher exposure to future AI-driven disruption?

To investigate this question empirically, we first develop a methodology to identify workers facing this specific 'adaptability risk'. We then use this framework to analyse which socio-demographic and labour market characteristics are associated with this vulnerability.

2.2. Methodology

Adaptability risk group

Our methodological design divides each country's labour force into four subgroups. (1) People with low digital skill use and low AI exposure, (2) people with low digital skill use and high AI exposure, (3) people with high digital skill use and low AI exposure and (4) people with high digital skill use and high AI exposure. To this aim, we first use 2022 EU LFS data to evaluate expected AI exposure based on the ISCO 2d occupation. Later on, we divide our sample according to the digital skill use at work.

AI Exposure

Our analysis employs the AI exposure scores from Lewandowski et al. (2025), which adapt the metrics from Felten et al. (2021) to country-specific task structures using PIAAC data.

As the first step, we segment respondents within each country into two groups: those above and those below the national median AI exposure. The AI occupational exposure (AIOE) measure was created by mapping AI applications to human abilities, using a 2021 perspective on AI capabilities. The mapping considered only the prospect of AI doing particular tasks in the future, and not the actual capabilities of the state-of-the-art AI models. Those prospects could have changed since then; however, the Felten et al. (2021) measure remains a standard in the literature.

AI applications—which include functions like text/image recognition, generation, translation, and speech recognition—were mapped against human abilities sourced from the O*NET database, which details the abilities required for various occupations. The mapping process involved random internet participants who assessed whether the O*NET definition of a specific ability (e.g., Peripheral Vision) could be performed by an AI application (e.g., image recognition). Based on this mapping, the resulting AIOE score measures the extent to which an occupation relies on abilities that AI can perform. The authors note important caveats: the measure indicates exposure, not necessarily substitution, as it could just as easily imply complementarity between AI and the worker. They also note that the measure is static, reflecting the abilities currently needed for these occupations, and does not account for future changes in how those jobs are performed.

Lewandowski et al. (2025) adapt the aforementioned US-based measure by adjusting it for the country-specific task content of jobs. This adjustment, among other things, results in professional and managerial occupations in high-income countries being more exposed to AI than in middle-income countries.

Digital skill use at work

Then, independently of the previous step, we divide the respondents into two groups based on their digital skill use at work. Respondents of the EU LFS 2022 were asked how much of their work time they spend using digital devices (on a 5-point scale). We classify workers as having 'low digital skill use' if they do not use digital devices at all or use them very little during their working time. Digital devices are "(…) computer, tablet, phablet or smartphone for work tasks, excluding phone calls" (Eurostat, 2023).

We acknowledge that this variable does not directly measure the level of their digital proficiency. The amount of time someone spends using a computer at work is likely the equilibrium result (inherently endogenous) of workers' supply of digital skills, as well as employers' demand for such skills. However, we believe it is reasonable to assume that by using these devices at work, workers develop a significant amount of digital skill, so we expect a high correlation between actual digital skills and their digital skill use at work. Moreover, workers possessing a high level of digital skills will likely choose jobs that require their use.

Groups of workers at the intersection of digital skill use and AI exposure

Combining digital skill use with the level of AI exposure yields four categories of workers.

The first group includes workers in occupations with relatively low AI exposure and low digital skill use. Examples include Cleaners and helpers (ISCO 91), Agricultural, forestry and fishery labourers (ISCO 92), and Building and related trades workers (ISCO 71). These workers are unlikely to face significant adaptation risks within their current occupations, so a lack of digital skills should not hinder their labour market outcomes in these roles. This low-skill equilibrium, however, will leave them in a worse position to transition to more digitally intensive occupations.

A second category consists of workers with low AI exposure and high digital skill use. This group includes, for example, Science and engineering professionals (ISCO 21), Science and engineering associate professionals (ISCO 31), and Health professionals (ISCO 22). They appear to be the group least affected by AI. Although they use digital devices extensively, their core work tasks do not overlap significantly with those tasks currently feasible by AI.

Then there is the third category - in which we have workers in occupations with high exposure to AI, and a high level of digital skills. Examples include Information and communications technology professionals (ISCO 25), General and keyboard clerks (ISCO 41), and Business and administration professionals (ISCO 24). These workers are likely to experience task transformation rather than full displacement, as AI tools can complement and enhance their productivity. Their familiarity with digital technologies positions them relatively well to adapt to new tools and workflows, though some tasks—particularly routine administrative ones—may still be at risk of automation.

Finally, the fourth category consists of workers with high exposure to AI and low use of digital skills. Examples include Teaching professionals (ISCO 23), Sales workers (ISCO 52), and Legal, social and cultural associate professionals (ISCO 34). This group may face greater adjustment challenges, as AI is increasingly capable of performing parts of their cognitive and interpersonal tasks, while their limited digital skill use constrains their ability to integrate AI tools effectively. The combination of high exposure and low preparedness suggests a risk of polarisation within these professions, where some workers adapt successfully while others fall behind. This is the group to whom we assign the adaptability risk.

Having defined this key 'adaptability risk' group, we now turn to the descriptive statistics to examine the prevalence and socio-demographic composition of all four categories.

Descriptive statistics on adaptability risk

Unsurprisingly, as shown in Table 1, there is a clear positive correlation between the use of digital skills at work and AI exposure. This is evident from the fact that the low-skill/low-exposure and high-skill/high-exposure groups combined account for 74% of the sample. Furthermore, the average level of AI exposure is higher among workers who use digital skills more frequently.

Table 1. Digital Skill Use at Work and AI Exposure subgroups sample structure.

	Low AI Exposure	High AI Exposure
High Digital Skill Use	12%	34%
Low Digital Skill Use	40%	14%

Note: N = 349 979
Source: Own elaboration based on EU LFS 2022 data.

Examining group composition reveals clear patterns. High skill use is concentrated among tertiary-educated workers. The high-exposure group is primarily women. Age differs little across groups. Migrants are underrepresented among the highly exposed. Workers on temporary contracts are slightly overrepresented in the low-skill-use/low-exposure group and underrepresented in the high-skill-use/high-exposure group. Underemployed temporary workers are overrepresented in low-digital-skill-use occupations.

Table 2. Composition of Digital Skill - AI Exposure groups.

Group	Low Skill Use - Low Exposure	Low Skill Use - High Exposure	High Skill Use - Low Exposure	High Skill Use - High Exposure
Tertiary Education	19%	47%	60%	67%
Women	40%	59%	42%	56%
Age 25-34	22%	22%	28%	26%
Age 35-54	55%	56%	55%	57%
Age 55-64	23%	22%	17%	17%
Migrants	19%	14%	17%	15%
Parents	22%	22%	26%	26%
Underemployed	11%	10%	10%	9%
Temporary Contracts	9%	7%	7%	6%
Underemployed & Temporary Contracts	2%	2%	1%	1%

Source: Own elaboration based on EU LFS 2022 data.

Sales workers (ISCO-08 52) represent the biggest group in our sample facing high AI exposure, combined with low daily digital skill use. This vulnerability is likely because, while those workers are currently not using digital tools extensively, many tasks they perform in stores, such as checkout and basic customer service, can be automated with tools like computer vision (e.g., self-checkout) and chatbots. At the same time, new technologies for managing in-store inventory, e-commerce integration, and customer data will likely increase the demand for higher digital proficiency. This trend may create a skills gap between the workers' current capabilities and emerging employer needs.

Teaching professionals (ISCO-08 23) face adaptability risk from generative tools that can assist with or partially automate tasks like lesson planning, creating assignments, grading, feedback, and routine parent communication. These tools are poised to significantly alter preparatory and assessment workflows, even if classroom delivery remains a fundamentally human-centric activity. Educators in under-resourced settings, or those with limited daily access to digital tools, may struggle to adapt when new technologies are introduced.

Legal, social, cultural, and related associate professionals (ISCO-08 34) face notable AI-adaptability risks. Many of their information-handling and document-based tasks are susceptible to automation, while some roles within this group involve limited daily digital practice. Routine activities, such as document drafting, report preparation, and basic research, can be streamlined with the help of AI tools.

Business and administration associate professionals (ISCO-08 33) face growing automation risks, as many tasks—such as bookkeeping support, compliance checks, and HR screening—can be handled by AI tools. Workers who do not use a computer system or perform data entry or use digital systems passively may be less prepared to adapt, increasing the likelihood of role consolidation and reduced demand for routine administrative work.

Numerical and material recording clerks (ISCO-08 43) are exposed to automation, as OCR (optical character recognition), e-invoicing, and robotic process automation can handle tasks such as data entry, invoice posting, and shipment tracking. In workplaces that rely on manual procedures, limited use of advanced digital systems may reduce opportunities to build adaptive digital skills, heightening the risk of displacement.

Table 3. Most common occupations in the high exposure - low digital skill use group

ISCO-08 Code	Occupation Name	Frequency	Percent
52	Sales workers	12,520	25.00%
23	Teaching professionals	11,628	23.22%
34	Legal, Social, Cultural and Related Associate Professionals	3,703	7.39%
33	Business and administration associate professionals	3,644	7.28%
43	Numerical and material recording clerks	2,736	5.46%
24	Business and administration professionals	2,204	4.40%
14	Hospitality, retail and other services managers	2,158	4.31%
26	Legal, social and cultural professionals	2,057	4.11%
13	Production and specialised services managers	2,026	4.04%
51	Personal services workers	1,793	3.58%
41	General and keyboard clerks	1,236	2.47%
12	Administrative and commercial managers	966	1.93%
42	Customer services clerks	781	1.56%
11	Chief executives, senior officials and legislators	536	1.07%
44	Other clerical support workers	531	1.06%
25	Information and communications technology professionals	333	0.66%
53	Personal care workers	305	0.61%
21	Science and engineering professionals	259	0.52%
35	Information and communications technicians	229	0.46%
95	Refuse workers and other elementary workers	160	0.32%
31	Science and engineering associate professionals	85	0.17%
32	Health associate professionals	78	0.16%
94	Food preparation assistants	68	0.14%
73	Handicraft and printing workers	52	0.10%

Source: Own elaboration based on EU LFS 2022 data.

While these descriptive statistics provide a clear profile of the 'adaptability risk' group, particularly which occupations are most common, they do not isolate the independent association of each socio-demographic factor. To move beyond these initial patterns and formally test these relationships while controlling for multiple variables, we now introduce our empirical design.

Empirical design

We estimate logistic regressions to identify workers in the adaptability-risk group—those with low digital skill use and high AI exposure—relative to other workers (models 1–3), and to assess how this status is associated with indicators of weak labour market attachment (models 4–5). All models include the core risk factors described in the previous section. Models 4–5 additionally include interactions between weak-attachment indicators and key covariates to test whether these associations differ across socio-demographic groups.

Table 4. Description of regressions performed

No.	Model	Outcome Variable	Control Variables
1	Multinomial Logit	4 risk groups on Digital Skill Use x AI Exposure Matrix	Gender, Age category (25-34, 35-54, 55-64), Parental obligations, Tertiary education, Migration status, Country group (EU15, NMS)
2	Binary Logit	0/1 variable on having Low Digital Skill Use and High AI Exposure	Gender, Age category (25-34, 35-54, 55-64), Parental obligations, Tertiary education, Migration status, Country group (EU15, NMS)
3	Binary Logit (separately for NMS and EU15)	0/1 variable on having Low Digital Skill Use and High AI Exposure	Gender, Age category (25-34, 35-54, 55-64), Parental obligations, Tertiary education, Migration status
4	Binary Logit (separately for NMS and EU15)	0/1 variable on having Low Digital Skill Use and High AI Exposure	Temporary Contract(*), Underemployment(*), Gender, Age category (25-34, 35-54, 55-64), Parental obligations, Tertiary education, Migration status
5	Binary Logit (separately for NMS and EU15)	0/1 variable on having Low Digital Skill Use and High AI Exposure	Underemployed on Temporary Contract(*), Gender, Age category (25-34, 35-54, 55-64), Parental obligations, Tertiary education, Migration status

Note: (*) Interacted with other control variables.

Throughout, we use cross-sectional weights provided by Eurostat (coeffy), which were normalised such that each country has an equal weight.

Using the four-group framework and the regression models defined above, we now turn to the findings.

2.3. Results – future of work

This section presents the results from the logistic regression models described in the empirical design. We first present the average marginal effects from the multinomial logit (Model 1) to show the socio-demographic correlates for all four groups. We then focus the analysis specifically on our 'adaptability risk' (LS-HE) group using a series of binary logit models. We show the pooled demographic results (Model 2), then disaggregate by country group (Model 3), and finally, we test the association with weak labour-market attachment indicators (Models 4 and 5).

Table 5 presents average marginal effects from a multinomial logit model estimating the likelihood of belonging to the low-digital-skills, high-AI-exposure (LS-HE) group. Women are 5.9

percentage points (pp) more likely than men to be in the LS-HE group. Compared to workers aged 35–54, those aged 25–34 are 1.2 percentage points less likely, while those aged 55–64 are 0.8 percentage points more likely to belong to this group. Parents are 1.5 percentage points less likely than non-parents, tertiary-educated individuals are 1.6 percentage points more likely than those without tertiary education, and migrants are 3.1 percentage points less likely than natives. Country-group effects are close to zero, suggesting minimal cross-country variation.

Overall, the profile most associated with LS-HE status is that of a female, older working-age individual, childless, and tertiary-educated, while migrants show a lower probability of belonging to this group. The modest age gradient and negligible country differences indicate that individual characteristics—particularly gender—are the strongest correlates of LS-HE status.

This partly aligns with the theory, as Acemoglu (2024) shows that native born women are most exposed to AI (however, he argues that the low-education women are especially vulnerable).

Table 5. Model 1 – Marginal Effects For being in one of four groups.

	(1) Low Skill Low Exposure	(2) Low Skill High Exposure	(3) High Skill Low Exposure	(4) High Skill High Exposure
Female	-0.0835^{***}	0.0588^{***}	-0.0406^{***}	0.0652^{***}
	(0.00247)	(0.00193)	(0.00177)	(0.00253)
Age 25-34 (ref. 35-54)	-0.00773^{*}	-0.0120^{***}	0.0166^{***}	0.00311
	(0.00337)	(0.00250)	(0.00239)	(0.00337)
Age 55-64 (ref. 35-54)	0.0284^{***}	0.00810^{***}	-0.00972^{***}	-0.0268^{***}
	(0.00301)	(0.00242)	(0.00210)	(0.00302)
Parent	-0.0135^{***}	-0.0155^{***}	0.0102^{***}	0.0187^{***}
	(0.00317)	(0.00242)	(0.00226)	(0.00316)
Tertiary	-0.403^{***}	0.0162^{***}	0.0770^{***}	0.310^{***}
	(0.00247)	(0.00198)	(0.00187)	(0.00265)
Migrant	0.101^{***}	-0.0311^{***}	-0.0112^{***}	-0.0585^{***}
	(0.00390)	(0.00281)	(0.00270)	(0.00382)
EU15	-0.0237^{***}	-0.000397	0.0400^{***}	-0.0159^{***}
	(0.00256)	(0.00200)	(0.00180)	(0.00261)
Observations	349979	349979	349979	349979
Pseudo R^2	0.093	0.093	0.093	0.093

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table presents marginal effects from a multinomial logit model in which the outcome variable is being in one of the four risk groups.

Results of the Binary Logit in Table 6, which simplify the outcome to being in the 'adaptability risk' group versus all others, confirm the multinomial logit findings from Table 5.: signs and significance match, and magnitudes differ only trivially (e.g., women +5.84 pp vs +5.88; ages 55–64 +0.75 vs +0.80; migrants −2.96 vs −3.10). The EU15 effect remains null. In sum, gender is the dominant correlate, the age gradient is mild, parenthood lowers risk, tertiary education slightly raises it, and migrant status lowers it. Pooling the three non-LS-HE categories in the binary model does not change the substantive conclusions drawn from the multinomial results.

Table 6. Model 2 – Marginal Effects for being in the “Adaptability Risk” group.

	(1)
Female	0.0584***
	(0.00193)
Age 25-34 (ref. 35-54)	-0.0122***
	(0.00250)
Age 55-64 (ref. 35-54)	0.00753**
	(0.00241)
Parent	-0.0160***
	(0.00242)
Tertiary	0.0156***
	(0.00198)
Migrant	-0.0296***
	(0.00284)
EU15	0.0000390
	(0.00200)
Observations	349979
Pseudo R^2	0.0115

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table presents marginal effects from a binomial logit model in which the outcome variable is 'being in the adaptability risk group'.

While the pooled model in Table 6 suggests negligible country-group effects, Table 7 reveals this masks notable heterogeneity. Running the binary logit separately for NMS and EU15 countries shows that the correlates of adaptability risk differ sharply between the two regions. In the NMS (New Member States), women are 11 percentage points (pp) more likely to be in the LS-HE group, whereas in the EU15, the gender gap is a smaller 3 pp. Other demographic factors primarily show effects in the EU15. Age effects are concentrated there: workers aged 25–34 have a reduced likelihood (–1 pp) and those aged 55–64 have an increased likelihood (+2 pp), with both findings being significant. In the NMS, age effects are negligible and not statistically significant. The impact of education reverses between the two groups: a tertiary degree is associated with a significant +3 pp risk of being LS-HE in the EU15, but a non-significant –1 pp effect in the NMS. Migrant status is associated with a lower risk in both regions, but the effect is larger and significant in the EU15 (–4 pp) compared to a small, non-significant effect in the NMS (–1 pp). Parenthood was not found to have a significant effect in either subsample.

Table 7. Model 3 – Marginal effects for being in the “Adaptability Risk” group, by country group.

	(1) NMS	(2) EU15
Female	0.11***	0.03***
	(0.00)	(0.00)
Age 25-34 (ref. 35-54)	-0.01	-0.01***
	(0.00)	(0.00)
Age 55-64 (ref. 35-54)	0.01	0.02***
	(0.00)	(0.00)
Parent	0.00	0.00
	(0.00)	(0.00)
Tertiary	-0.01	0.03***
	(0.00)	(0.00)
Migrant	-0.01	-0.04***
	(0.01)	(0.00)

Observations	113130	236849
Pseudo R^2	0.0275	0.0077

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table presents marginal effects from a binomial logit model in which the outcome variable is 'being in the adaptability risk group'. Columns (1) and (2) show the marginal effects for NMS and EU15, respectively.

Having established the key demographic correlates, we now turn to the question of whether this adaptability risk aligns with existing labour market vulnerabilities. Table 8 introduces indicators for weak labour-market attachment (underemployment and temporary contracts). The results again indicate stark regional heterogeneity in how these factors correlate with "adaptability risk" (LS-HE). In NMS, underemployment has no detectable effect, while temporary contracts are associated with a lower LS-HE probability (−2 pp, p<0.001). Conversely, in EU15, both forms of weak labour market attachment are associated with a higher LS-HE risk: underemployment by +1 pp (p<0.001) and temporary contracts by +1 pp (p<0.01). Subgroup margins reinforce this split. In NMS, the temporary-contract penalty is broadly negative across sexes and age groups, for non-parents and non-tertiary workers, for natives, and is largest for migrants (−10 pp, p<0.001). In EU15, underemployment increases LS-HE risk for men (+2 pp), younger prime-age workers (+3 pp at 25–34), parents (+3 pp), tertiary-educated (+3 pp), and natives (+2 pp); temporary contracts show smaller but positive effects, notably for women (+1 pp), ages 25–34 (+3 pp), parents (+2 pp), tertiary-educated (+2 pp), and natives (+1 pp).

Table 8. Model 4 – Marginal effects for "Adaptability risk" for Underemployment and Temporary Contracts by risk group.

	(1)	(2)	(3)	(4)	(5)	(6)
	NMS	EU15	NMS		EU15	
	_	_	Underemployment	Temporary Contracts	Underemployment	Temporary Contracts
Underemployed	0.00	0.01***				
	(0.01)	(0.00)				
Temporary Contract	-0.02***	0.01**				
	(0.01)	(0.00)				
Male			0.02	-0.02*	0.02***	0.01
			(0.01)	(0.01)	(0.01)	(0.01)
Female			-0.02	-0.03**	0.01	0.01*
			(0.01)	(0.01)	(0.01)	(0.01)
Age 25-34			0.02	0.01	0.03***	0.03***
			(0.02)	(0.01)	(0.01)	(0.01)
Age 35-54			-0.00	-0.03***	0.01	0.00
			(0.01)	(0.01)	(0.00)	(0.01)
Age 55-64			-0.02	-0.03*	0.02	0.01
			(0.02)	(0.02)	(0.01)	(0.01)
Not Parent			-0.00	-0.02***	0.01*	0.01
			(0.01)	(0.01)	(0.00)	(0.00)
Parent			0.02	-0.02	0.03**	0.02*
			(0.02)	(0.02)	(0.01)	(0.01)
Below Tertiary			-0.01	-0.03***	0.00	0.00
			(0.01)	(0.01)	(0.00)	(0.01)
Tertiary			0.02	-0.01	0.03***	0.02**
			(0.01)	(0.01)	(0.01)	(0.01)
Native			-0.00	-0.02*	0.02***	0.01*
			(0.01)	(0.01)	(0.00)	(0.00)
Migrant			0.02	-0.10***	0.00	0.01

			(0.02)	(0.01)	(0.01)	(0.01)
Observations	113 130	236 849	113 130		236 849	
Pseudo R^2	0.0395	0.0181	0.0395		0.0181	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table presents marginal effects from a binomial logit model in which the outcome variable is 'being in the adaptability risk group'. The explanatory variables are Underemployment, Temporary Contract, and a set of controls. Columns (1) and (2) show the marginal effects for NMS and EU15, respectively. The next columns show the heterogeneous marginal effects for Underemployment (3) and Temporary Contracts (4) for NMS. The last two columns, (5) and (6), show the analogous results for EU15.

While Table 8 examined these two forms of precarity separately, Table 9 investigates their combined correlational association. It reports the average marginal effects for being in the adaptability-risk group (LS-HE) when workers are simultaneously underemployed and on a temporary contract. The pooled effect is nil in NMS (−2 pp, ns;) and positive in EU15 (+4 pp, p<0.001). Subgroup margins show the split clearly. In NMS, joint precarious status is neutral for most groups but is associated with lower LS-HE risk for women (−5 pp, p<0.05), older workers 55–64 (−13 pp, p<0.001), and migrants (−9 pp, p<0.01). In EU15, it raises risk across many strata: women +5 pp (p<0.001), men +3 pp (p<0.05), ages 25–34 +7 pp (p<0.001) and 35–54 +3 pp (p<0.05), non-parents +4 pp (p<0.001) and parents +6 pp (p<0.01), tertiary-educated +8 pp (p<0.001), natives +4 pp (p<0.001), and migrants +5 pp (p<0.05). Interpretation: dual precarious status maps to higher adaptability risk in EU15 but is neutral on average in NMS.

Table 9. Model 5 – Marginal effects for "Adaptability risk" for joint Underemployment on Temporary Contracts by risk group.

	(1) NMS	(2) EU15	(3) NMS	(4) EU15
Underemployed and Temporary Contract	-0.02	0.04^{***}		
	(0.02)	(0.01)		
Male			0.01	0.03^{*}
			(0.03)	(0.01)
Female			-0.05^{*}	0.05^{***}
			(0.02)	(0.01)
Age 25-34			0.01	0.07^{***}
			(0.03)	(0.02)
Age 35-54			0.01	0.03^{*}
			(0.03)	(0.01)
Age 55-64			-0.13^{***}	0.05
			(0.01)	(0.03)
Not Parent			-0.02	0.04^{***}
			(0.02)	(0.01)
Parent			-0.02	0.06^{**}
			(0.04)	(0.02)
Below Tertiary			-0.03	0.00
			(0.02)	(0.01)
Tertiary			-0.00	0.08^{***}
			(0.03)	(0.02)
Native			-0.01	0.04^{***}
			(0.02)	(0.01)
Migrant			-0.09^{**}	0.05^{*}
			(0.03)	(0.02)

Observations	113130	236849	113130	236849
Pseudo R^2	0.0381	0.0180	0.0381	0.0180

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: The table presents marginal effects from a binomial logit model in which the outcome variable is 'being in the adaptability risk group'. The explanatory variables are 'being both Underemployed and on a Temporary Contract' and a set of controls. Columns (1) and (2) show the marginal effects for NMS and EU15, respectively. The next columns, (3) and (4), show the heterogeneous marginal effects for NMS and EU15, respectively.

3. Discussion and conclusions

Technology is fundamentally reshaping the world of work, creating new forms of employment while simultaneously rendering low digitized jobs obsolete. The rise of artificial intelligence, automation, and digital platforms has accelerated job displacement in some sectors, while generating demand for workers with advanced digital skills and technical expertise. This technological shift may intensify the risk factors for labour market withdrawal or underemployment, as workers without adequate digital literacy or adaptable skill sets face heightened vulnerability to long-term unemployment.

The aim of our study was to deepen the understanding of both the new factors associated with the risk of underemployment, unemployment and inactivity, while at the same time investigating the new dimensions of labour market vulnerability. We discuss the characteristics associated with being employed in occupations that are highly exposed to AI, yet currently (as of 2022) involve limited use of digital skills. Our measure incorporates country-specific task structures at work, drawing on the data developed by Lewandowski et al. (2025). How should the results be interpreted? Take, for example, sales workers: their high exposure to AI stems from developments such as automated checkouts, AI tools for consumer demand forecasting, and advanced systems for store organization. However, many workers in this occupation currently engage minimally with digital technologies. However, interpreting this vulnerability requires looking beyond individual preparedness. While those lacking computer literacy would likely be disadvantaged in a subsequent job search, this risk is not only a matter of individual skills. The broader workers' rights climate is also critical, as it strongly influences how digitalisation develops and is ultimately integrated by organisations, mediating the final impact on these workers.

What we uncover is not merely a risk of technological displacement, but rather a risk of insufficient adaptability and resilience—an increasingly relevant factor influencing weak labour market attachment.

We find that for some social groups, the risk of low adaptability is correlated with current weak labour market attachment measures like underemployment and temporary contracts. For example, the correlation of those measures for tertiary-educated workers is much higher than for non-tertiary-educated workers.

Further research is needed to refine measures of occupational AI exposure and better assess future risks across specific job categories. It is plausible that individuals in highly exposed occupations may, on average, benefit more from advancements in AI technologies, though with greater variability in outcomes than those in less exposed roles.

Future studies could analyse other cutoffs for the created variables to assess result heterogeneity with respect to various levels of AI exposure and digital skill use. Researchers could also utilise other databases that measure digital skill use, such as the European Skills and Jobs Survey (developed by Cedefop), which provides more detailed information on the digital skills used at work.

One limitation of this study is its focus on a static measure of AI exposure. This does not capture current technological diffusion, the associated changes in task structures, and the ways firms and workers adapt. Further research should address these challenges.

Our findings also highlight the urgent need for targeted interventions that address not only current unemployment but also the emerging risk of insufficient adaptability in the face of technological transformation. Policymakers should prioritize digital literacy and continuous upskilling programs, particularly for workers in high-AI-exposure occupations who currently have limited digital skills. These programs must be accessible, affordable, and designed with the specific needs of less digitally literate workers in mind. Moreover, social protection systems should evolve to support workers during technological transitions, potentially through extended unemployment benefits tied to reskilling efforts, or wage insurance schemes that cushion income losses during career changes. Early intervention is critical: waiting until mass layoffs occur will leave the most vulnerable workers—those lacking digital competencies—at a severe disadvantage in an increasingly digitized labour market.

The differential vulnerability we observe across education levels suggests that policy responses must be carefully calibrated to different worker groups. While tertiary-educated workers facing adaptability risks may benefit from targeted professional development and career counselling services, non-tertiary-educated workers require more fundamental support—including basic digital literacy training, recognition of prior learning, and pathways to credential acquisition. Employers should be incentivized through tax credits or subsidies to invest in workforce training, particularly in sectors undergoing rapid AI integration. Additionally, labour market information systems must be modernized to better track AI exposure and digital skill gaps in real time, enabling more responsive policy adjustments. Finally, social dialogue involving trade unions, employers, and government is essential to ensure that technological transitions are managed in ways that protect worker rights while fostering innovation and productivity growth.

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Appendix

Figure A1. Underemployment among 25-34.

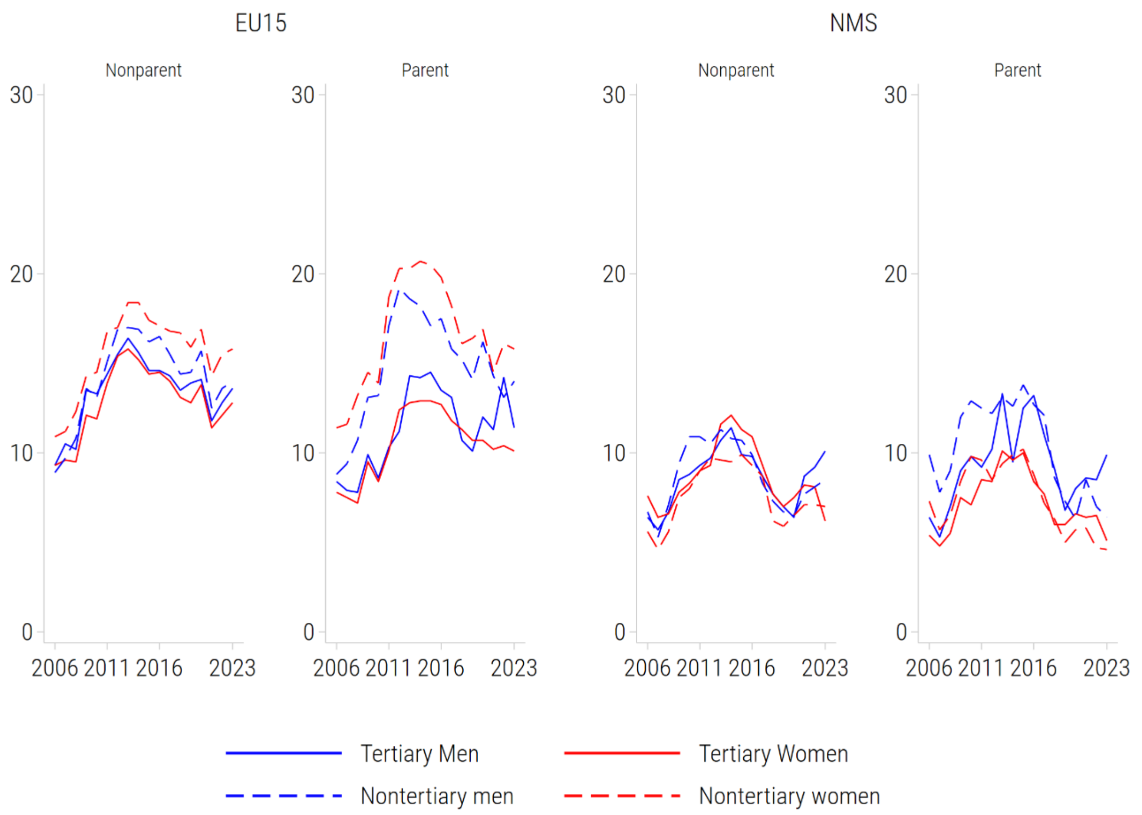


Figure A2. Underemployment among 55+ year old by education

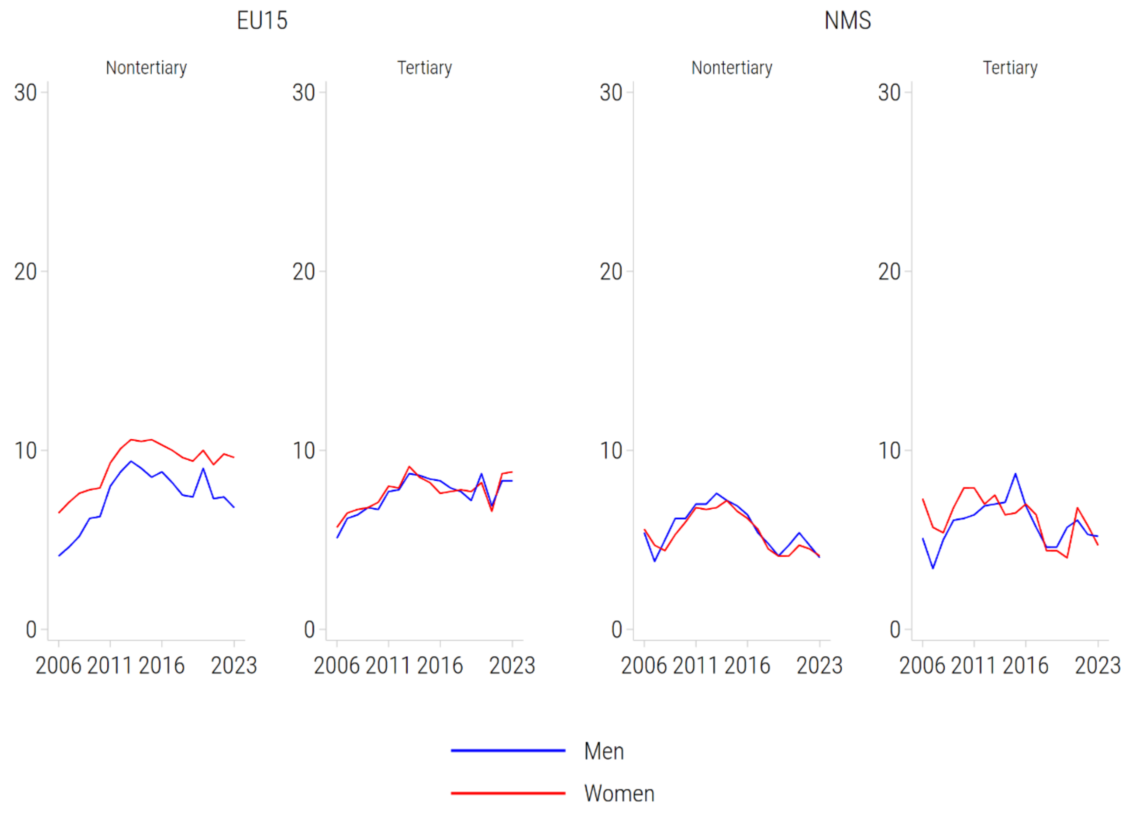


Figure A3. Labour force participation among 25-34 year old

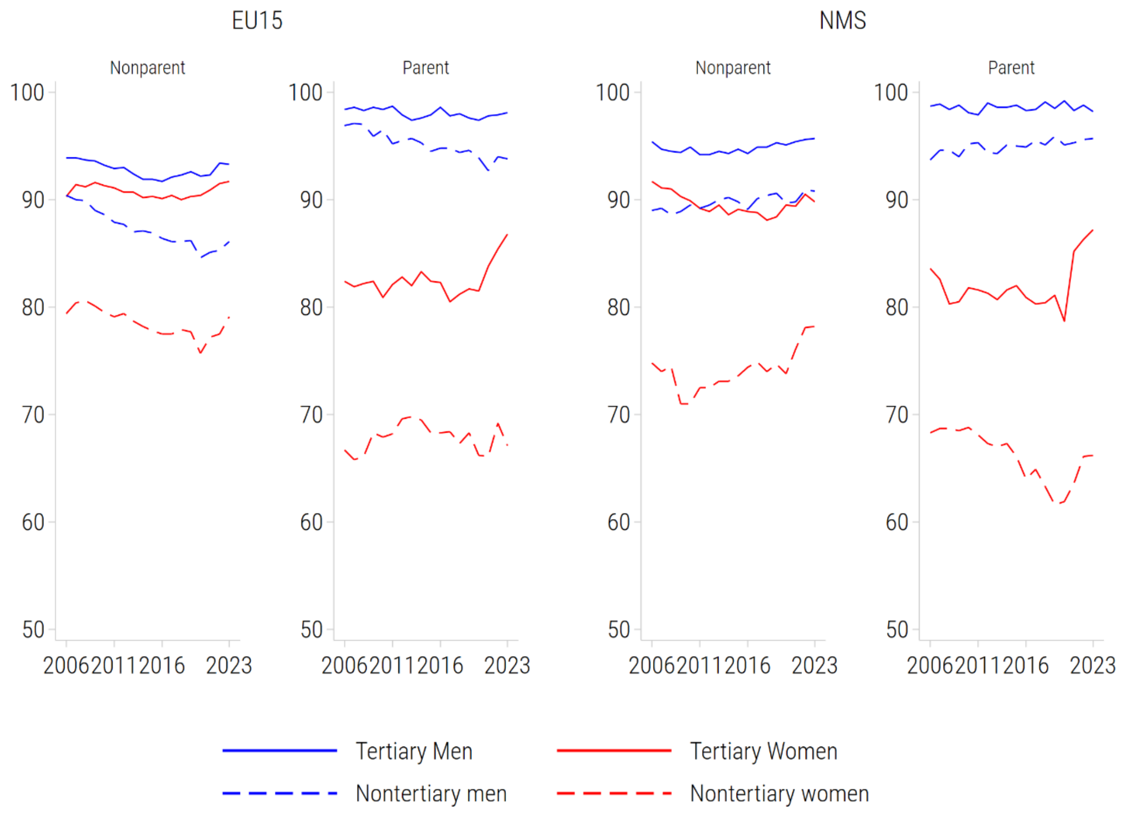


Figure A4. Labour force participation among 55+ year old

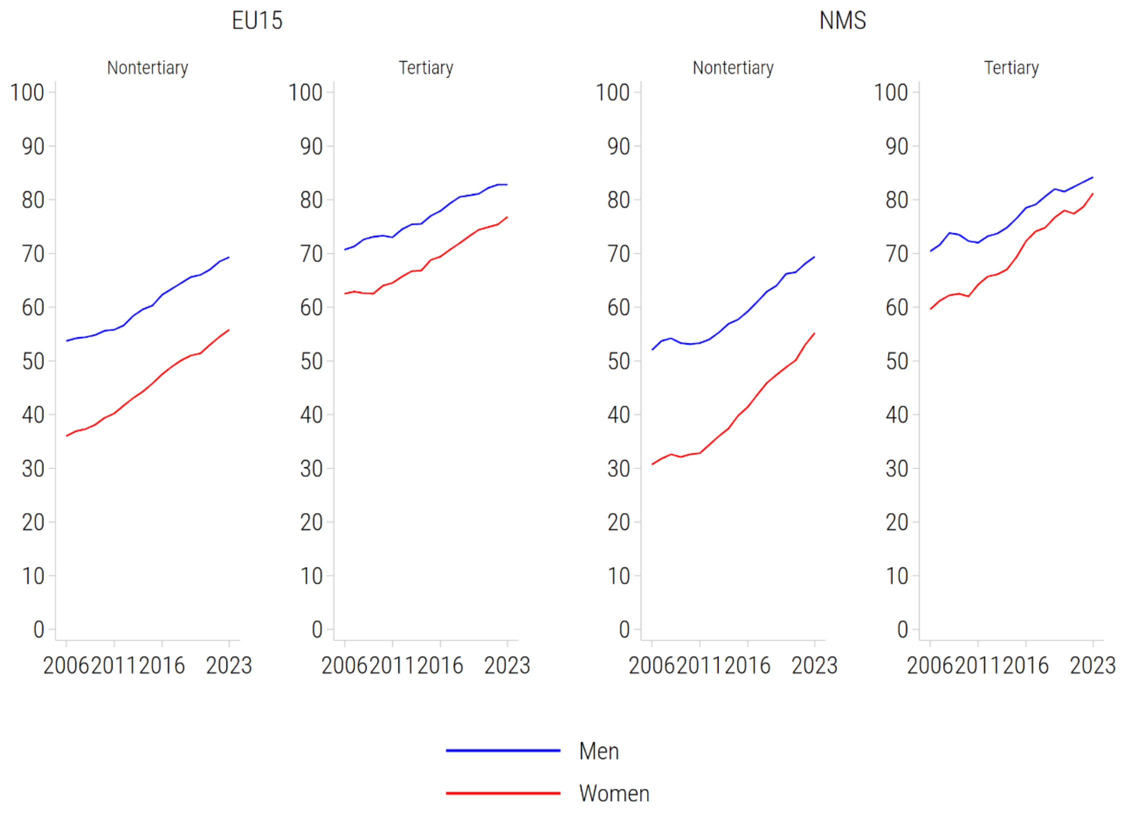


Figure A5. Labour market slack among 25-34 year old

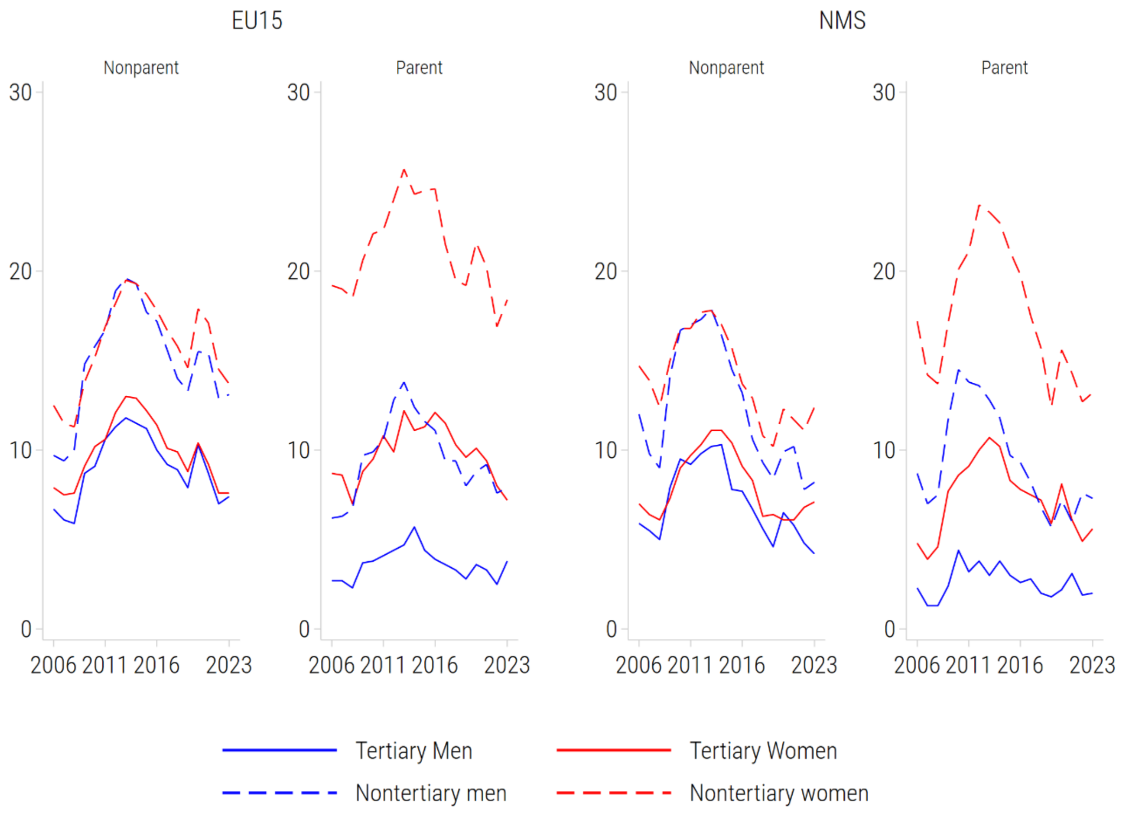
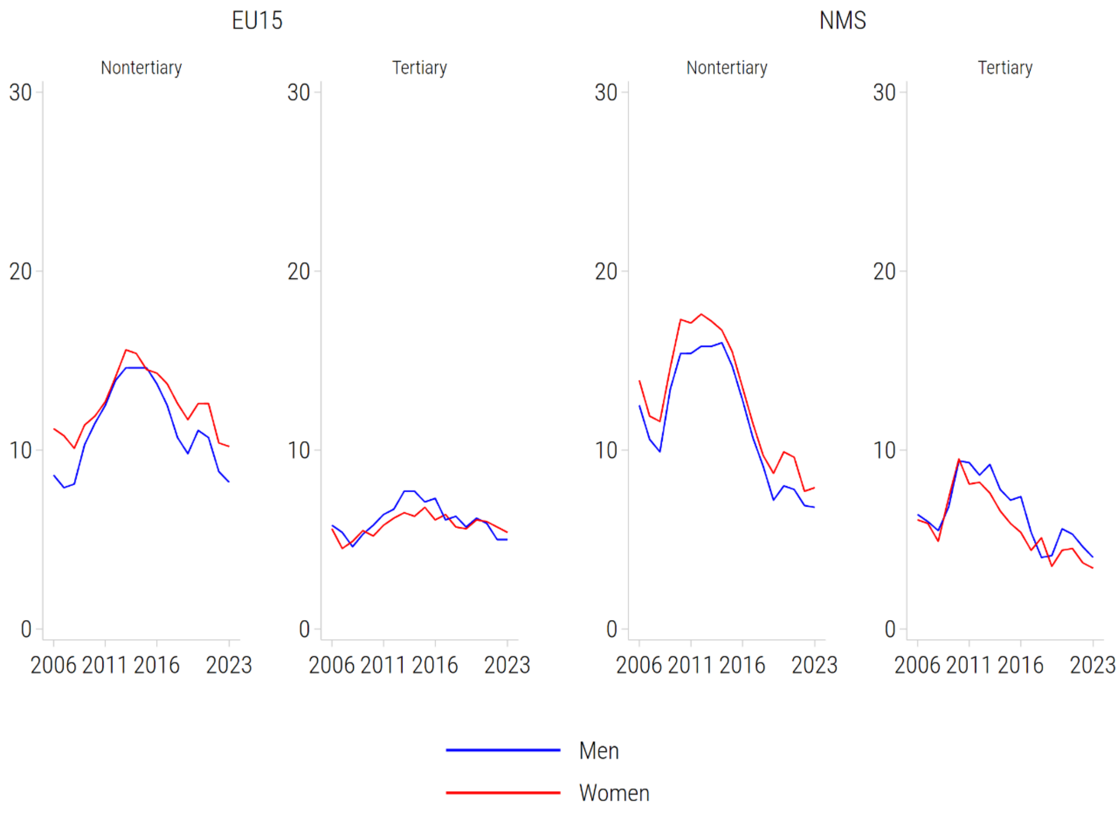


Figure A6. Labour market slack among 55+ year old



Note about weights

When presenting the indicators, we apply COEFFY weights to the observations to reflect the actual population structures within each country. However, when calculating averages across countries within the two groups—EU15 and NMS—we treat each country equally. To achieve this, we adjust the individual weights such that respondents from more populous countries are assigned relatively smaller weights. Specifically, each individual's COEFFY weight is divided by the total sum of COEFFY weights within their country, ensuring that each country contributes equally to the overall average. As a result, individuals from smaller countries are overrepresented, and individuals from larger countries are underrepresented in the analysis.

Occupations sorted by AI Exposure, risk groups and weak labour market attachment

Table 10. Occupations sorted by AI Exposure, risk groups and weak labour market attachment.

Name	AI Exposure	Low digital skill use	Tertiary	Woman	Age 25-34	Age 35-54	Age 55-64	Migrant	Parent	Under-employed	Temporary Contract	Both Underemployed and Temporary Contract
General and Keyboard Clerks	0.77	5%	38%	80%	21%	57%	21%	9%	24%	8%	6%	1%
Numerical and Material Recording Clerks	0.50	16%	29%	53%	25%	56%	19%	11%	22%	8%	6%	1%
Business and Administration Professionals	0.44	2%	87%	57%	29%	57%	14%	20%	26%	7%	5%	1%
Business and Administration Associate Professionals	0.40	6%	54%	58%	24%	57%	19%	10%	24%	8%	4%	0%
Administrative and Commercial Managers	0.30	4%	80%	42%	16%	65%	19%	13%	28%	6%	2%	0%

Teaching Professionals	0.29	28%	92%	75%	21%	58%	22%	9%	25%	11%	11%	3%
Customer Services Clerks	0.24	8%	41%	73%	30%	53%	17%	12%	24%	9%	10%	2%
ICT Professionals	0.24	1%	81%	20%	38%	53%	10%	21%	22%	7%	4%	1%
Refuse Workers and Other Elementary Workers	0.15	93%	6%	24%	19%	53%	28%	28%	24%	27%	9%	4%
Production and Specialized Services Managers	0.13	11%	68%	32%	14%	63%	23%	11%	24%	6%	1%	0%
Chief Executives, Senior Officials, Legislators	0.12	7%	73%	31%	9%	64%	27%	11%	28%	7%	6%	1%
Legal Social And Cultural Professionals	0.09	13%	90%	63%	26%	58%	16%	15%	25%	10%	8%	2%
Other Clerical Support Workers	0.08	25%	36%	64%	22%	55%	23%	11%	18%	10%	8%	2%
ICT Technicians	0.06	5%	45%	17%	36%	53%	11%	14%	18%	8%	6%	1%
Other Associate Professionals	0.06	42%	49%	59%	29%	53%	17%	14%	22%	15%	11%	3%
Hospitality, Retail and Other Services Managers	0.04	28%	44%	39%	18%	62%	20%	16%	22%	6%	2%	0%
Sales Workers	0.03	52%	18%	69%	27%	56%	18%	13%	24%	9%	6%	1%
Science and Engineering Professionals	-0.25	5%	90%	32%	32%	54%	14%	15%	25%	8%	6%	1%
Personal Services Workers	-0.44	77%	16%	60%	27%	53%	20%	19%	21%	12%	9%	2%
Personal Care Workers	-0.45	74%	19%	88%	21%	53%	26%	19%	20%	15%	15%	4%
Health Associate Professionals	-0.47	30%	48%	80%	27%	53%	20%	11%	24%	8%	6%	1%
Health Professionals	-0.48	33%	89%	75%	29%	51%	20%	13%	24%	9%	8%	1%
Science and Engineering Associate Professionals	-0.54	26%	39%	18%	23%	56%	21%	9%	21%	7%	4%	0%
Handicraft and Printing Workers	-0.61	60%	17%	38%	17%	58%	25%	12%	20%	9%	4%	1%
Cleaners and Helpers	-0.65	96%	8%	88%	15%	55%	30%	40%	19%	19%	17%	4%
Food Preparation Assistants	-0.65	95%	10%	74%	22%	54%	24%	39%	19%	15%	16%	5%
Electrical and Electronic Trades Workers	-0.81	63%	15%	3%	25%	55%	21%	11%	22%	7%	4%	1%
Food Processing, Woodworking, Garment Trades	-0.91	81%	11%	46%	20%	59%	21%	12%	22%	6%	4%	1%

Stationary Plant and Machine Operators	-0.98	90%	6%	2%	21%	60%	19%	19%	24%	8%	6%	1%
Building and Related Trades Workers (excl. Electricians)	-1.00	77%	8%	4%	24%	56%	21%	12%	21%	7%	4%	1%
Protective Services Workers	-1.03	52%	25%	16%	22%	59%	19%	8%	22%	9%	6%	1%
Metal, Machinery and Related Trades Workers	-1.06	83%	10%	44%	26%	58%	16%	11%	19%	5%	7%	1%
Other Elementary Workers	-1.17	85%	9%	28%	19%	52%	29%	14%	19%	10%	14%	2%
Drivers and Mobile Plant Operators	-1.28	81%	8%	39%	22%	59%	20%	13%	22%	6%	7%	1%
Labourers in Mining, Construction, Manufacturing	-1.28	83%	7%	29%	26%	55%	19%	20%	22%	9%	12%	2%
Assemblers	-1.32	84%	6%	4%	18%	57%	25%	13%	20%	8%	5%	1%
Agricultural, Forestry and Fishery Labourers	-1.45	95%	5%	37%	25%	52%	23%	19%	21%	10%	27%	3%

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