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Automation and the risk of labor market exclusion across Europe

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ABSTRACT

Labor market exclusion represents a major concern in several European economies, particularly affecting highly exposed demographic groups. This paper examines the potential effect of automation technologies on the risk of being locked into protracted unemployment or inactivity, using Labour Force Survey data for the European Union 27 countries and the United Kingdom, between 2009 and 2019. Our study employs repeated cross-sections of individual-level data to compute probabilities of exclusion outcomes due to automation adoption, controlling for several individual, macroeconomic, and region-specific characteristics, and for potential selection mechanisms. Findings highlight that, on average, the adoption of new automation technologies is associated with a higher probability of being inactive. This is consistent with the view that automation may exacerbate job insecurity, psychological discouragement, and detachment from job-seeking. This relationship is heterogeneous across demographic groups, with younger individuals being relatively more affected.

1. Introduction

Past years have seen profound transformations in the labor markets of advanced economies, driven by the diffusion of labor-saving technologies such as industrial robots, artificial intelligence, and automation more broadly. These advances have shifted production toward increasingly digitalized processes and are shaping new technological paradigms (Damioli et al., 2025). Automation has been argued to increase the risk of replacing middle-skilled workers engaged in manual and routinized tasks (Acemoglu and Restrepo, 2019; Frey and Osborne, 2017; Graetz and Michaels, 2018), and more recent contributions point to potential effects on high-skilled workers as well (Squicciarini and Nachtigall, 2021). Consequently, many individuals express growing concern about their future employment prospects, with declining expectations and heightened risks of labor market exclusion (Grigoli et al., 2020; Schmidpeter and Winter-Ebmer, 2021). These developments have attracted substantial scholarly attention, generating a rapidly expanding body of theoretical and empirical work.

Labor market exclusion occupies a central place in this debate, given the profound implications of automation for workers at risk of long-term unemployment and detachment from the labor force (Apergis and Apergis, 2020; Krueger et al., 2014). Excluded individuals face persistent barriers to employability, increasing their vulnerability to poverty. Evidence shows that long-term unemployment and inactivity are often procyclical and amplified by adverse macroeconomic conditions (Krueger et al., 2014), by skill mismatches (Apergis and Apergis, 2020), and by labor market inefficiencies (Leibrecht et al., 2023). Workers exposed to exclusion may become permanently trapped in low-quality jobs as automation progresses—particularly when lacking complementary skills—thereby reducing their chances of re-employment (Blien et al., 2021; Goos et al., 2021). Accordingly, unemployed and inactive individuals remain particularly exposed to automation, which explains the growing academic focus on these groups (Schmidpeter and Winter-Ebmer, 2021).

Despite its relevance, evidence on how automation shapes the risk of labor market exclusion remains limited. Most existing studies concentrate on unemployment, generally finding a positive relationship between automation and unemployment rates in advanced economies (Leibrecht et al., 2023; Nguyen and Vo, 2022). At the individual level, digitalization has been shown to reduce job-finding probabilities and increase unemployment and inactivity risks (Grigoli et al., 2020; Schmidpeter and Winter-Ebmer, 2021). However, this literature predominantly relies on routinization measures, overlooking the distinct role of the adoption of automation technologies and related advanced digital innovations. Moreover, it rarely considers alternative exclusion outcomes, such as heterogeneous inactivity statuses or unemployment by duration.

Our paper contributes to this literature by providing a

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comprehensive analysis of the European labor market between 2009 and 2019, i.e. after the 2008 global financial crisis and before the Covid-19 pandemic. Using large-scale microdata from the Labour Force Survey (LFS) for 27 European Union (EU) countries and the United Kingdom, we track individual unemployment and inactivity dynamics across Europe. Unlike most existing studies, which rely on routinization indexes, we focus on the adoption of advanced physical capital embodying automation technologies—industrial robots, additive manufacturing, and internet-of-things—while accounting for a wide set of factors affecting the labor market, including innovations in artificial intelligence (AI), additive manufacturing, information and communication technologies (ICTs), and nanotechnologies.

Our study provides cross-country evidence on how these technologies affect the probability of experiencing different exclusion outcomes, explicitly considering general equilibrium effects linked to innovation, globalization, climate change, labor market institutions, migration, and demographic factors. We further control for region-fixed effects and a broad range of individual characteristics to account for selection into unemployment and inactivity. Our findings show that, on average, the adoption of automation technologies is significantly associated with a higher probability of inactivity. This pattern is consistent with the view that automation may raise job insecurity and intensify psychological discouragement and detachment from job-seeking (Blasco et al., 2025; Yam et al., 2023), manifested in a reduced willingness to work among inactive individuals. These effects are broadly similar across gender and educational attainment but are more pronounced for prime-age individuals (25–54).

The remainder of the paper is structured as follows. Section 2 briefly outlines the main mechanisms linking automation to labor market exclusion. Section 3 presents the data and econometric strategy. Section 4 describes stylized facts on long-term unemployment, inactivity, and automation trends in Europe. Section 5 presents the econometric results, while Section 6 discusses the findings and concludes.

2. Background literature

2.1. Theoretical perspectives on automation and employment

The recent debate on the labor market consequences of automation and AI builds upon long-standing theoretical frameworks that have examined how technological progress affects employment. A first strand of research is rooted in the compensation theory (Freeman et al., 1982; Vivarelli, 1995; see also Montobbio et al., 2024; Pianta, 2006; Vivarelli, 2014), which identifies several direct and indirect mechanisms—of a classical, neoclassical, or Keynesian nature—through which the job-destroying effects of innovation may be mitigated or offset. In this tradition, the literature has distinguished between product and process innovations (e.g., Bianchini and Pellegrino, 2019; Bogliacino and Pianta, 2010) and between embodied and disembodied technological change (Barbieri et al., 2019; Dosi et al., 2021), highlighting that different forms of innovation can generate heterogeneous labor demand responses.

With the diffusion of automation technologies such as industrial robots, AI, and internet-of-things systems, theoretical attention has increasingly shifted toward task-level substitution mechanisms. Beginning in the 1990s, models of skill-biased, routine-biased, and task-biased technological change (e.g., Acemoglu and Autor, 2011; Autor, 2013) formalized how new technologies can reconfigure the task content of jobs. As emphasized by Acemoglu and Restrepo (2019), highly productive automation may generate two contrasting effects: a productivity effect that raises value added and, potentially, employment in non-automated tasks; and a displacement effect, whereby capital substitutes labor in tasks previously performed by humans. These negative effects may, in turn, be mitigated by a reinstatement effect if automation gives rise to new complementary tasks in which human labor retains a comparative advantage. Overall, these theoretical contributions highlight the coexistence of "*techno-optimist*" mechanisms linked to productivity and task creation, and "*techno-pessimist*" mechanisms linked to displacement and skill mismatch.

2.2. Empirical evidence

Empirical research has examined the employment effects of technological change at multiple levels of analysis—individuals, firms, industries, and countries—using a wide range of indicators such as survey data, R&D and investment expenditure, routinization indexes, patent-based measures, and import data (see Mondolo, 2022; Montobbio et al., 2024, for recent reviews). Overall, the evidence on total employment effects remains mixed. While some studies support the *techno-pessimist* view and report negative impacts of automation adoption (e.g., Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Bonfiglioli et al., 2024), other studies focus on innovation dynamics and find small but positive job-creating effects, rooted in the *techno-optimist* mechanisms (Damioli et al., 2024; Felice et al., 2022; Mann and Püttmann, 2023). Yet, results are more consistent in documenting labor market polarization, substantial reallocation across sectors, and marked changes in occupational task content (e.g., Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Bessen et al., 2025; Bisio et al., 2025; Bonfiglioli et al., 2024; Camiña et al., 2020; Dauth et al., 2021; Domini et al., 2021; Felice et al., 2022; Frey and Osborne, 2017; Graetz and Michaels, 2018; Mann and Püttmann, 2023).

Such a nuanced picture emerges particularly from firm- and individual-level studies. For example, evidence from Swiss (Balsmeier and Woerter, 2019), French (Bonfiglioli et al., 2024) and Spanish (Camiña et al., 2020) firms suggests that investments in digital technologies have a modest positive net effect on employment, combining increased demand for high-skilled workers with displacement of low-skilled workers. Evaluating worker flows across 16 European countries, Bachmann et al. (2024) find that robotization has only a minor impact on job separation, with no discernible effect on job finding rates. Moreover, several firm-level studies find compositional effects—hinting at the two distinct views—when comparing small and large firms (Acemoglu et al., 2020; Bessen et al., 2025; Bisio et al., 2025) or employees of different age cohorts (Bessen et al., 2025; Dauth et al., 2021).

Closely related to our study, a strand of this literature also focuses on unemployed workers and the role of digital skills in re-employment outcomes. Evidence consistently points to persistent polarization even among the unemployed, with lower digital skills reducing job-finding probabilities and technical training partly mitigating these negative effects (Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Olsson and Tåg, 2017; Schmidpeter and Winter-Ebmer, 2021). These dominant *techno-pessimist* mechanisms likely become stronger the longer individuals remain unemployed, given skill obsolescence and heightened risk of transitioning into inactivity.

Direct evidence on the relationship between automation and exclusion outcomes, such as unemployment and inactivity, is more limited but generally points at reinforcing the negative effects. For example, Leibrecht et al. (2023) show that weaker collective bargaining institutions exacerbate the negative effects of automation, while Nguyen and Vo (2022) document an inverse U-shaped relationship between AI-related innovations and unemployment, depending on inflationary conditions. Studies closer to our approach, such as Grigoli et al. (2020), find that automation reduces job-finding probabilities and raises the likelihood of becoming inactive, particularly for workers employed in optimizable occupations. Schmidpeter and Winter-Ebmer (2021) also show that younger individuals (25–40) are more likely to withdraw from the labor force as automation rises, reinforcing the importance of re-skilling and up-skilling programs.

Considering this evidence and the dominant *techno-pessimist* view characterising individual-level studies, we expect that *automation, on average, increases the likelihood of labor market exclusion*. Such a relationship is likely to be heterogeneous, varying in magnitude and nature of its effects across unemployment and inactivity outcomes. Specifically, while unemployment risks are often shaped by skill endowments and are particularly relevant for older workers struggling to adapt to new technologies, inactivity risks appear more polarized among younger individuals—an insight that motivates our focus on heterogeneous exclusion outcomes in the empirical analysis that follows.

3. Methodology

3.1. Data sources

The empirical analysis is conducted at the individual level. We exploit highly detailed information from Eurostat's Labour Force Survey (LFS) database for EU27 countries and the UK from 2009 to 2019, the last pre-pandemic year. The LFS' microdata covers both active and inactive populations ranging between age 15 and 64, and includes highly detailed information on employment, unemployment, and inactivity status—which we use to build our dependent variables capturing exclusion outcomes. The LFS also provides information on other individual's characteristics, such as country of birth, nationality, marital status, place of living (mostly, at the NUTS-2 level), education (highly detailed ISCED-1/8 categories), degree of urbanization, and several others.[1]

In principle, it could be possible to track surveyed, anonymized individuals over time by means of a combination of individual, country, and household identifiers. However, this is rarely done in practice because only a few thousand respondents (out of tens of millions) can be tracked longitudinally, and only for a limited amount of time due to participant rotation. For this reason, our analysis relies on repeated cross-sections.

Since Eurostat's data collection procedure and questionnaire have changed over time and differ across EU countries, we perform different preliminary cleaning and harmonization steps. These are aimed at reconciling variations in variable labels, the formatting of collected answers, and the level of aggregation.[2] We then discarded all individuals for whom key information common to employed, unemployed, and inactive individuals was missing.[3] This procedure resulted in a final sample of about 29 million individuals, of which we cross-checked and confirmed the representativeness across employment (by gender, age group, and educational attainment), unemployment (total, long-term, and short-term), and inactive statuses against official aggregate LFS statistics. We use this larger sample for descriptive purposes, while in the econometric analysis, to reduce the burden of computation complexity, we rely on a representative sample of about 10 % the original size, stratified by country, NUTS-2 region, year, employment/activity status, gender, age, educational attainment, nationality, country of birth, years of residency, and degree of urbanization of the place where the individual lives.

Data for computing the key explanatory variable capturing trends in automation adoption refers to imports in highly automated manufacturing technologies—namely, industrial robots, additive manufacturing, and internet-of-things—as defined by Castellani et al. (2022). Concerning the main control variables, we first consider innovations in advanced and digital fields drawing on patent information on AI, additive manufacturing, various ICTs, and advanced technologies like nanotechnologies, sourced from the OECD REGPAT database. We also include various measures of participation in global value chains (GVCs) and trade using data from OECD's Trade in Value Added (TiVa) database and World Bank data, which potentially mediate the effect of automation on the probability of labor market exclusion. Additionally, we control for other main macroeconomic trends characterizing the observation period and potentially influencing unemployment and inactivity dynamics. Specifically, we account for climate change using various measures in the OECD database on climate hazards, and for demographic changes using data on each country's demographic characteristics from the OECD and Eurostat databases.

3.2. Variables

3.2.1. Dependent variables

The main dependent variable used to analyze unemployment outcomes is a dummy taking value 1 if the individual experiences a condition of *long-term unemployment* (LT), as defined by a duration longer than one year, and 0 otherwise. Additionally, we use a dummy taking value 1 if the individual is *unemployed* (UNE) and 0 otherwise, to analyze overall unemployment.

In the inactivity analysis, we focus specifically on individuals in the LFS that report to be inactive and are deliberately not seeking any employment opportunity. Specifically, we exclude from the analysis all those individuals that are: (i) temporarily inactive—those who, at the time of the interview, reported to be about to start working in the near future; (ii) those who were studying or undergoing some form of training, and; (iii) those who are permanently unable to work. Therefore, inactive individuals in our sample may be either truly unwilling to work individuals—who are more likely to remain locked in the exclusion condition—or discouraged workers—that is, jobless people who are not searching for one because they think no suitable job is available. Consistently, our second main dependent variable (NW) is a dummy equal to 1 if the individual is *inactive and not willing to work*, 0 if they are

[1] For employed individuals, LFS microdata also reports various characteristics pertaining the sector of employment, the occupation, employment duration/tenure, the NUTS-2 region where the place of work is located, the type of contract, etc. For unemployed and inactive individuals, additional variables measure the duration and the reason for being unemployed or inactive.

[2] This procedure was conducted following information and guidelines from the EU LFS Explanatory Notes (April 2018 version) and the EU LFS Database User Guide (September 2020 version).

[3] The only exception relates to information on educational attainment: dropping individuals with missing education information would result in a too small and, most importantly, not representative sample. Therefore, we imputed missing values for educational attainment as the average educational attainment over the same demographic group (i.e., based on non-missing information for individuals in the same year, country, NUTS-2 region, gender, age group, and employment/activity status), then rounded to the nearest whole number to obtain the corresponding ISCED category. The imputation procedure grants representativeness compared to official Eurostat statistics. Nonetheless, we include a dummy variable identifying imputed observations in each of our econometric specifications.

a *discouraged worker*. We further compute a dummy variable taking value 1 if the individual is *inactive* (INA) and 0 otherwise.

3.2.2. Explanatory variables and controls

We measure automation adoption using the total import stock in industrial robots, additive manufacturing, and internet-of-things at the country-level, based on the definition of Castellani et al. (2022), who measure trade and net consumption of automation capital goods using highly disaggregated product categories at 8-digit level of detail, sourced by Eurostat's Comext database.[4] This trade-related approach of measuring technology adoption is a well-established procedure, employed in several studies (e.g., Acemoglu and Restrepo, 2022; Acemoglu et al., 2020; Bonfiglioli et al., 2024; Bisio et al., 2025; Domini et al., 2021).

Regarding key control variables, we consider several factors that—alike adopting automation—are likely to influence labor market exclusion and therefore bias our measurement of the effect of adopting automation technologies. First, we consider the intensity of the innovative effort in advanced and digital technology fields by computing each country's number of patent applications filed at the European Patent Office (EPO), looking at priority date, applying fractional counting to distribute patents across countries, and considering inventor's country of residence. Patents in AI, ICTs broadly defined—including, for instance, also the internet-of-things—and nanotechnologies are identified following the technological classification of selected OECD technology domains (Baruffaldi et al., 2020; Friedrichs and van Beuzekom, 2018; Inaba and Squicciarini, 2017). We also identified patents in additive manufacturing following Felice et al. (2022). By accounting for advanced/digital innovations we can disentangle the distinct and potentially confounding effects of adoption and innovation measures documented in the literature (see Section 2).

Second, we construct a measure of country-level total participation in GVCs by summing together information on forward (i.e., domestic value added in foreign exports as a share of gross exports) and backward (i.e., foreign value-added share of gross exports) GVC participation. We also compute a country's export surplus, as the difference between exports and imports over GDP, to account for the role of specific trade patterns in shaping unemployment and inactivity outcomes. Third, we measure climate change using: (i) information on land-related extreme climate events, such as droughts (measured by the % change in soil moisture) and heavy precipitations (measured by the % of land exposed for less than one week, and for between one and two weeks); and (ii) population-related information on extreme events across European countries, such as exposure to hot days, tropical nights, and icing days (measured as the % of the total population exposed to such events for up to two weeks). Finally, we account for demographic changes measuring the share of total population above age 65, and net migration rates measuring the difference between inflows of migrants and outflows of expatriates over total population. These controls allow us to account for all the most relevant general equilibrium effects that are likely to drive the dynamics of employment, unemployment, and inactivity in our cross-country setting.

Finally, as additional controls, we include country-specific, time-varying characteristics, such as the level of aggregate unemployment or inactivity, the ratio between service and manufacturing sectors value added, and different measures capturing characteristics of the labor market: (i) a wage coordination index, capturing the degree of centralization of wage negotiation and measured on a 1 to 5 scale; (ii) an employment protection legislation index for individual and collective dismissals for regular workers, measured by a continuous indicator taking values from 0 to 6, and; (iii) a measure of the generosity of unemployment benefits, measured as gross unemployment benefit levels as a percentage of previous gross earnings and averaged across two earnings levels, two family situations, and three durations of unemployment following Grigoli et al. (2020). We source data for these additional controls from the World Bank, Eurostat and various OECD datasets.[5]

We first assess potential high correlations and multicollinearity among the covariates by computing variance inflation factors (VIFs). To further reduce the number of key explanatory variables and controls—and, in turn, the complexity of our econometric model—we performed a principal component analysis (PCA) on advanced/digital innovation and extreme climate events variables. Figure A1 in the Online Appendix presents the results of the PCAs: patent data on AI, additive manufacturing, ICTs, and nanotechnologies are all well-measured by one principal component (eigenvalue > 1), capturing about 77 % of the total variance. Similarly, extreme climate events are sufficiently well-measured by the first two principal components, cumulatively capturing about 61 % of the total variance. More specifically, the first component features as a good proxy for soil-related extreme events, while the second one closely relates to population-related extreme events, as discussed above. Table 1 summarizes the variables used in our econometric analysis, how they are measured, and the related data sources. Table 2 presents the correlation matrix, VIFs, and summary statistics for the key explanatory variables and the main controls.

3.3. Econometric specification

Our aim is to empirically estimate the relationship between automation technologies and the probability of exclusion outcomes for individuals. To this end, a standard probit model comparing individuals in the excluded groups to all other individuals in the reference population may lead to biased estimates. For instance, in the case of long-term unemployment, individuals are likely to be affected by a selection mechanism by which they first become unemployed then, as unemployment persists with time and the worsening of their condition, they become long-term unemployed. Alternatively, the individuals' likelihood of being inactive and of showing no willingness to seek any job opportunity likely depends on their objective probability of successfully re-entering the labor force (see Section 3.2.1).

To correct for this potential selection, we estimate both the Heckman (1979) model, and its extension proposed by van de Ven and van Praag (1981), which is specifically designed to accommodate binary outcomes.[6] This procedure helps us to purge estimates from the potential bias arising from unobservable factors leading some individuals to become unemployed (or inactive) and for us to achieve partial identification even in situations where proper exclusion restrictions are not easy to identify (Honoré and Hu, 2020; 2024). Specifically, for each exclusion outcome, we estimate the following sets of reduced form equations:

[4] Stocks are computed using the perpetual inventory method and considering a depreciation rate of 15%. See Castellani et al. (2022) for a detailed description of the computation methodology, the list of product codes and the identification procedure, and for descriptive statistics across European countries. See also Lamperti et al. (2024; 2025) for empirical applications.

[5] Preliminary estimates also included measures of foreign direct investment (FDI) openness, country-level CO_2 emissions, mortality from a range of pollutants (e.g., ozone, lead, PM2.5, and radon), the shares of population below age 15 and between age 15 and 64, fertility rates, life expectancy, real GDP, the share of R&D expenditure in GDP, and the share of agricultural sector value added in GDP. These variables were omitted from the final empirical analysis either because of multicollinearity or because they were hardly ever significant across specifications.

[6] According to van de Ven and van Praag (1981), by jointly estimating the two equations in a conditional mixed process setting, the coefficients resulting from the second equation account for the factors that might induce a selection bias, and the cross-equation correlation of residuals can be used to formally test for the presence of selection.

$$P(UNE_{i,c,r,t} = 1) = \Phi[\alpha_0 + \boldsymbol{\alpha}_1 \boldsymbol{I}_{i,c,r,t} + \alpha_2 Aut_{c,t-1} + \boldsymbol{\alpha}_3 \boldsymbol{C}_{c,t-1} + \boldsymbol{\alpha}_4 \boldsymbol{Z}_{c,t-1} + \lambda_{c,r} + \rho_t + \varepsilon_{i,c,r,t}] \quad (1a)$$

$$P(LT_{i,c,r,t} = 1) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{I}_{i,c,r,t} + \beta_2 Aut_{c,t-1} + \boldsymbol{\beta}_3 \boldsymbol{C}_{c,t-1} + \beta_4 IMR_{i,c,r,t} + \vartheta_{c,r} + \tau_t + \mu_{i,c,r,t}] \quad (1b)$$

$$P(INA_{i,c,r,t} = 1) = \Phi[\gamma_0 + \boldsymbol{\gamma}_1 \boldsymbol{I}_{i,c,r,t} + \gamma_2 Aut_{c,t-1} + \gamma_3 \boldsymbol{C}_{c,t-1} + \boldsymbol{\gamma}_4 \boldsymbol{V}_{c,t-1} + \nu_{c,r} + \sigma_t + e_{i,c,r,t}] \quad (2a)$$

$$P(NW_{i,c,r,t} = 1) = \Phi[\delta_0 + \boldsymbol{\delta}_1 \boldsymbol{I}_{i,c,r,t} + \delta_2 Aut_{c,t-1} + \boldsymbol{\delta}_3 \boldsymbol{C}_{c,t-1} + \delta_4 IMR_{i,c,r,t} + \psi_{c,r} + \omega_t + u_{i,c,r,t}] \quad (2b)$$

where $UNE_{i,c,r,t}$ in Eq. (1a) takes value equal to 1 if an individual is unemployed and 0 if they are employed. Conditional on being unemployed, in Eq. (1b), $LT_{i,c,r,t}$ takes value 1 for all individuals in long-term unemployment—that is, they have been unemployed for more than year. In Eq. (2a), $INA_{i,c,r,t}$ identifies inactive vs active individuals, and, conditional on being active, in Eq. (2b) $NW_{i,c,r,t}$, identifies inactive individuals who are unwilling to work. Individual i is based in NUTS-2 region $r = 1, \ldots 217$ within country $c = 1, \ldots 28$ and is observed at one moment in time $t = 2009, \ldots 2019$. $Aut_{c,t}$ represents the automation adoption variable; vector $\boldsymbol{I}_{i,c,r,t}$ includes individual-level controls capturing some relevant characteristics common to both active and inactive individuals that may influence the probability of labor market exclusion; vector $\boldsymbol{C}_{c,t}$ includes the advanced/digital innovation variable, export surplus, and total GVC participation, capturing macroeconomic trends in globalization; finally, vectors $\boldsymbol{Z}_{c,t}$ and $\boldsymbol{V}_{c,t}$ include additional controls included in Eqs. (1a) and (2a) and used as exclusion restrictions in the selection equations. They include the relative sectoral composition of the economy, key features of the labor market, and measures of climate and demographic changes. Vector $\boldsymbol{Z}_{c,t}$ includes also aggregate unemployment, while vector $\boldsymbol{V}_{c,t}$ includes overall inactivity levels in country c at time t. ε, μ, e and u are the error terms.

Given the multilevel structure of the data, different modelling approaches could be used to correctly estimate our main parameters of interest (Bryan and Jenkins, 2016)—β_2 and δ_2 in the second stage equations. The two most common approaches are: (i) a common model for pooled data including fixed effects (FE) to absorb all unobserved factors at the various levels in the data, or; (ii) a common model for pooled data with random intercepts at different levels. In our baseline estimations, we rely on models with region FE. Given the nature of the data, country FE are subsumed into region-specific intercepts. This allows us to account for unobserved heterogeneity (i.e., $\vartheta_{c,r}$ and $\psi_{c,r}$), capturing differences in the institutional and policy setting, and labor market features such as training policies and decentralized collective agreements. We further include time FE to account for common trends (i.e., τ_t and ω_t) characterising all individuals, countries, and regions in our sample, such as the average level of technological progress and the cost of capital. We cluster standard errors at the NUTS-2 region level to account for the correlation of error terms across individuals in the same region.

Our econometric strategy addresses potential endogeneity concerns by accounting for the selection mechanisms and the multilevel nature of our data, which may lead to biased estimates. Furthermore, to alleviate the risk of reverse causality and simultaneity bias in our estimates, all regressors are lagged by one year in both first and second stage equations. To avoid the risk of producing biased estimates by unobserved mediation effects (i.e., some of the key explanatory variables measuring automation might capture indirect effects happening through other variables),[7] we account for a large set of macroeconomic factors simultaneously and by means of various measures capturing distinct aspects. This strategy has the advantage of capturing the general equilibrium effects of various drivers of labor market exclusion, by further accounting for possible mediating relationships between automation adoption and labor market exclusion. Additionally, the high granularity of the individual-level controls capturing a large set of demographic characteristics and the FE we include in all our specifications should limit concerns for our estimates to be affected by omitted variable bias.

In the second step of the analysis, we investigate the potential heterogeneity in the effect of automation on the probability of long-term unemployment and inactivity, across demographic characteristics of individuals (i.e., gender, age, and education). Specifically, we run three sets of the system of equations in (1b) and (2b), where first and second stage equations are alternatively augmented with the interaction terms between automation adoption and demographic characteristic.

[7] For instance, some of the effect of automation on unemployment may appear through globalisation due to trade in tasks (Autor et al., 2015; Grossman and Rossi-Hansberg, 2008) and growing functional specialisation of trade (Timmer et al., 2019; Bontadini et al., 2024). Alternatively, some automation-related effects might pass on to employment through demographic changes such as population aging, which leads to higher automation due to the induced shortage of middle-aged workers (Acemoglu and Restrepo, 2022).

Table 1
Variables description, computation details and sources.

Variable	Measurement unit	Measure	Data source
Dependent variables			
Long-term unemployment (LT)	Individual	Dummy = 1 if unemployment duration is > 1 year, 0 otherwise (short-term unemployment, ST)	Eurostat's LFS
Unemployment (UNE)	Individual	Dummy = 1 if unemployed, 0 otherwise (employed, EMP)	Eurostat's LFS
Inactive unwilling to work (NW)	Individual	Dummy = 1 if inactive (deliberately) and not willing to work, 0 otherwise (discouraged workers, DW)	Eurostat's LFS
Inactivity (INA)	Individual	Dummy = 1 if inactive, 0 otherwise (active, ACT)	Eurostat's LFS
Automation			
Automation adoption	Country	Stock of imports in advanced manufacturing technologies (industrial robots, additive manufacturing, internet-of-things) over total employment, measured in log, at time t-1	Eurostat's Comext
Main controls			
Advanced/digital innovation	Country	Principal component computed using data on the cumulated number of patent applications in ICTs, AI, additive manufacturing and nanotechnologies, at time t-1	OECD REGPAT
Total GVC participation	Country	Sum of forward and backward GVC participation, at time t-1	OECD TiVa
Export surplus	Country	Difference between exports and imports over GDP, measured in %, at time t-1	World Bank
First stage controls			
Aggregate unemployment (log)	Country	Number of unemployed (thousands), measured in log, at time t-1	OECD/Eurostat statistics
Aggregate inactivity (log)	Country	Number of inactive (thousands), measured in log, at time t-1	OECD/Eurostat statistics
Service-to-manufacturing ratio	Country	Ratio between service and manufacturing value added, measured in %, at time t-1	World Bank
Wage coordination	Country	Strictness of the norms binding the coordination of workers and employers (and their representatives) in wage negotiation, score ranging from 1 (no coordination) to 5 (max coordination), at time t-1	OECD/AIAS ICTWSS
Employment protection legislation	Country	Indicator for individual and collective dismissals for regular workers, continuous indicator ranging from 0 to 6, at time t-1	OECD
Generosity of unemployment benefits	Country	Gross unemployment benefit levels as a percentage of previous gross earnings, average of the measure for two earnings levels, two family situations, and three durations of unemployment, at time t-1	OECD Benefits and Wages Statistics
Extreme climate events 1 (soil-related)	Country	Principal component computed using data on extreme climate events (droughts, heavy precipitations, hot days, tropical nights, icing days), at time t-1	OECD-Eurostat database on climate hazards
Extreme climate events 2 (people-related)	Country	Principal component computed using data on extreme climate events (droughts, heavy precipitations, hot days, tropical nights, icing days), at time t-1	OECD-Eurostat database on climate hazards
Population share aged 65+	Country	Share of individuals aged above 65 years in total population, measured in %, at time t-1	OECD/Eurostat statistics
Net migration rate	Country	Difference between inflows of migrants and outflows of expatriates over total population, measured in %, at time t-1	OECD/Eurostat statistics
Individual controls			
Gender	Individual	Dummy = 1 if female, 0 if male	Eurostat's LFS
Age group	Individual	Ordinal variable ranging from 1 to 10, corresponding to 5-year age bands going from age 15–19 to age 60–64	Eurostat's LFS
Educational attainment	Individual	Ordinal variable, ranging from 1 to 8, corresponding to ISCED1–8 categories	Eurostat's LFS
Marital status	Individual	Categorical variable, assuming value 1 if single, 2 if married, and 0 if widowed, divorced, or legally separated	Eurostat's LFS
Nationality	Individual	Dummy = 1 if has nationality, 0 if does not	Eurostat's LFS
Country of birth	Individual	Dummy = 1 if native, 0 if born abroad	Eurostat's LFS
Degree of urbanization	Individual	Categorical variable assuming value 1 if lives in cities (densely populated area), 2 if lives in towns and suburbs (intermediate density area), and 3 if lives in rural areas (thinly populated area)	Eurostat's LFS

4. Stylized facts

4.1. Patterns of employment, unemployment and inactivity in europe

Fig. 1 describes trends in employment, unemployment, and inactivity across EU27 countries and the UK, using the whole sample of about 29 million individuals from the LFS. Panel 1 shows that the employed population represents, on average, 64.8 % of the population aged 15–64, while the total unemployed population ranges around 6.4 %. The remaining 28.8 % of our sample represents inactive individuals.[8] Overall, employment has increased steadily over the observation period, growing from about 62 % in 2009 to 68 % in 2019. Conversely, the unemployment rate has remained quite stable, experiencing a slight rise from 6 % in 2009 to about 8 % in 2013, and then a decrease to 5 % in 2019. The larger drop, compensating for the increase in the employment share, has been absorbed by the inactive population, whose share has progressively decreased from about 32 % in 2009 to 27 % in 2019. Focusing on unemployment patterns by duration, Panel 2 highlights that long-term unemployment (duration > 1 year) accounts for about 45.3 % of total unemployment (43.2 % in official statistics), followed by short-term unemployment (duration < six months) with 37.8 % and only a minor share of medium-term unemployment (16.9 %). During the eleven-years period leading to the outbreak of the Covid-19 pandemic, short-term unemployment slightly decreased, on average, dropping from 47 % in 2009 to 34 % in 2014, and then growing again to 41 % in 2019. Conversely, long-term unemployment experienced an inverse trend characterized by a steep increase from 33 % in 2009 to 50 % in 2014, and then a slight drop to 44 % in 2019, while medium-term unemployment has steadily decreased over time, from 20 % in 2009 to 15 % in 2016, then remaining constant until 2019. Panel 3 shows the composition of inactive individuals: while temporarily inactive workers and discouraged workers (i.e., inactive, not seeking a job, but willing to work) represent a small fraction of total inactive individuals (2 % and 16

[8] Our sample is an accurate representation of the population of individuals, as demonstrated by the fact the according to official Eurostat statistics, the percentage of employed population in the 15–64 age range is 64.3%, unemployment stands at 6% and 29.7 of the population are inactive.

Table 2
Summary statistics: correlation, variance inflation factors, and summary statistics of the key explanatory variables and main controls.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Automation														
[1] Automation adoption (stock of AMT imports, log)	1.000													
Main controls														
[2] Advanced/ digital innovation (patents, PCA)	0.365	1.000												
[3] Export surplus (% GDP)	0.635	0.123	1.000											
[4] Total GVC participation	0.555	−0.382	0.484	1.000										
First stage controls														
[5] Aggregate unemployment (log)	−0.314	0.585	−0.333	−0.638	1.000									
[6] Aggregate inactivity (log)	−0.174	0.684	−0.291	−0.578	0.937	1.000								
[7] Service-to-manufacturing ratio	−0.225	−0.041	−0.182	−0.209	−0.021	−0.151	1.000							
[8] Wage coordination	0.254	0.536	0.082	−0.287	0.132	0.199	0.007	1.000						
[9] Employment protection legislation	−0.209	0.179	−0.341	−0.344	0.333	0.349	0.108	0.364	1.000					
[10] Generosity of unemployment benefits	0.103	0.233	0.076	−0.116	−0.006	−0.077	0.260	0.223	−0.012	1.000				
[11] Extreme climate events 1 (soil-related, PCA)	−0.379	−0.085	−0.285	−0.247	0.302	0.238	0.075	0.002	0.407	−0.161	1.000			
[12] Extreme climate events 2 (people-related, PCA)	0.189	0.155	−0.016	0.192	−0.021	0.078	−0.100	−0.084	−0.022	0.216	−0.254	1.000		
[13] Population share > 65 years (% population)	−0.108	0.442	−0.255	−0.486	0.399	0.436	0.077	0.421	0.456	−0.024	0.353	0.001	1.000	
[14] Net migration rate (% population)	0.534	0.372	0.338	0.140	−0.198	−0.060	0.154	0.555	0.094	0.033	−0.161	−0.051	0.144	1.000
VIF	5.32	7.2	2	4.69	5.03	6.42^	1.38	2.61	1.76	1.51	1.75	1.49	2.17	2.54
Mean	14.08	0.97	2.80	50.08	6.59	9.18	4.78	2.55	2.63	3.76	0.39	0.02	15.49	0.19
S.D.	0.78	1.94	5.72	7.23	1.17	1.20	2.28	1.24	0.40	0.38	1.51	1.57	1.95	0.40
Min	12.08	−2.03	−9.78	33.48	2.32	5.45	1.55	1.00	1.57	2.83	−1.89	−3.54	9.91	−0.97
Max	16.97	5.46	33.76	77.15	8.71	10.60	19.57	5.00	3.69	4.47	4.86	5.77	18.74	2.32

Notes: Authors' own computation.
^ VIF value for Aggregate inactivity (log) obtained from separate model excluding Aggregate unemployment (log).

%, respectively, on average), the largest share is composed of unwilling workers (81 %), all showing rather stable trends over time.

Fig. 2 presents descriptive evidence on employment, unemployment, and inactivity across European countries. Looking at Panel 1, the European labor market presents consistent heterogeneities in terms of the relative distribution of the population across the three categories. Countries like the Netherlands, Sweden, and Germany feature the highest employment rates (above 75 %), while Spain and Greece spike in unemployment rates (above 13 %), and Italy and Hungary emerge for the highest inactivity rates across Europe (above 37 %). Panel 2 shows a strong heterogeneity even within types of unemployment with different durations between 2009 and 2019: short-term unemployment mostly characterizes countries such as Austria, Denmark, Finland, Luxembourg, Sweden, and the UK, while countries featuring the highest exposure to labor market exclusion due to long-term unemployment are Bulgaria, Greece, Hungary, Ireland, Italy, Portugal, and Slovakia. Finally, Panel 3 presents the composition of inactive individuals across countries, highlighting consistent heterogeneity, particularly concerning not-willing-to-work inactive individuals, whose share ranges between 70 % and 93 %, ranking lowest in Austria, Denmark, Italy, and Latvia. Tables A1 and A2 in the Online Appendix explore the heterogeneity of these categories across age, gender, and education groups.

4.2. *Automation trends in europe*

The digitalization process of European economies has steadily grown over the decade 2009–2019. From Fig. 3, European countries display a robust growth in terms of import, production, and adoption stocks of industrial automation technologies, growing respectively by 59 %, 96.3 %, and 69.5 % in absolute terms (as measured per person employed).

Examining cross-country differences in imports of automation technologies, Fig. 4 reveals that all European economies witnessed substantial, yet heterogeneous, levels of adoption. Specifically, the Netherlands, Hungary, Luxembourg, and Belgium feature as major

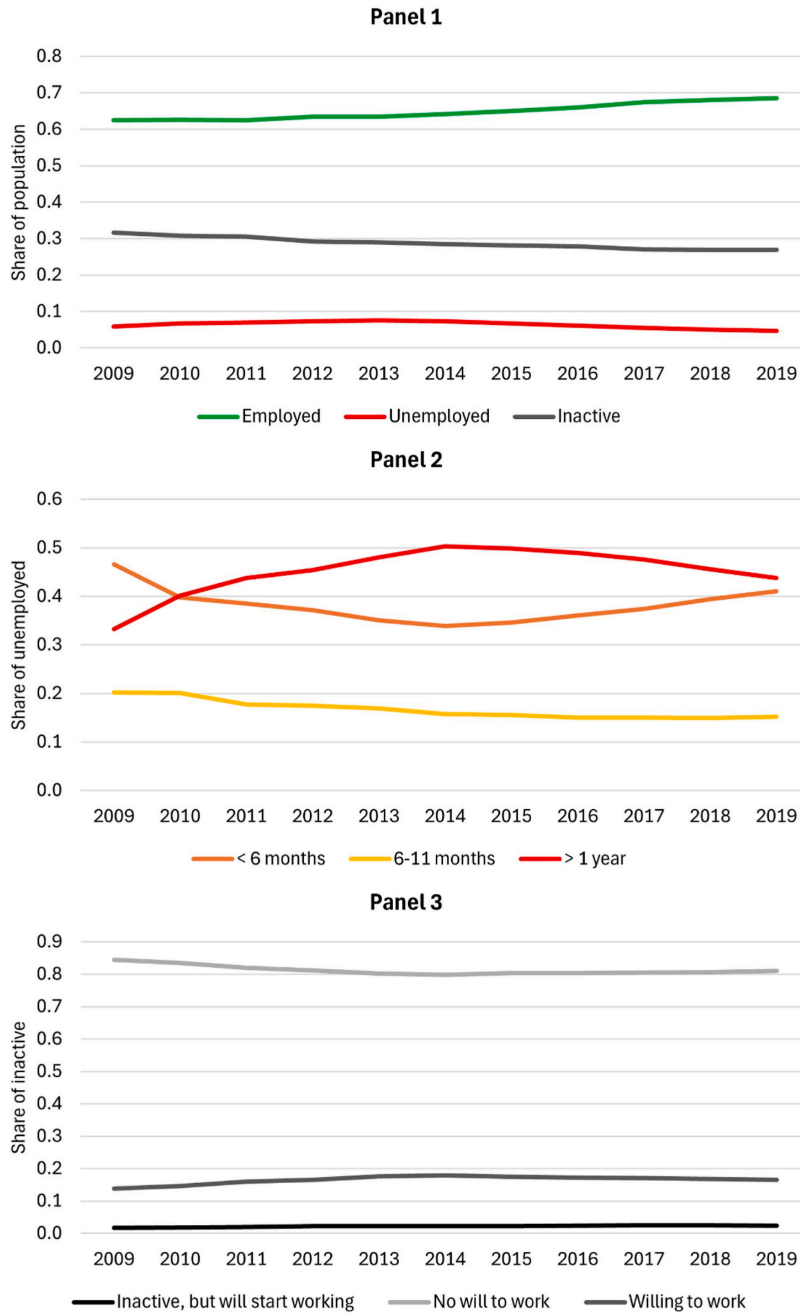

Fig. 1. Trends in employment, unemployment and inactivity by category between 2009 and 2019.
Notes: Authors' own computations based on LFS data.

importers but non-producing countries. Conversely, Germany, France, Italy, Denmark, and Austria display consistently high levels of imports despite being major producers of these technologies across the continent. Notably, as discussed by Castellani et al. (2022), while several EU27 economies are characterized by import-export patterns—still, remaining net importers, hence adopters of these technologies—those featuring the highest net consumption mostly correspond to producing countries like Germany, Denmark, and Italy. This emphasizes the role of local production hubs in boosting technology adoption.

5. Results

5.1. Main results

Table 3 presents the results of the probit models defined by Eqs. (1a) and (2a) of Section 3.3, showing the determinants of an individual probability of being long-term unemployed (columns (1)–(4)) and inactivity (columns (5)–(8)). We report coefficients as average marginal effects (AME) and from weighted estimates computed using sampling weights provided in the LFS.[9] Results from the Heckman's (1979) model are reported in columns (1)–(2) and (5)–(6), while results for van de Ven and van Praag's (1981) conditional mixed process model are reported in

[9] Although the sub-sample used in the econometric analyses is fully representative of the whole LFS population along many demographic and social characteristics, one crucial assumption behind unweighted regressions is that individuals in the sample are equally representative of the full population. This is frequently not the case and most large-scale surveys provide sampling weights to account for such differences in representativeness.

Fig. 2. Employment, unemployment and inactivity by category across EU27 + UK by country.
Notes: Authors' own computations based on LFS data.

columns (3)–(4) and (7)–(8). First stage (selection equation) estimates for unemployment in columns (1) and (3) are virtually identical and highlight the key role of aggregate unemployment in driving individuals' unemployment probability (1 % level statistical significance), while the intensity of employment protection legislation and immigration are factors mitigating chances of being unemployed (1 % and 5 % level statistical significance, respectively). Notably, automation adoption is not significantly correlated with an individual's unemployment probability overall, nor does it play any significant role in the second stage, reported in columns (2) and (4), suggesting no average effect on unemployment outcomes of any duration. Concerning model diagnostics, both the inverse Mills ratio (IMR) in column (2) and the

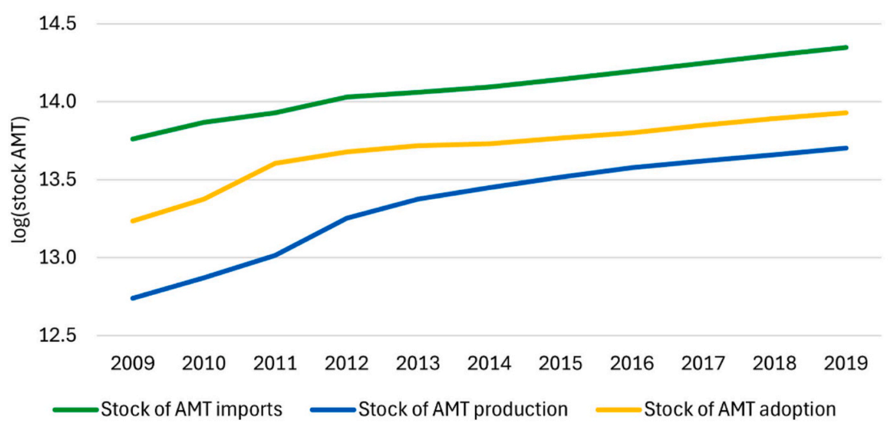

Fig. 3. Trends in measures of automation adoption between 2009 and 2019.
Notes: Authors' own computations based on Comext and Prodcom data. Automation adoption variables are normalized by total country employment and expressed in log. Stocks are computed following the PIM using a 15 % depreciation rate. AMT are industrial robots, additive manufacturing, internet-of-things.

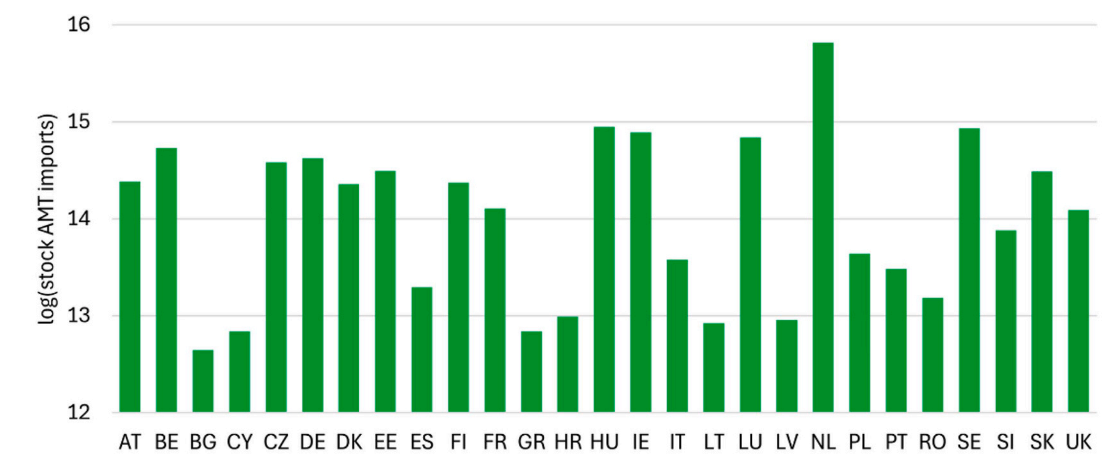

Fig. 4. Automation adoption across EU27 + UK by country.
Notes: Authors' own computations based on Comext, Prodcom, Eurostat, and OECD REGPAT data.

cross-equation correlation of residuals in column (4) are statistically significant, confirming the presence of selection and supporting the model's choice.

Columns (5) and (7) report AMEs from first stage estimates for inactivity. Aggregate inactivity level and a higher share of elder population are key drivers of the likelihood of individuals being out of the labor force (significant at the 1 % and 5 % level), while a higher presence of the service sector relative to manufacturing contributes to higher labor force participation, together with higher migration rates (5 % level statistical significance). Automation adoption is also found to contribute significantly to the individual's probability of being inactive, which is consistent with prior studies (e.g. Grigoli et al., 2020). Such a relationship implies that a 10 % growth in automation adoption brings about a 0.24 pp. higher probability of being inactive. Conditional on being inactive, our results from columns (6) and (8) highlight that adopting automation technologies exerts a stronger effect on labor market exclusion for unwilling-to-work inactive individuals. Specifically, a 10 % increase in the adoption of automation equipment is associated with between 0.68 and 0.91 pp. higher odds of being unwilling to work. We submit that one possible interpretation of this result is that growing automation in the workplace exacerbates job insecurity, a sense of psychological discouragement, and detachment from the idea of seeking a job (Blasco et al., 2025; Yam et al., 2023). Indeed, the complementary interpretation of this result goes in the direction of a significant drop in the willingness to work of discouraged workers. As for the diagnostics, the IMR and the cross-equation correlation of residuals are also statistically significant in inactivity models, suggesting good identification of the underlying selection process. Robustness of these results, based on unweighted estimates and mixed effect models with random intercept (ME–RI), are reported in Table A3 in the Online Appendix, showing no substantial difference compared to the main FE estimates.

5.2. Robustness checks

5.2.1. Two-step multilevel model

Besides FE and ME–RI models, Bryan and Jenkins (2016) discuss a two-step procedure where a pooled individual-level model is first estimated, including FE for a specific level of analysis, then these intercepts are fitted and regressed over variables of interest at the specific level of analysis, like automation variables in our case. This approach is more efficient than alternative approaches when the number of individuals per level (within-level variation) is large, but the number of levels (between-levels variation) is relatively small, leading to unbiased coefficients and correct standard errors for level-specific predictors, which can be estimated in the second step via OLS (Bryan and Jenkins, 2016). We leverage on this two-step approach to further test the robustness of our main results. Specifically, in the first step, we estimate, for each year *t* from 2009 to 2019, two sets of selection and treated models, including

Table 3
Probit models of long-term unemployment, inactivity and exposure to automation.

	Unemployment estimates				Inactivity estimates			
	Heckman		Conditional mixed process		Heckman		Conditional mixed process	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1st stage FE: UNE vs EMP	2nd stage FE: LT vs ST§	1st stage FE: UNE vs EMP	2nd stage FE: LT vs ST	1st stage FE: INA vs ACT	2nd stage FE: NW vs DW#	1st stage FE: INA vs ACT	2nd stage FE: NW vs DW
Aggregate unemployment	0.078***		0.078***					
	(0.007)		(0.007)					
Aggregate inactivity					0.228***		0.236***	
					(0.061)		(0.062)	
Service-to-manufacturing ratio	−0.003*		−0.003*		−0.005***		−0.005***	
	(0.002)		(0.002)		(0.002)		(0.002)	
Wage coordination	0.002		0.002		−0.002		−0.002	
	(0.002)		(0.002)		(0.002)		(0.002)	
Employment protection legislation	−0.033***		−0.033***		−0.012		−0.013	
	(0.012)		(0.012)		(0.011)		(0.011)	
Generosity of unemployment benefits	−0.007		−0.007		0.002		0.002	
	(0.007)		(0.007)		(0.006)		(0.006)	
Extreme climate events 1	−0.000		−0.000		−0.002*		−0.001	
	(0.001)		(0.001)		(0.001)		(0.001)	
Extreme climate events 2	−0.000		−0.000		−0.001**		−0.001**	
	(0.001)		(0.001)		(0.001)		(0.001)	
Pop. share > 65 years	0.010*		0.010*		0.009**		0.009**	
	(0.005)		(0.005)		(0.004)		(0.004)	
Net migration rate	−0.012**		−0.012**		−0.013**		−0.013**	
	(0.005)		(0.005)		(0.007)		(0.006)	
Automation adoption	0.007	−0.027	0.007	−0.036	0.024***	0.068***	0.024***	0.091***
	(0.008)	(0.033)	(0.008)	(0.033)	(0.008)	(0.013)	(0.008)	(0.016)
Advanced/digital innovation	−0.001	0.018**	−0.001	0.032***	0.002	−0.001	0.002	0.000
	(0.002)	(0.007)	(0.002)	(0.009)	(0.002)	(0.004)	(0.002)	(0.005)
Export surplus	0.000	0.001	0.000	0.004**	0.000	0.002***	0.000	0.003**
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)	(0.001)
Total GVC participation	−0.001	0.011***	−0.001	0.014***	0.001	0.003*	0.001	0.001
	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
IMR / Cross-equation corr(Residuals)^		−0.534***		−0.057**		0.690***		0.228***
		(0.109)		(0.030)		(0.157)		(0.041)
Constant	−2.931***	−1.977	−2.933***	−2.274	−8.677***	−4.404***	−8.959***	−3.518***
	(1.011)	(1.342)	(1.010)	(1.447)	(2.162)	(0.899)	(2.200)	(0.796)
Observations	2020,741	180,714	2020,741	180,714	2817,795	796,850	2817,795	796,850
Individual controls	YES		YES		YES		YES	
Region (NUTS-2) FE	YES		YES		YES		YES	
Year FE	YES		YES		YES		YES	

Notes: Reported coefficients are average marginal effects from weighted estimates. Linearized standard errors in parentheses (clustered at the NUTS-2 level). All regressors are lagged by one year. Individual controls: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Models (3), (4), (7) and (8) estimated using Roodman's (2011) `cmp` STATA command. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
^ In columns (2) and (6) we report the Inverse Mills Ratio (IMR) from the Heckman selection model, while in columns (4) and (8) we report the cross-equation correlation of residuals from the conditional mixed process model.
§ LT denotes individuals experiencing unemployment of duration higher than one year, while ST denotes individuals experiencing unemployment of duration lower than one year.
# NW denotes inactive individuals which are not willing to work, while DW denotes inactive individuals which are willing to work (discouraged workers).

only individual characteristics and country FE, which are estimated:

$$P(UNE_{i,c}=1) = \Phi[\alpha_0 + \alpha_1 I_{i,c} + \lambda_c + \varepsilon_{i,c}] \quad (3a)$$

$$P(LT_{i,c}=1) = \Phi[\beta_0 + \beta_1 I_{i,c} + \vartheta_c + \mu_{i,c}] \quad (3b)$$

$$P(INA_{i,c}=1) = \Phi[\gamma_0 + \gamma_1 I_{i,c} + \nu_c + e_{i,c}] \quad (4a)$$

$$P(NW_{i,c}=1) = \Phi[\delta_0 + \delta_1 I_{i,c} + \psi_c + u_{i,c}] \quad (4b)$$

where we still account for within-country, cross-region correlation among the error terms by clustering standard errors at the NUTS-2 level. We take predicted values of country FE $\widehat{\vartheta}_{c,t}$ and $\widehat{\psi}_{c,t}$ for each year t from Eqs. (3b) and (4b) and use these vectors as dependent variables in a second step estimation:

$$\widehat{\vartheta}^{LT}_{c,t} = \sigma_0 + \sigma_1 Aut_{c,t-1} + \boldsymbol{\sigma_2 C}_{c,t-1} + \boldsymbol{\sigma_3 Z}_{c,t-1} + \vartheta_c + \tau_t + \epsilon_{c,t} \quad (5)$$

$$\widehat{\psi}^{NW}_{c,t} = \varphi_0 + \varphi_1 Aut_{c,t-1} + \boldsymbol{\varphi_2 C}_{c,t-1} + \boldsymbol{\varphi_3 V}_{c,t-1} + \psi_c + \eta_t + \zeta_{c,t} \quad (6)$$

where we are interested in estimating σ_1 and φ_1 for our key explanatory variables on automation. Results for the second step of this multilevel model are reported in Table 4, with long-term unemployment in column (1) and inactive individuals who are unwilling to work in column (2).[10] The role of automation variables in affecting inactivity outcomes is supported, finding a statistically significant (5 % level) and economically sizable positive effect for the automation adoption variable, which is coherent with our main findings.

5.2.2. *Three-stage model*

The identification of individuals in the inactivity status may be seen as an additional selection process between the inactive and the active population, working on top of the selection process defining the identification of individuals in the unemployment and then in the long-term

[10] First step estimates are computed from weighted regressions. Second step results obtained from first step unweighted estimates are reported in Table A4 in the Online Appendix.

Table 4
Robustness: two-step multilevel model for long-term unemployment, inactivity and exposure to automation, second step (FE within-group) estimates.

	(1) LT	(2) NW
Aggregate unemployment	0.186	
	(0.135)	
Aggregate inactivity		−0.566
		(0.950)
Service-to-manufacturing ratio	−0.016	0.019
	(0.045)	(0.035)
Wage coordination	−0.022	−0.018
	(0.058)	(0.032)
Employment protection legislation	0.241	0.159
	(0.158)	(0.149)
Generosity of unemployment benefits	0.192	−0.034
	(0.178)	(0.126)
Extreme climate events 1	−0.028	−0.015*
	(0.023)	(0.008)
Extreme climate events 2	−0.042*	−0.007
	(0.021)	(0.008)
Pop. share > 65 years	0.060	−0.015
	(0.070)	(0.041)
Net migration rate	0.018	−0.021
	(0.120)	(0.079)
Automation adoption	−0.047	0.228**
	(0.201)	(0.105)
Advanced/digital innovation	0.086**	0.010
	(0.040)	(0.030)
Export surplus	0.007	0.007
	(0.009)	(0.006)
Total GVC participation	0.035	0.011
	(0.021)	(0.009)
Observations	283	283
Number of clusters	28	28
R-squared (within)	0.416	0.304
R-squared (between)	0.003	0.007
Year FE	YES	YES

Notes: Bootstrapped standard errors in parentheses (500 replications). Models are estimated following Bryan and Jenkins (2016) two-step multilevel model. Estimates are based on weighted regressions in the first step. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

unemployment condition. To disentangle this double selection process affecting long-term unemployment outcomes, we estimate a three-stage sample selection model using a recursive conditional mixed-process estimator based on the following set of three reduced form equations:

$$\begin{aligned} P(ACT_{i,c,r,t}=1) &= \Phi[\gamma_0+\boldsymbol{\gamma}_1\boldsymbol{I}_{i,c,r,t}+\gamma_2 Aut_{c,t-1}+\boldsymbol{\gamma}_3\boldsymbol{C}_{c,t-1}+\boldsymbol{\gamma}_4\boldsymbol{V}_{c,t-1}+\pi_{c,r}+\tau_t+e_{i,c,r,t}] \\ P(UNE_{i,c,r,t}=1) &= \Phi[\alpha_0+\boldsymbol{\alpha}_1\boldsymbol{I}_{i,c,r,t}+\alpha_2 Aut_{c,t-1}+\boldsymbol{\alpha}_3\boldsymbol{C}_{c,t-1}+\boldsymbol{\alpha}_4\boldsymbol{Z}_{c,t-1}+\lambda_{c,r}+\tau_t+\varepsilon_{i,c,r,t}] \\ P(LT_{i,c,r,t}=1) &= \Phi[\beta_0+\boldsymbol{\beta}_1\boldsymbol{I}_{i,c,r,t}+\beta_2 Aut_{c,t-1}+\boldsymbol{\beta}_3\boldsymbol{C}_{c,t-1}+\vartheta_{c,r}+\tau_t+\mu_{i,c,r,t}] \end{aligned} \tag{7}$$

where $ACT_{i,c,r,t}$ is defined as the inverse of $INA_{i,c,r,t}$ (i.e., it takes value 1 for active individuals, 0 for inactive individuals) and all other variables are defined as in Table 1 and Section 3.3. Results for both weighted and unweighted regressions are reported in Table A5 in the Online Appendix, estimated via a conditional mixed process. The estimated AMEs from the first stage are coherent with those reported in Table 3 concerning the inactivity models (columns (5) and (7)): coefficients are similar in magnitude and statistical significance. As the first selection equation is now looking at the probability of individuals to be active, coefficients have opposite signs to those found in Table 3. Similarly, estimates from the second and third stages are qualitatively and statistically in line with our results from columns (3) and (4) of Table 3, supporting the robustness of our main estimates and highlighting no significant effect of adopting automation technologies on the likelihood or duration of unemployment. Concerning the diagnostic test, cross-equation correlations of residuals are significant between activity and unemployment equations, and between unemployment and long-term unemployment equations, while it is not statistically significant between activity and long-term unemployment equations.

5.2.3. Leave-one-country-out replication

To check that our results are not disproportionately driven by specific countries, we computed a leave-one-out robustness test by re-estimating our main regression model on subsamples and omitting one country at a time. Results based on weighted estimations are reported in Figure A2 in the Online Appendix and do not highlight any country to be the main driver in our results.

5.2.4. Pooling unemployment and inactivity

Despite long-term unemployment and different inactivity status (e.g., discouraged workers) are distinct conditions, formally identified by precise definitions—for example, the former is still part of the labor force, while the latter not—actual boundaries between the categories may blur if long-term unemployment protracts way beyond one year of duration, depending on institutional and cultural and macroeconomic circumstances. Therefore, to further test the robustness of our results, we replicate the main estimates presented in Tables 3 and A3 for a sample where: (i) in the first stage, inactive and unemployed individuals are compared to employed individuals conditional on our regressors; then, (ii) in the second stage, conditional on being inactive or unemployed, we estimate the effect of automation variables on the likelihood of being either long-term unemployed or unwillingly inactive. Results are reported in Table A6 in the Online Appendix: the effects previously uncovered across inactive individuals drive the results of pooled estimates, highlighting a positive effect from automation adoption both on overall inactivity probabilities and on odds of losing the willingness to work—although this effect is smaller in magnitude as compared to estimates focusing solely on inactivity.

5.3. Heterogeneity analysis

The heterogeneity analysis, discussed in Section 3.3, explores how the average effect of adopting automation on labor market exclusion outcomes is moderated by demographic characteristics, like gender, age, and education. Estimates are reported in Fig. 5, showing AMEs for each demographic group. Panel 1 presents AMEs from interactions included in the first stage equation, looking at individual probabilities of being unemployed overall, conditional on individual characteristics and other controls. Here, the adoption of automation technologies—on average, not significant—is found to significantly raise odds of being unemployed only for highly educated individuals. Panel 2 shows differences in AMEs across demographic groups from first stage inactivity estimates: automation adoption—on average, significant—mostly affects female, less educated, and individuals aged 25–64, implying no relevant effect on chances of being out of the labor force for more educated individuals.

Moving to second stage estimates, Panel 3 explores moderation effects in the case of long-term unemployment. Also in this case, the average, not significant effect from automation adoption reported in Table 3 is confirmed across demographic groups, with an exception

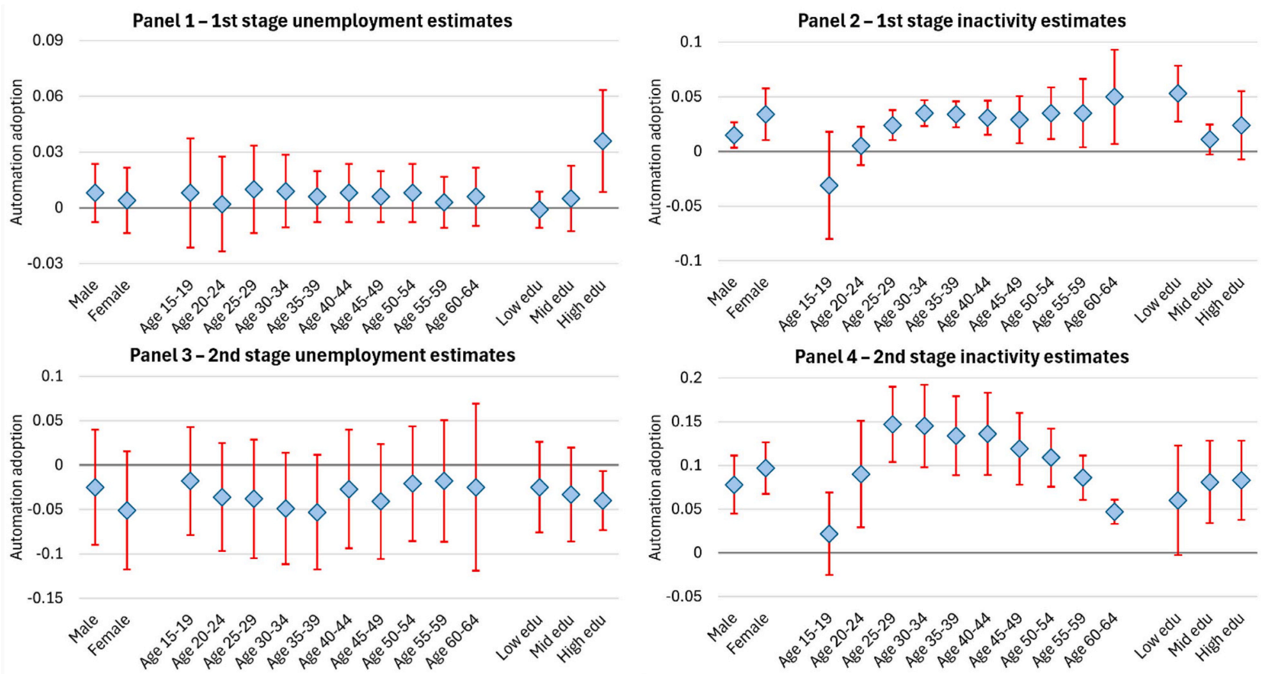

Fig. 5. Heterogeneity in the relationship between long-term unemployment, inactivity and exposure to automation adoption.
Notes: Reported coefficients are average marginal effects, based on weighted regressions. 95 % confidence intervals from linearized standard errors (clustered at the NUTS-2 level) are reported. Panel 1 reports estimated AMEs of the interaction terms for overall unemployment (UNE); Panel 2 reports estimated AMEs of the interaction terms for overall inactivity (INA); Panel 3 reports estimated AMEs of the interaction terms for long-term unemployment (LT); Panel 4 reports estimated AMEs of the interaction terms for not willing to work inactive individuals (NW). All models include individual characteristics, key controls, and all country-level controls. All regressors are lagged by one year. All models are estimated via conditional mixed process using Roodman's (2011) `cmp` STATA command.

made for highly educated individuals, who experience a lower probability of long-term unemployment. This suggests that some capital-labor (skilled) complementarity relates to a shorter duration of unemployment and faster re-employment, as found in previous works (e.g., Bachmann et al., 2024; Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Olsson and Tåg, 2017; Schmidpeter and Winter-Ebmer, 2021). Finally, Panel 4 presents AMEs of technology variables across demographic groups of unwillingly inactive individuals: the point estimate of the effect of automation adoption is larger among women, individuals aged 25–54, and middle/highly educated individuals, which is consistent with findings from similar studies (e.g., Grigoli et al., 2020). However, considering the size of the standard errors, differences across prime-age workers of different age bands do not appear to be statistically significant, although they are statistically different, and higher than the estimated effect for the over 60 group, who are the least affected by the rising unwillingness to work associated with the adoption of automation technologies.

6. Discussion and conclusions

Labor market exclusion has become a major concern in many advanced economies, exacerbated by the spread of automation and recent macroeconomic shocks, such as the Covid-19 pandemic. The issue is particularly salient in European countries marked by high unemployment (e.g., Spain, Greece) or elevated inactivity (e.g., Italy, Hungary). Although prior studies have examined how automation affects unemployment and re-employment prospects, evidence of its role in shaping different forms of exclusion remains limited. Our contribution is to systematically assess how the adoption of automation technologies relates to individuals' likelihood of entering and remaining in distinct unemployment and inactivity statuses.

Controlling for individual characteristics, macroeconomic confounders, and potential selection bias, we find that automation only contributes partially to exclusion dynamics. While it does not significantly affect the probability of unemployment or long-term unemployment, it does increase the likelihood of labor force detachment. This pattern aligns with the view that advanced digital technologies may heighten job insecurity and psychological discouragement, eroding the motivation of already inactive individuals to re-engage with the labor market (Blasco et al., 2025; Yam et al., 2023). Consistent with theoretical arguments on slow structural adjustment, and with a *techno-pessimist* view of automation, these mechanisms may amplify social and psychological barriers and increase vulnerability, ultimately leading to withdrawal from the labor force (Fang and Gunderson, 2015). Our results align with individual-level evidence documenting similar exclusion patterns (Grigoli et al., 2020; Leibrecht et al., 2023; Schmidpeter and Winter-Ebmer, 2021).

Heterogeneity analysis further shows that effects on the unemployed are broadly similar across groups, whereas the impact on inactivity is consistently stronger for prime-age individuals (25–54). Further inspection reveals that this group constitutes 26.7 % of the inactive population unwilling to work. Among them, around 16 % are those aged 25–29 who are not in education, employment or training (NEETs), while the remaining 84 % (aged 30–54) includes mostly married individuals—predominantly female (86 %, which may include housewives)—and single individuals, predominantly male (60 %). These patterns help identify which subgroups are most vulnerable to automation-related inactivity.

Existing research highlights the importance of up-skilling programs in mitigating adverse effects for displaced workers—particularly older or middle-/low-educated males—by improving resilience and employability (Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Schmidpeter and Winter-Ebmer, 2021). Our finding of no adverse unemployment effects, and no heterogeneity across unemployed groups, may indicate that such programs have been relatively effective in Europe. However, one-size-fits-all approaches appear insufficient for inactive individuals. NEETs—who are more vulnerable to psychological setbacks and long-term discouragement towards employment (Ralston et al., 2022)—and single adults aged 30–54 may benefit more from apprenticeships or vocational re-skilling, combined with social support or wage-based fiscal incentives. Married women, by contrast, would gain more from enhanced labor market flexibility, improved childcare (e.g., afterschool programs), and clearer information on new technology-enabled opportunities (e.g., government information campaigns, local vocational initiatives). These tailored interventions could help counteract discouragement and support labor force re-entry. At the same time, our results show that conventional labor market institutions—wage coordination, employment protection legislation, and unemployment benefits—have limited association with exclusion risks, consistent with other evidence on labor force participation (Grigoli et al., 2020). This underscores the need for more finely targeted policy tools.

More broadly, our results contribute to an ongoing paradox in the literature: while dominant narratives portray ICTs, AI, and robotics as transformative forces, empirical evidence often reveals modest or inconsistent labor market effects. This contrast mirrors the broader productivity slowdown documented since the mid-2000s in major OECD economies (Bergeaud et al., 2016; Cette et al., 2021). Explanations include structural shifts toward lower-productivity sectors (Pariboni and Tridico, 2020) and weakened innovation incentives under flexible labor market regimes (Kleinknecht, 2020; Wachsen and Blind, 2016). Brynjolfsson et al. (2017) further argue that diffusion lags, mismeasurement, and unequal distribution of gains may limit observable impacts in the short run. Our findings align with this broader body of work, suggesting that substantial technological advances may yield limited labor market effects when institutional and structural conditions constrain their translation into productivity and employment gains, associated with a *techno-optimist* view.

Our work is not exempt from limitations. While we address several econometric concerns, endogeneity may persist due to measurement issues arising from aggregate automation indicators, which may not fully capture differences in exposure across countries or technological domains. For unemployed individuals, exposure may depend on past occupations (Autor et al., 2015; Grigoli et al., 2020; Schmidpeter and Winter-Ebmer, 2021). Moreover, our education variable relies partly on imputation, which may introduce residual bias despite extensive checks. Looking forward, future research could draw on more granular measures of technological exposure and examine how new digital technologies shape wages and incentives for vulnerable and excluded groups.

Data availability

The data used in this paper are subject to Eurostat's microdata restrictions.

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CRediT authorship contribution statement

Fabio Lamperti: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Davide Castellani:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.strueco.2025.12.014.

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